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VIDEOTREE: Adaptive Tree-based Video Representation for LLM Reasoning on Long Videos

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https://videotree2024.github.io/

Abstract

Long-form video understanding is complicated by the high redundancy of video data and the abundance of query-irrelevant information. To tackle these challenges, we propose VIDEOTREE*, a training-free framework which builds a query-adaptive and hierarchical video representation for LLM reasoning over long-form videos. First,* VIDEOTREE *extracts query-relevant information from the input video through an iterative process, progressively refining the selection of keyframes based on their relevance to the query. Furthermore,* VIDEOTREE *leverages the inherent hierarchical structure of long video data, which is often overlooked by existing LLM-based methods. Specifically, we incorporate multi-granularity information into a tree-based representation, allowing* VIDEOTREE *to extract query-relevant details from long videos in a coarse-to-fine manner. This enables the model to effectively handle a wide range of video queries with varying levels of detail. Finally,* VIDEOTREE *aggregates the hierarchical query-relevant information within the tree structure and feeds it into an LLM reasoning model to answer the query. Our experiments show that our method improves both reasoning accuracy* and *efficiency. Specifically,* VIDEOTREE *outperforms existing training-free approaches on EgoSchema and NExT-QA with less inference time, achieving* 61.1% *and* 75.6% *accuracy on the test set without additional video-specific training. Moreover, on the long split of Video-MME (average 44 minutes),* VIDEOTREE *achieves better performance than GPT-4V and many other MLLMs that were extensively trained on video data.*

1. Introduction

With the surge in accessible long video content and the growing importance of applications such as long-form human behavior analysis and movie analysis, developing models capable of reasoning over and answering questions about long-form videos has become increasingly crucial. Recently, several approaches [19, 72, 89] have emerged that leverage the long-sequence reasoning capabilities of Large Language Models (LLMs) to tackle the challenge in long-form video understanding in a training-free manner. Typically, these approaches leverage vision-language models (VLM) to caption densely sampled frames, thus representing the video in text format. This text representation is then subsequently fed into an LLM, which reasons over the video and responds to the provided query. Although this strategy has demonstrated great potentials on long-form video understanding benchmarks, it still faces two major limitations:

1) Informational Overload: Long videos inherently contain high levels of information redundancy, and current approaches [7, 89] lack a principled method to effectively address this challenge. A deluge of redundant and irrelevant

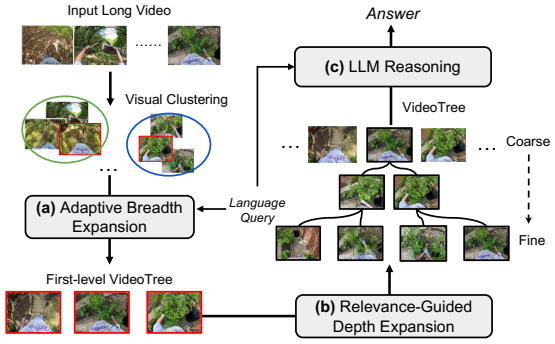


Figure 1. Overview of VIDEOTREE for LLM reasoning on long videos. Given the long video input, we first apply adaptive breadth expansion to identify the first-level keyframes for VIDEOTREE. Next, we use relevance-guided depth expansion to explore the inherent hierarchical structure of the video, forming a tree-based representation. Finally, the coarse-to-fine information extracted by VIDEOTREE is fed into the LLM reasoner to answer the query.

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information can overwhelm the LLM, leading to mistakes in long-form video reasoning and reduced efficiency.

2) Inability to Capture the Coarse-to-Fine Video Structure: Existing approaches [67, 89] often simplify video content into a list of captions without any structure, failing to account for the hierarchical nature of video information. Especially in long videos, some regions are information-dense – requiring fine-grained temporal understanding – while others are irrelevant to the query, or information-sparse. Because of this, existing approaches not only suffer from overload problems, as mentioned above, but also omit key information from the captions, leading to missed details.

These limitations underscore the pressing need for a new long-form video understanding method. To this end, we introduce **VIDEOTREE**, a training-free framework for long-form video understanding. VIDEOTREE dynamically extracts query-relevant keyframes from the video input in a coarse-to-fine manner and organizes them within a tree structure, with child nodes representing more fine-grained information. VIDEOTREE is *adaptive*, meaning that our method allocates more frames to relevant video regions and fewer frames to irrelevant ones based on the given query. VIDEOTREE is also *hierarchical*. Unlike existing approaches [67, 89], which treat video as a list of frames, we explore the inherent structure within the video data (e.g., events, scenes) to extract fine-grained information relevant to the query.

VIDEOTREE relies on three crucial steps: **adaptive breadth expansion** (Fig. 1a), **relevance-guided depth expansion** (Fig. 1b), and **LLM-based reasoning** (Fig. 1c). To address redundancy in long videos, VIDEOTREE first leverages an adaptive breadth expansion module to extract query-relevant information, forming the initial level of representation. We utilize an iterative process of visual clustering, keyframe captioning, and relevance scoring until sufficient query-relevant information is gathered. Compared to existing approaches [19, 89] that rely on dense frame captions, VIDEOTREE selects only sparse keyframes for captioning, which significantly improves inference efficiency and helps avoid irrelevant information that could interfere with accurate video reasoning. To capture more fine-grained information, we introduce a relevance-guided depth expansion step that adds finer, query-specific details in a hierarchical structure, forming a tree-based representation. Finally, we generate video descriptions from the structured representation using a captioner and provide them, along with the query, to the LLM for long video reasoning.

We demonstrate the effectiveness and efficiency of VIDEOTREE by evaluating it on two mainstream long video question answering (LVQA) datasets, EgoSchema [42]and NExT-QA [81]. Compared existing training-free approaches, VIDEOTREE achieves 2.1% and 4.3% improvements on EgoSchema(subset) and NExT-QA validation set with less inference time or LLM calls. To further validate VIDEOTREE effectiveness on very long videos, we test our method on the long split of the recent Video-MME benchmark [10] and VIDEOTREE achieves better performance than the strong proprietary GPT-4V model. Our ablation studies show that VIDEOTREE outperforms the the same category methods (VideoAgent [67] and LLoVi [89]) under all number of captions and observes better efficiency-effectiveness trade-off. We further provide addition results on open-source LLM, where VIDEOTREE shows strong generalization ability across different language backbone models and achieves 4.8% improvements against the LangRepo approach [19].

2. Related Work

Structural Video Representation. Video understanding [26, 30, 32, 34, 35, 39, 52, 56, 61, 64, 74, 76, 78, 83] has shown impressive advancement in both views of comprehension and efficiency. Recently, several video-language methods [1, 15, 28, 38, 50, 53, 77, 80, 84, 85, 87, 88] have further introduced a structured understanding of video frames to allow compact and efficient recognition of scene contexts. For example, HierVL [1] proposes a *bottom-up* hierarchical video-language embedding that capture video representations across short and long time periods. VideoReCap [15] introduces a progressive video captioning approach that generates short clip-level captions and summarizes them into longer segments. These methods process long videos by progressively building high-level knowledge from local temporal information, i.e. in a bottom-up fashion that first captures all low-level details and then aggregates. This results in significant computational and time overhead. In contrast, inspired by the existing coarse-to-fine video understanding works [73, 79], VIDEOTREE proposes a novel top-down approach with a tree structure, enabling efficient and effective long video understanding by dynamically extracting query-relevant keyframes for LLM reasoning.

Video Understanding with LLMs. Inspired by the powerful reasoning capabilities of LLMs, recent works have explored using LLMs to address complex video-related tasks. Since LLMs primarily process text, various methods [2, 12, 18, 22, 25, 27, 29, 31, 40, 44, 59, 71, 75, 90**?**] have been developed to efficiently train multimodal projectors to connect the visual encoder and LLMs or leverage caption-centric information. Past works [6, 9, 19, 21, 58, 60, 65, 67, 72] has investigated training-free combinations of captioners and LLMs for video understanding. Specifically, LLoVi [89] proposes a simple language-guided video understanding method. First, it extracts short-term video descriptions with a captioning model, and then an LLM summarizes these dense captions and responds to the given prompt. VideoAgent [67] introduces a multi-round frame search strategy using an LLM agent. Unlike existing approaches, we propose a novel

method to extract the key information from videos in an adaptive and coarse-to-fine manner with the agent, improving both efficiency and performance on long video understanding tasks. Moreover, VIDEOTREE improves interpretability by highlighting key visual clues for LLM reasoning via its human-readable tree structure.

3. VIDEOTREE Method

We present VIDEOTREE, a framework for constructing a query-adaptive, hierarchical video representation for efficient LLM reasoning over long videos. As illustrated in Fig. 2, the VIDEOTREE framework consists of three main steps: adaptive breadth expansion, relevance-guided depth expansion, and LLM video reasoning. Given the highly redundant nature of long videos, VIDEOTREE first leverages an adaptive breadth expansion module to extract query-relevant information from the video, forming the initial level of representation (Sec. 3.1). To capture finer-grained details, we propose a relevance-guided depth expansion module that progressively adds finer-grained, query-specific details to in a hierarchical manner, forming a tree-based representation (Sec. 3.2). Finally, we extract the video description from the constructed tree representation by using a captioner to caption selected frames. We feed it, along with the query, into the LLM for long video reasoning (Sec. 3.3).

3.1. Adaptive Breadth Expansion

Video data is often highly redundant, and long videos can contain substantial amounts of irrelevant information relative to the given video query. Addressing this redundancy and filtering out irrelevant content is crucial for efficient and effective long video understanding. Existing approaches [66, 86] select a fixed number of keyframes as the key information. However, as discussed in Sec. 1, this fixed keyframe selection is sub-optimal for a general long video-language understanding framework, since the information density varies across videos—some contain numerous scene changes, while others remain largely static. To address this, we propose an adaptive breadth expansion module that constructs the first level of the tree representation by dynamically identifying keyframes that are relevant to the given query. Specifically, as shown in the left of Fig. 2 (Step 1), given the video and a query about it, we build the first level of the tree by iterating three operations: **visual clustering**, **cluster captioning,** and **relevance scoring**. These operations first group similar frames together, then generate captions for each cluster, and use the LLM to determine how relevant each cluster is to the query. VIDEOTREE iterate these operations until getting enough query-relevant information from long videos in an *adaptive* manner. In the following paragraphs, we provide a detailed motivation and introduction for each operation.

Visual Clustering. To reduce the redundancy, we first propose a visual clustering operation that groups the video frames based on semantic similarity, allowing the model to focus on representative frames from each cluster while discarding repetitive or irrelevant content. Specifically, given a video sequence $V = (F_1, F_2..., F_n)$, where F_i is the frame at the time step i and n is the length of the video, we extract visual features for each frame with the pre-trained visual encoder [57] E, such that $f_i = E(F_i)$, where $f_i \in \mathbb{R}^d$ is the visual features extracted by the frame F_i. These features serve as a compact representation of each frame's visual content, capturing diverse semantics of each frame, such as scenes and objects. We then use K-Means clustering [41] to group frame features into k distinct clusters based on their similarity, which we denote as:

$$(C_1, \ldots, C_k), (c_1, \ldots, c_k) = \text{K-Means}((f_1, \ldots, f_n), k) \quad (1)$$

where, C_i is the ith cluster that groups multiple frames, c_i is the centroid vector for the ith cluster and k is the number of clusters. This clustering process reduces the redundancy within the video by converting the input from n frames into k clusters of similar frames (where $n \gg k$), effectively summarizing the video into k keyframes (cluster center frame) that capture the essential semantics.

Cluster Captioning. To better extract the key semantics from each cluster, we leverage a captioner to convert the keyframe information (a single frame or short clip around the keyframe) from each cluster to a textual description. Specifically, for the cluster C_i, we find the keyframe F_i that is closest to the centroid vector c_i and consider it as the keyframe of the ith cluster. We then feed the extracted keyframe (or the key clip) into the VLM-based captioner $Cap(\cdot)$ [36, 93] and obtain a text caption $t_i = Cap(F_i)$ for each cluster. These text captions serve as detailed descriptions of the key semantics from the corresponding clusters.

Relevance Scoring. To encourage the model to extract query-relevant information, after obtaining the cluster captions t, we leverage the reasoning capability of the LLM to assess whether the extracted information are sufficient for answering the given query. To this end, we first feed all cluster captions $\{t_i \ \forall i \in [1, \ldots, k]\}$ from the last operation and the video query Q into the LLM and output a set of relevance scores $\{r_i \ \forall i \in [1, \ldots, k]\}$ for each cluster, where r_i is the relevance of the i_{th} cluster. Specifically, to obtain each r_i, we prompt the LLM with the captions and the query, asking it to assign a relevance score to each caption, with three levels: 1 (not relevant), 2 (somewhat relevant), and 3 (highly relevant). See Tab. 16 for all detailed prompts.

Then, we adaptively extract the query-relevant information within the video by iterating the clustering, captioning,

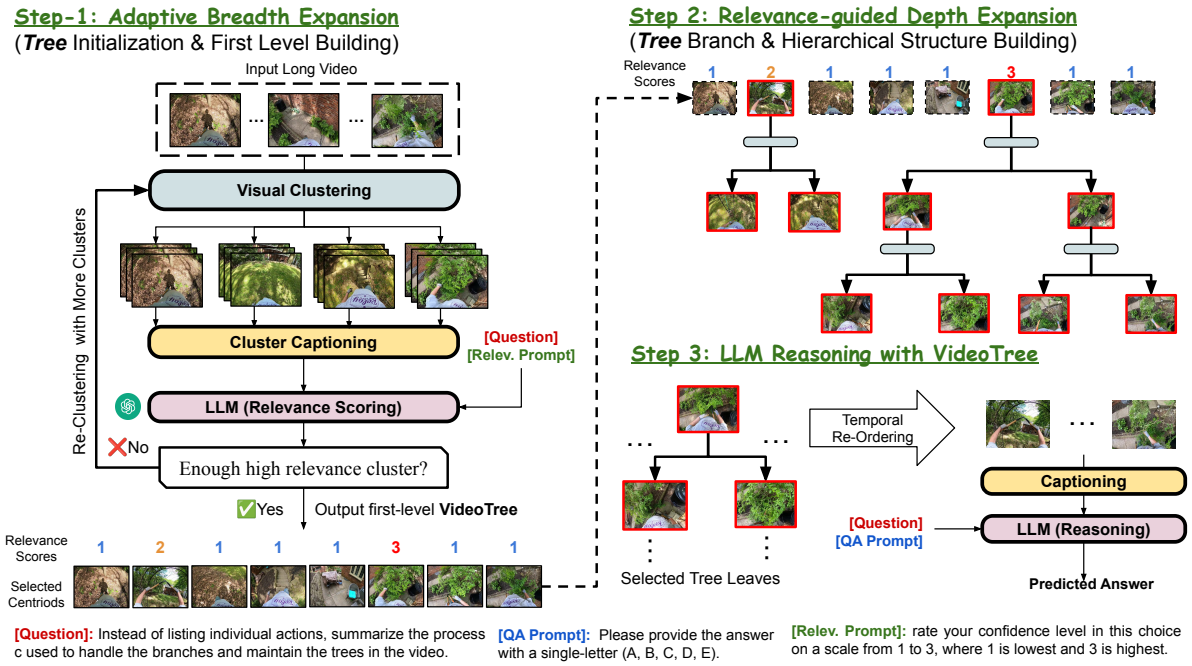


Figure 2. A detailed view of VIDEOTREE. To construct the tree structure, we begin with *Adaptive Breadth Expansion* (Step 1), which dynamically extracts query-relevant key information, considering both video and question inputs. Then, starting from the highly relevant root nodes, we explore deeper into the tree branches with *Relevance-guided Depth Expansion* (Step 2), re-clustering at each level to capture finer visual cues. Finally, we gather the selected nodes (keyframes), caption them, and arrange them in temporal order for *LLM reasoning* (Step 3).

and relevance scoring operation. Specifically, given the list of relevance scores for each cluster, we set a threshold of the number of highly relevant clusters $rele_num_thresh$ to decide the stop of the adaptive process. We also set a maximum value for the number of clusters ($max_breadth$) to avoid infinite loops. If the number of highly relevant clusters is below the requirement, that indicates the information extracted from the current cluster assignment is insufficient for the LLM to answer the video query. In that case, we increase the number of clusters k by double the original number and repeat the clustering, captioning, and relevance scoring operations. If the number of high-relevance clusters meets the threshold $rele_num_thresh$ or the number of clusters reaches $max_breadth$, we append the extracted clusters with their keyframes to the tree's first layer and continue to the next step (Algorithm 1, lines 2-11 for details).

3.2. Relevance-Guided Depth Expansion

After obtaining the first-level clusters and their keyframes, VIDEOTREE captures high-level query-relevant information from the video input. However, some video regions are information-dense and critical for answering the query, requiring a more detailed selection of keyframes.

Existing approaches, such as SeViLA [86] and VideoAgent [67], typically treat the selected frames as an unstructured list, overlooking the potential internal structure within the video data. To address this, as shown in Step 2 of Fig. 2, we construct a hierarchical video representation on top of the clusters from the previous breadth expansion step, allowing us to efficiently extract query-relevant details by leveraging the semantic relationships within the video data. Specifically, we expand the depth of the tree by sub-clustering the clusters with higher relevance scores from the first step. The intuition is that for high-relevance clusters, the LLM requires more detailed, granular information, while for low-relevance clusters, more information could actually lead to irrelevant details being included and could thus overwhelm the LLM, leading to incorrect reasoning.

To build the hierarchical structure, we use the relevance of a top-level cluster to determine how many levels of more granular information will be extracted from it. Since the relevance score r falls into one of three levels, we handle each first-level cluster differently based on its assigned relevance level. For "somewhat relevant" clusters, we re-cluster the first-level cluster into w sub-clusters, where w represents the tree's branch width, ensuring that more keyframes are allocated to these moderately relevant clusters. For "highly relevant" clusters, we re-cluster into a two-level tree with a branch width of w using hierarchical clustering while keeping the 1st-level cluster information from the previous K-Means step. This coarse-to-fine exploration strategy allows for the detailed extraction of relevant information, supporting comprehensive video analysis for complex

queries. We repeat this process for all first-level medium- and highly-relevant clusters and build the hierarchical structure of VIDEOTREE (lines 12-15 in Algorithm 1). After the breadth and depth expansion steps, we obtain the tree-based video representation for LLM reasoning over the long video.

3.3. LLM Video Reasoning

Finally, in order to use the LLM's ability on video reasoning, we need to present the LLM with a text-based video description. To this end, we traverse the nodes of the tree starting at the roots and expanding to the leaves, extracting keyframes from the tree's clusters at all levels and passing them into the captioner to obtain keyframe (short clip) captions. We then sort these keyframe (short clip) captions in temporal order and concatenate them into a textual description of the video. Finally, we pass this description and the input query to the LLM and output the final answer (see line 16-18 in Algorithm 1). Our full prompt is in Tab. 17.

4. Experimental Setup

Tasks & Datasets. We test VIDEOTREE on three diverse long-form video question-answering benchmarks: (1) **EgoSchema** [42], a long-range video question-answering benchmark consisting of 5K multiple choice question-answer pairs spanning 250 hours of video and covering a wide range of human activities. Our ablation studies are conducted on the official validation set of EgoSchema which contains 500 questions (referred to as the EgoSchema Subset). The videos are 180 seconds long on average. (2) **NExT-QA** [81], a video question-answering benchmark for causal and temporal reasoning. It contains 5440 videos with an average length of 44s and approximately 52K questions. NExT-QA contains 3 different question types: Temporal (Tem.), Causal (Cau.), and Descriptive (Des.). (3) **Video-MME** [10] is a recent-proposed comprehensive evaluation benchmark for video analysis. We test VIDEOTREE on the "long-term videos" split of the dataset (long split), whose average video length is 44 minutes, ranging from 30-60 minutes.

Implementation Details. We adopt GPT-4[1] [46] as our LLM for all the main results. We also provide the results with open-source LLM (Sec. 5.2) and other proprietary LLMs (Sec. 9). Following VideoAgent [67], we leverage EVA-CLIP-8B [57] as our visual encoder and also provide experimental analysis with smaller visual encoder in Sec. 5.2. Following VideoAgent [67], we leverage CogAgent [13] as the captioner for NExT-QA benchmark and use LaViLa [93] as our captioner for the EgoSchema benchmark due to its ego-centric video pretraining (we also show results in Tab. 14 using a unified captioner (LLaVA1.6-7B [36]) for all benchmarks). For Video-MME, we directly use the default unified LLaVA1.6-7B captioner. We preprocess videos by simply sampling the original frames at 1FPS for EgoSchema and NExT-QA benchmark and 0.125 FPS for Video-MME. The best-performing average number of captions for EgoSchema subset, Next-QA and Video-MME is 62.4, 12.6 and 128, respectively. We ablate our hyper-parameter choices in Sec. 9.

[1]version 1106

Evaluation Metrics. We evaluate VIDEOTREE on all datasets under the multiple-choice QA setting. We utilize standard accuracy metrics for all experiments.

5. Results

5.1. Comparison with Existing Approaches

Comparison with training-free methods. Sec. 5.1 shows a comparison of the existing training-free works and VIDEOTREE on EgoSchema and NExT-QA benchmarks. We compare our methods with three types of systems: those using all open-source LLMs [19, 51, 54], those with proprietary MLLMs [20, 49], and the most similar class to ours, which consists of methods with open-source captioners and proprietary LLMs [6, 9, 43, 65, 67, 72, 89]. Specifically, compared with the methods that leverage the same VLM (captioner) and LLM [67, 72, 89], VIDEOTREE significantly outperforms these methods on both EgoSchema and NExT-QA benchmarks. Comparing with VideoAgent [9] which also uses video-specific models (Video-LLaVA [30], ViCLIP from InternVid [69]) which were trained on extensive video data, VIDEOTREE still performs better on EgoSchema. Moreover, comparing with the methods that utilize strong multimodal LLMs, VIDEOTREE significantly outperforms IG-VLM [20] (based on GPT-4V[45]) on both EgoSchema and NExT-QA benchmarks and obtains comparable results on the EgoSchema full test set compared to the recent LVNet [49] (which uses the more powerful GPT-4o for both captioner and LLM) while outperforming LVNet on NExT-QA benchmarks. Additionally, we observe a significant gap between VIDEOTREE and the open-source LLM-based approaches, highlighting the need of strong LLM reasoning module in our method. For the sake of making a fair comparison, we also show VIDEOTREE's ability using open-source LLM in Tab. 4, where we obtain an 4.8% improvement on the EgoSchema subset. These results showcase the effectiveness of VIDEOTREE compared with existing training-free methods. Moreover, VIDEOTREE is also more efficient: we show analyses measuring the number of captions in Fig. 3 and inference time in Tab. 3, where VIDEOTREE is more efficient than relevant baselines.

[1]We de-emphasize the EgoSchema results of LangRepo since it predicts the answers via a log-likelihood classifier rather than generation, making it different from all other methods (including VIDEOTREE). We provide a comparison using the same classifier and LLM in Tab. 4 and show 4.8% improvements under same settings.

Model	(M)LLM	EgoSchema		NExT-QA			
		Sub.	Full	Tem.	Cau.	Des.	Avg.
Based on Open-source Captioners and LLMs							
MVU [51]	Mistral-13B	60.3	37.6	55.4	48.1	64.1	55.2
LangRepo [19]	Mixtral-8×7B	66.2[1]	41.2	51.4	64.4	69.1	60.9
Video-LLaVA+INTP [54]	Vicuna-7B v1.5	-	38.6	58.6	61.9	72.2	62.7
Based on Proprietary MLLMs							
IG-VLM [20]	GPT-4V	59.8	-	63.6	69.8	74.7	68.6
LVNet [49] [2]	GPT-4o	68.2	61.1	65.5	75.0	81.5	72.9
Based on Open-source Captioners and Proprietary LLMs							
ProViQ [6]	GPT-3.5	57.1	-	-	-	-	64.6
LLoVi [89]	GPT-3.5	57.6	50.3	-	-	-	-
MoReVQA [43]	PaLM-2	-	51.7	64.6	70.2	-	69.2
Vamos [65]	GPT-4	51.2	48.3	-	-	-	-
LLoVi [89]	GPT-4	61.2	-	61.0	69.5	75.6	67.7
VideoAgent [67]	GPT-4	60.2	54.1	64.5	72.7	81.1	71.3
VideoAgent [9]	GPT-4	62.8	60.2	-	-	-	-
LifelongMemory [72] [3]	GPT-4	64.1	58.6	-	-	-	-
VIDEOTREE (Ours)	GPT-4	**66.2**	**61.1**	**70.6**	**76.5**	**83.9**	**75.6**

Table 1. Comparison with other training-free methods on EgoSchema and NExT-QA. VIDEOTREE outperforms the existing approaches on all evaluation metrics.

Method	Acc
Proprietary MLLM	
GPT-4V	53.5
GPT-4o	65.3
Gemini 1.5 Pro	**67.4**
Open-Source MLLM	
LongVA	46.2
VITA	48.6
InternVL2-34B	52.6
VILA-1.5-40B	53.8
Oryx-1.5-34B	59.3
LLaVA-NeXT-Video-72B	61.5
Qwen2-VL-72B	**62.2**
Training-free Approach	
LLoVi	48.8
VIDEOTREE (Ours)	**54.2**

Table 2. Video-MME long split results. VIDEOTREE outperforms the strong proprietary GPT-4V model and many other specially-trained open-souce video MLLMs (e.g. InternVL2-34B, VILA-1.5-40B) despite being training-free.

Evaluating on Very Long Videos. To further highlight the strength of our approach on longer videos, we includue results on Video-MME [10]'s long split, which contains a diverse set of very long videos (up to 1 hour, with an average of 44 minutes). We compare our training-free method with three types of models, including proprietary MLLMs [8, 45, 47] and open-source MLLM [3, 4, 11, 37, 63, 66, 91, 92], both of which are trained on large-scale video(image) data, and training-free baseline LLoVi [89]. As shown in Sec. 5.1, compared to the training-free baseline, LLoVi, VIDEOTREE achieves a substantial 5.4% improvement on the long split of the Video-MME benchmark, demonstrating its effectiveness in understanding videos across long time-scales. Compared to proprietary MLLMs, VIDEOTREE outperforms the strong GPT-4V [45] model by 0.7%. However, there is still a gap between VIDEOTREE and powerful long-context proprietary MLLMs (GPT-4o [47], Gemini 1.5 Pro [8]). When comparing to open-source MLLMs that were extensively trained on video data, our training-free VIDEOTREE method outperforms a number of these strong MLLMs including ViLA-1.5-40B [33] and Intern-VL2 [4]. VIDEOTREE achieves strong performance without additional training on long video data.

5.2. Analysis

Below, we provide a detailed analysis of VIDEOTREE framework. All quantitative analyses are conducted on the validation subset of the EgoSchema dataset. First, we analyze the trade-off between efficiency and effectiveness, showing that our method has better efficiency *and* performance across all settings compared to existing methods. We then provide an comprehensive ablation study for different design choice of VIDEOTREE. Finally, we visualize the tree from VIDEOTREE and show the clusters VIDEOTREE chooses to expand, qualitatively supporting its quantitative gains.

5.2.1. Efficiency-Effectiveness Analysis

In Tab. 3, we show the efficiency-effectiveness trade-off of our approach compared to existing methods. Specifically, we compare VIDEOTREE with LLoVi [89] using the same GPT-4 model as LLM (and same captioner). Comparing to the best model, LLoVi, VIDEOTREE-fast (which uses fewer frames by changing the hyper-parameters) achieves a 2.4% improvement on the EgoSchema subset with only 33% the time cost. Moreover, our best model obtains a 5.0% improvement with less overall inference time compared to both LLoVi models. Profiling the inference time spent in different modules (including frame captioning, extracting keyframes/caption summarization, performing QA), we find that our hierarchical keyframe selection consumes a reasonable amount of time while significantly reducing the time cost in the captioning stage and boosting long video understanding performance. We also provide an ablation of average LLM calls and compared with VideoAgent [67] in Tab. 9 showing that VIDEOTREE requires fewer LLM calls while having better performance. These results show that

[2] For fair comparison, we de-emphasize methods that use a much stronger MLLM (GPT-4o) as both the captioner and the LLM.

[3] Reproduced results, implementation details in Sec. 11

Method	Captions	Captioner (s)	Keyfr. (s)	QA (s)	Overall (s)	Acc.
LLoVi-fast	16	2.0	0	1.9	**3.9**	57.8
LLoVi-best	180	22.4	0	2.4	24.8	61.2
VIDEOTREE-fast	**13.6**	**1.6**	4.4	**1.8**	7.8	63.6
VIDEOTREE-best	62.4	7.8	10.2	2.1	20.1	**66.2**

Table 3. Efficiency-Effectiveness comparison between LLoVi and our approach. We benchmark the time cost of VIDEOTREE and LLoVi [89], split into seconds spend in frame captioning, extracting keyframes, performing QA, and also report overall time. Using only 33% inference time, VIDEOTREE(fast) already achieves both better performance compared to LLoVi(best).

Method	# Caption	Acc.	Inf Time (s)
Based on Mistral-7B			
LLoVi	180	50.8	-
LangRepo	180	60.8	87.2
VIDEOTREE (ours)	32	**63.0**	**24.3**
Based on Mistral-8×7B (12B)			
LangRepo	180	66.2	162.1
VIDEOTREE (ours)	32	**71.0**	**50.3**

Table 4. Accuracy on the EgoSchema subset when using open-source LLM Reasoners and log-likelihood classifier. VIDEOTREE obtains better performance with less inference time on both 7B and 12B LLMs comparing to the LangRepo baseline [19].

Module	ES Acc.
VIDEOTREE	66.2
- Depth Expansion	64.4
- Adaptive Breadth Expansion	61.2

Table 5. Effect of different VIDEOTREE components. Both Adaptive Breadth Expansion and Depth Expansion modules contribute significantly to the effectiveness of VIDEOTREE.

VIDEOTREE has better effectiveness and efficiency compared to the existing method.

5.2.2. Ablation Study

In this section, we conduct ablating different parts of VIDEOTREE on the EgoSchema subset. We ablate three features: Number of captions, applying open-source LLM and different VIDEOTREE components. We include more extensive ablations (including hyper-parameters and the design of captioner/LLM/vision encoder) in Appendix Sec. 9.

Number of Captions. In Fig. 3, we compare VIDEOTREE with existing methods under different caption settings. Under similar average frame caption settings (7, 9, 11), VIDEOTREE outperforms LLoVi [89] and VideoAgent [67] by 6.5% and 2.0% on average accuracy across all three settings. Moreover, unlike the non-hierarchical VideoAgent baseline, which suffers from performance degradation after 11 frame captions (performing worse with 14 frame captions), our method continues improving, generalizing to 62.4 frame captions and achieving 6% boost at its peak. It highlights the importance of VIDEOTREE's hierarchical nature.

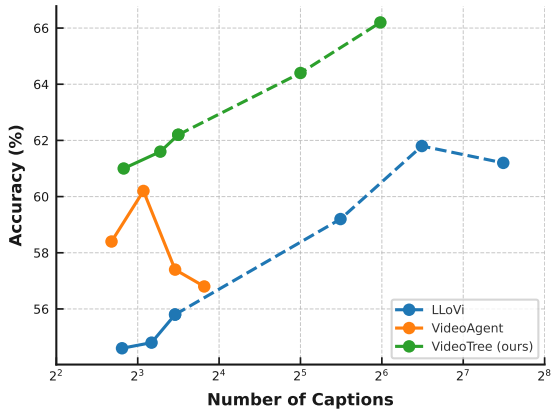


Figure 3. Ablating the number of captions. Given approximately the same number of frames, VIDEOTREE substantially outperforms LLoVi and VideoAgent. Our hierarchical nature also allows it to generalize better to more frames and perform better overall.

Open-source LLM Reasoner. To validate the effectiveness of VIDEOTREE with open-source LLM reasoners (rather than GPT4), in Tab. 4, we report the performance of VIDEOTREE using 7B and 12B versions of the Mistral model [16, 17] as the LLM reasoner. We compare with LLoVi [89] and LangRepo [19]. For a maximally fair comparison, we follow LangRepo's evaluation pipeline, using a log-likelihood classifier that scores all options and takes the highest-scoring one. VIDEOTREE substantially outperforms the baseline approaches on both 7B and 12B Mistral models while only requiring 20% of the frame captions. Specifically, compared to LangRepo, which uses complex textual summarization modules, VIDEOTREE achieves 2.2% and 4.8% better EgoSchema subset performance while using about 72.5% and 69.0% less inference time on Mistral 7B and 12B LLM, respectively. These results confirm that VIDEOTREE's effectiveness and efficiency transfer to open-source models.

VIDEOTREE Components. In Tab. 5, we report the effectiveness of the different components in VIDEOTREE. Specifically, removing the depth expansion module brings a 1.8%

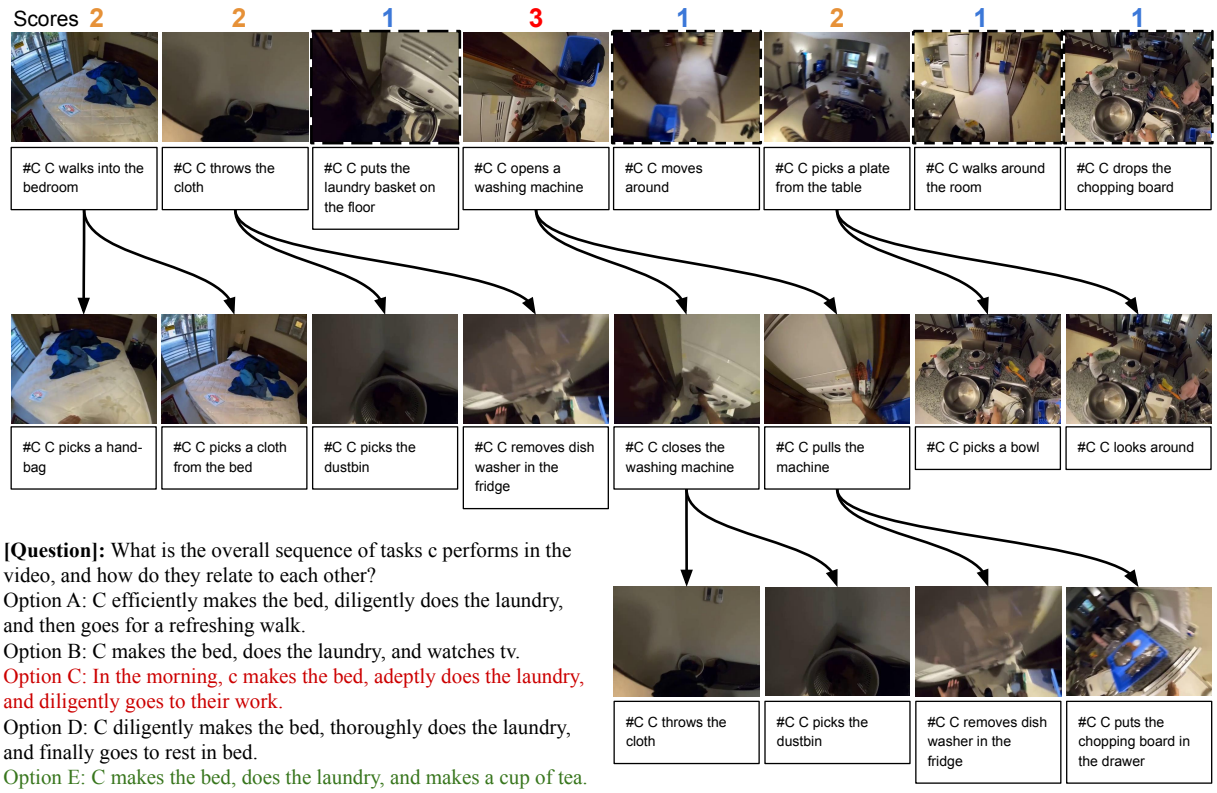


Figure 4. Qualitative examples of VIDEOTREE. Red options are answered wrongly with uniformly sampled 32 frames. Green options are answered correctly with VIDEOTREE. Best viewed in color.

drop in performance, showing the importance of the hierarchical design of VIDEOTREE. Removing the adaptive breadth expansion brings another 3.2% decrease, verifying the effectiveness of the adaptive nature of VIDEOTREE.

5.2.3. Qualitative Analysis

In Figure 4, we visualize qualitative results from VIDEOTREE. Specifically, we show the keyframes and their captions extracted by our adaptive tree representation given a video query. This example is drawn from EgoSchema, and shows the query format, which consists of a query and multiple-choice answers. With the proposed VIDEOTREE strategy, we split a complex multi-scene video (*e.g. cleaning house across rooms*) into several key scenes via visual clustering and determine the most query-relevant scene via the relevance score. We then obtain more fine-grained visual cues by descending into each relevant cluster (Levels 2 and 3 in Figure 4). For example *"C opens a washing machine"* is deemed highly relevant to the question, which asks about the sequence of events. At the same time, frames like *"C moves around"* are deemed irrelevant to the query and not expanded. In the end, VIDEOTREE shows a dynamic ability to select relevant segments and answer the given question correctly with only 50% of the baseline's 32 input captions. The LLoVi (fixed uniformly sampling) fails to correctly answer the question, sampling a large number of redundant and irrelevant frames. We also provide additional qualitative results in supplementary materials Sec. 12.

6. Conclusion

In this work, we proposed VIDEOTREE, an adaptive and hierarchical framework for LLM reasoning over long-form videos. VIDEOTREE adaptively extracts query-relevant keyframes from the video input in a coarse-to-fine manner and organizes them into a hierarchical representation, enabling the LLM to effectively handle complex queries. VIDEOTREE resulted in strong performance on three popular datasets (EgoSchema, NExT-QA, and Video-MME), while also improving efficiency by reducing the inference time and LLM calls. In our qualitative analysis, we showed that given a complex multi-scene video and its query, VIDEOTREE is capable of extracting key scenes and zooming into more detailed information that is highly related to the query. In the future, as more advanced captioners and stronger LLMs become available, the modular design of VIDEOTREE holds the potential for even greater performance and adaptability.

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