

Re-thinking Temporal Search for Long-Form Video Understanding

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<https://longvideohaystack.github.io>

Abstract

Efficiently understanding long-form videos remains a significant challenge in computer vision. In this work, we revisit temporal search paradigms for long-form video understanding and address a fundamental issue pertaining to all state-of-the-art (SOTA) long-context vision-language models (VLMs). Our contributions are twofold: **First**, we frame temporal search as a **Long Video Haystack** problem – finding a minimal set of relevant frames (e.g., one to five) from tens of thousands based on specific queries. Upon this formulation, we introduce **LV-HAYSTACK**, the first dataset with 480 hours of videos, 15,092 human-annotated instances for both training and evaluation aiming to improve temporal search quality and efficiency. Results on LV-HAYSTACK highlight a significant research gap in temporal search capabilities, with current SOTA search methods only achieving 2.1% temporal F_1 score on the LONGVIDEOBENCH subset.

Next, inspired by visual search in images, we propose a lightweight temporal search framework, T^* that reframes costly temporal search as spatial search. T^* leverages powerful visual localization techniques commonly used in images and introduces an adaptive zooming-in mechanism that operates across both temporal and spatial dimensions. Extensive experiments show that integrating T^* with existing methods significantly improves SOTA long-form video understanding. Under an inference budget of 32 frames, T^* improves GPT-4o’s performance from 50.5% to 53.1% and LLaVA-OneVision-OV-72B’s performance from 56.5% to 62.4% on the LONGVIDEOBENCH XL subset. Our code, benchmark, and models are provided in the Supplementary material.

1. Introduction

As video understanding research expands from seconds-long to hour-long videos, [6, 18, 72], video understanding tasks

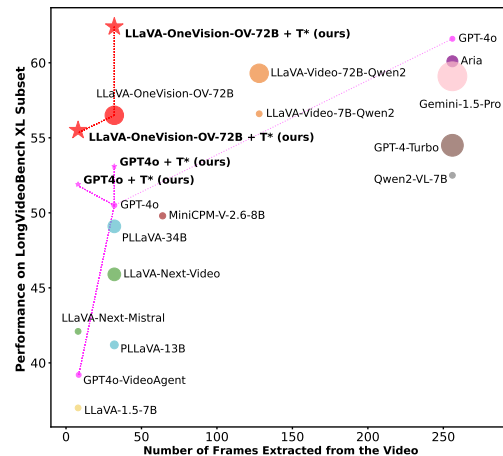


Figure 1. **Long-form video understanding performance comparison on LongVideoBench [72] XL subset (900-3600s).** Open-sourced model size is indicated by marker size. Our lightweight temporal search algorithm T^* (§3) improve SOTA models significantly: GPT-4o (50.5% \rightarrow 53.1% and LLaVA-OneVision-OV-72B (56.5% \rightarrow 62.4%), both with 32 frames.

face fundamental challenges in quickly and accurately locating relevant frames in long-form videos [12, 26, 36]. Current large vision-language models (VLMs) often require a large number of tokens for frame processing, e.g., 576 tokens per image for LLaVA [41] and Tarsier [64]. This makes frame-by-frame analysis of long videos, which contain thousands of frames, computationally challenging to all state-of-the-art VLMs. To overcome this challenge, temporal search [71, 76] has emerged as a fundamental paradigm, which is framed as a **Long Video Needle-in-a-Haystack** [34, 35]: locating a minimal set of frames (needles) within thousands of frames from a long video (haystack) which is essential to answer the question. Unlike traditional temporal localization [1, 17, 27, 55, 61, 78, 80, 82, 87, 91] which identifies continuous temporal segments, temporal search focuses on selecting relevant frames across the entire video.

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To this end, we introduce benchmark **LV-HAYSTACK** specifically designed for temporal search on real-world long-form video. Unlike needle-in-a-haystack benchmarks [4, 25, 45, 46, 63, 66, 89] using randomly inserted synthetic frames as “needles”, LV-HAYSTACK is built from real-world scenarios where humans answer questions by identifying few essential frames. We compile LV-HAYSTACK using videos and questions from Ego4D (Egocentric videos, Grauman et al. [18]) and LongVideoBench (Allocentric videos, Wu et al. [72]), ensuring each question has an answer and a set of keyframes. For LongVideoBench, we use keyframes and answers from the original dataset. For Ego4D, we annotate **15,092** QA instances from 988 videos spanning 423 hours with **45.7 million** frames, where each video lasts around 25 minutes with about 15 questions. Furthermore, previous long-form video evaluations [32, 53, 65, 72, 93] primarily focus on task performance and overlook the evaluation of temporal search capabilities. We propose frame-centered temporal and visual metrics and derive frame-set similarity metrics like temporal and visual F_1 to compare model-selected and reference keyframes to evaluate search capabilities.

Building upon the proposed benchmark, we examine the fundamental nature of temporal search in VLMs. Existing cluster- [22, 49, 56, 70, 86] or agent-based [14, 31, 68, 75, 83] methods rely on costly frame-by-frame processing with VLM to identify keyframes. We draw inspiration from *visual* search techniques like V^* [73], which effectively conduct spatial search in Vision Transformers [44] in a coarse-to-fine manner, suggesting that *temporal* search could be performed similarly. To unify temporal and spatial dimensions for video temporal search, we leverage the superior performance of image-language models over video-language models [20], effectively recasting temporal search as a spatial search task.

Specifically, we propose T^* , a temporal search framework reframed as a spatial search task by transforming frame sequences into a single large image, gradually refining temporal resolution by discarding irrelevant frames and inserting frames around key temporal regions. Acting like an agent, T^* dynamically balances the spatial-temporal trade-offs by determining what spatial details to sacrifice, enhancing the temporal sampling probability in the promising time regions, and zooming-in images to achieve higher spatial resolution and recover details. This approach reduces search costs through multi-step zooming-in refinement, enabling more efficient and effective temporal search. With this unified approach, T^* seamlessly integrates both temporal and spatial dimensions within a single image space to achieve efficient long-form video understanding.

Empirically, the iterative sampling-scoring-reweighting paradigm of T^* results in 3x computational efficiency in terms of FLOPs compared to frame-by-frame search. On long-form video understanding tasks, T^* applied GPT-4o [47] and LLaVA-Onevision-OV-72B [28] achieves com-

Subset	HAYSTACK-EGO4D	HAYSTACK-LVBENCH
Video Type	Egocentric	Allocentric
# video	988	114
# length	423 h - 25.7 min per video	26.7 h - 14.1 min per video
# frame	45,700,000 - 46,300 per video	2,200,000 - 19,100 per video
# QA pair	15,092 - 15.3 per video	342 - 3.0 per video
# keyframe	28,300 - 1.9 per question	496 - 1.5 per question

Table 1. Data Statistics of LV-HAYSTACK.

patible performance while using 4x fewer frames, outperforming pervious search and non-search methods. Furthermore, our fine-grained evaluation framework provides interpretable metrics for different components of video understanding, and our findings reveal that temporal search capabilities closely aligns with downstream performance.

2. Temporal Search in Video Understanding

To explore efficient temporal search with long-context VLMs, we formulate Temporal Search (TS) similar to the needle-in-a-haystack [63] task, i.e., selecting few keyframes from the video to answer questions, which is critical for VLMs in processing long videos [37, 49, 59, 67, 70, 84].

2.1. Task Formulation

Given a video $V = \{f_1, f_2, \dots, f_N\}$ with N frames and a question Q , temporal search tries to find a minimal subset of k keyframes $V^K = \{f_1^K, f_2^K, \dots, f_k^K\} \subseteq V$ that contains all critical information required to answer Q . Specifically, the identified keyframe set requires two features:

- **Completeness:** V^K should be a complete frame set to answer questions. If the answer to Q based on V is A , then the answer derived from V^K should also be A .
- **Minimality:** V^K should contain only essential frames, with no redundant or irrelevant frames while maintaining completeness.

2.2. The LV-HAYSTACK Benchmark

Based on this task formulation, we construct a benchmark specifically designed for Temporal Search. Each search instance in our dataset is represented as a tuple comprising four elements $\langle V, Q, V^K, A \rangle$, with a video $V = \{f_i\}_{i=0}^N$, a question Q , annotated keyframes $V^K = \{f_j^K\}_{j=0}^k$ and the answer A . Our benchmark consists of both ego-centric and allocentric videos, sourced from Ego4D [18] and LongVideoBench [72], respectively. For HAYSTACK-EGO4D, we select video segments from the Ego4D NLQ validation set, with an average duration of 8.3 minutes per segment. These segments capture diverse scenarios such as object finding and shopping activities. We hire crowdworkers to identify the minimal set of keyframes required

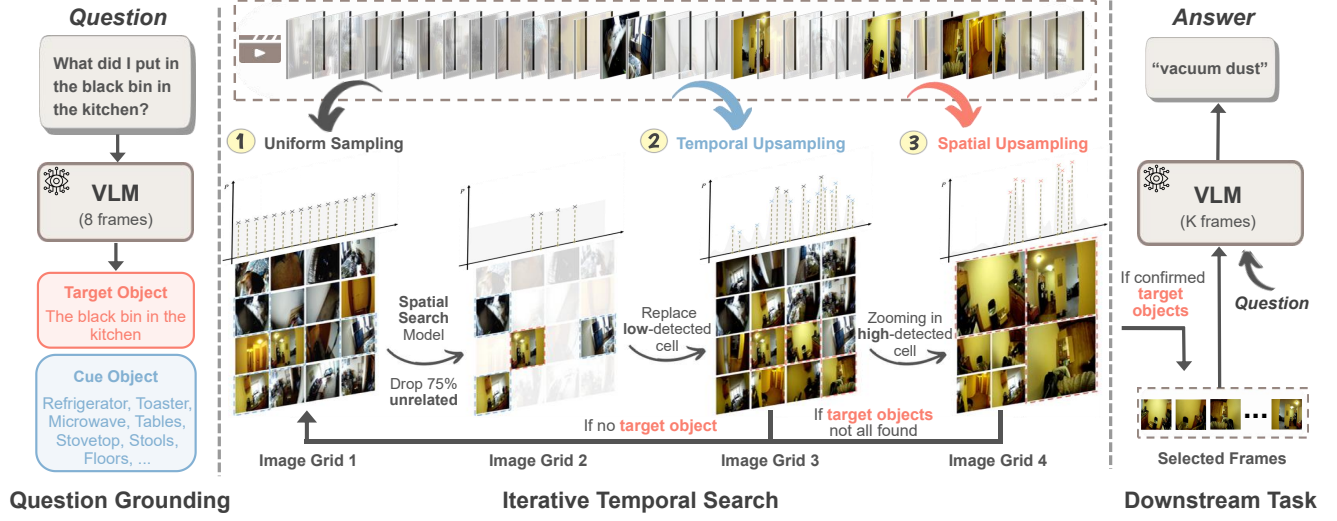


Figure 2. **The T^* framework that employs efficient temporal search for long-form video understanding.** T^* employs an iterative temporal search approach to search keyframes essential to answer questions. Left: Question Grounding, where a visual language model identifies visual cues (target and cue object) from the textual question. Center: Iterative Temporal Search, formulated as Spatial Search where a spatial search model iteratively detects visual cues and upsamples relevant temporal/visual regions. Right: Downstream Task, where the visual language model answer questions using K keyframes sampled from the final temporal search distribution as visual input.

to answer task-specific questions and provide corresponding answers. For HAYSTACK-LVBENCH, we repurpose the LongVideoBench dataset for the temporal search task, where annotators verify and refine the original reference timestamps to ensure the frames contain minimal sufficient information to answer each question. Statistics of our dataset can be found in Table 1 and more data annotation details are listed in the Appendix E.

2.3. Evaluation Metrics for Search Utility

Our evaluation framework focuses on both search utility and efficiency. For search utility, we develop metrics comparing model-predicted keyframes with human annotations at both frame and set levels, addressing the challenge that multiple valid keyframe sets may exist for the same question.

Frame-to-Frame Metrics. To evaluate alignment between a model-predicted frame f_{pt} and a human-annotated frame f_{gt} , we consider two dimensions. **1) Temporal Similarity** measures the timestamp difference between f_{pt} and f_{gt} , using a binary threshold to mitigate outlier effects. Two frames are considered similar if their temporal difference falls within this threshold. **2) Visual Similarity** adopts the Structural Similarity Index Measure (SSIM) [5] to identify the visual similarity between the frames f_{pt} and f_{gt} based on structural details, luminance, and contrast.

Set-to-Set Metrics. The major challenge in extending frame-to-frame metrics to frame set evaluation is defining what makes two sets *similar*. We introduce **Precision** and **Recall** as two complementary metrics. Precision measures

whether each model-selected frame aligns with at least one reference frame, while Recall evaluates whether reference frames are represented in the model’s selection.

Let $F_{gt} = \{f_{gt}^j\}_{j=1}^N$ denote the reference frame set and $F_{pt} = \{f_{pt}^i\}_{i=1}^M$ represent the model-predicted frame set. We define precision and recall as follows:

$$\text{Precision}(F_{pt}, F_{gt}) = \frac{1}{|F_{pt}|} \sum_{f_{pt}^i \in F_{pt}} \text{sim}(f_{pt}^i, F_{gt}), \quad (1)$$

$$\text{Recall}(F_{pt}, F_{gt}) = \frac{1}{|F_{gt}|} \sum_{f_{gt}^j \in F_{gt}} \text{sim}(f_{gt}^j, F_{pt}), \quad (2)$$

where $\text{sim}(f^i, F') = \max_{f^j \in F'} \text{sim}(f^i, f^j)$ defines the frame-to-set similarity for any frame and set. The sim function can measure either temporal or visual similarity. To balance search relevance (Precision) and coverage (Recall), we compute the F_1 score as the harmonic mean of them.

2.4. Evaluation Metrics for Search Efficiency

Previous research [14, 49, 67, 70, 73] have primarily focused on downstream task performance and overlook the temporal search computational efficiency. We evaluate search efficiency with three key metrics: **1) Frame Cost**, which measures the total number of frames processed, **2) FLOPs**, which quantifies the computational complexity, and **3) Latency**, which captures the total search time.

Algorithm 1: Efficient Temporal Search with Dynamic Sampling

Input : Video V , target/cue objects $\{T, C\}$, keyframe count K , search budget B , threshold θ
Output : Keyframes F with timestamps τ

```
1 Initialize:  $S, N \leftarrow \mathbf{0}^L, \mathbf{1}^L, P \leftarrow \frac{1}{L}\mathbf{1}^L, R \leftarrow T, F, \tau \leftarrow \emptyset$ ; //  $L = |V|$ 
2 while  $R \neq \emptyset$  and  $B > 0$  do
3    $I \leftarrow \text{Sample}(P \odot N, g^2), G \leftarrow \text{Grid}(V[I]), B \leftarrow B - g^2$ ; // Sample and grid
4    $(C, O) \leftarrow \text{Detect}(G)$ ; // Get confidence maps and objects
5   for  $i \in [1..|I|]$  where  $O_i \cap R \neq \emptyset$  do
6      $S[I_i], N[I_i] \leftarrow C_i, 0$ ; // Update scores and mark visited
7     if  $\text{Verify}(V[I_i]) > \theta$  then
8        $F, \tau \leftarrow F \cup \{V[I_i]\}, \tau \cup \{I_i/\text{fps}\}, R \leftarrow R \setminus (O_i \cap R)$ 
9    $P \leftarrow \text{Normalize}(\text{Spline}(S, N))$ ; // Update distribution
10 return  $\text{Sample}(V, S, K)$ 
```

3. T^* : Efficient Temporal Search

T^* facilitates long-form video understanding through temporal search, reformulated as spatial search with spatial search models. The framework (Figure 2) comprises three phases: question grounding (§3.1), iterative temporal search (§3.2), and downstream task completion (§3.3). The first two phases conduct temporal search to identify keyframes, and the last phase forward these frames to a vision language model to answer questions. The temporal search process is shown in Algorithm 1, and explained in detail as follows.

3.1. Question Grounding

The question grounding phase aims to obtain target objects T and cue objects C essential for temporal search with spatial search models. We sample N frames at fixed intervals from video V , denoted as \overline{V}_N for the VLM to scan. The VLM processes these frames with question Q to identify two types of elements: (1) **Target Objects** T , visual elements directly relevant to answering the question, (2) **Cue Objects** C , contextual elements indicating potential regions of interest. These objects are formally represented as:

$$\{T, C\} = \text{VLM}(\overline{V}_N, Q). \quad (3)$$

This query grounding phase identifies both primary targets and contextual cues helpful to answer the question, which are then used to guide the search process (§3.2). As shown in Figure 2, for the question “What did I put in the black dustbin?”, the VLM identifies both target object (dustbin) and cue objects (room corners, furniture placement).

3.2. Iterative Temporal Search

Initialization The temporal search begins by initializing a uniform probability distribution P over frames, and a confidence threshold θ for object detection. The initial score distribution S and non-visiting indicator N_v are initialized as zero and one vectors over the total frame count L (Algorithm 1, line 1). Each object $o \in \mathcal{O}$ is weighted at 1.0 for targets and 0.5 for cues to reflect search importance. The

remaining target set R starts with all targets T , while two empty sets F and τ are created for storing keyframes and timestamps, respectively.

Frame Sampling and Grid Construction In each iteration, the algorithm samples frames according to the current probability distribution P . We arrange sampled frames into a grid layout G sized $g \times g$, where indices I are first sampled and then used to construct the grid (Algorithm 1, line 3). The sampling process is defined as:

$$I = \text{Sample}(P \odot N_v, g^2) \quad (4)$$

where g^2 is the number of frames to sample and \odot denotes element-wise multiplication. The search budget B is then reduced by g^2 after grid construction.

Object Detection and Scoring For each grid image, we perform object detection using a pre-trained model to identify both target and cue objects (line 4). The detection confidence for each grid cell (i, j) is computed as:

$$C_{i,j} = \max_{o \in \mathcal{D}_{i,j}} (c_o \cdot w_o) \quad (5)$$

where $\mathcal{D}_{i,j}$ represents the detected objects in cell (i, j) , c_o is the detection confidence, and w_o is the object weight. When target objects are detected with sufficient confidence, they are added to the keyframe set and removed from the remaining targets (lines 5-8).

Distribution Update The score distribution is updated by spline-based interpolation (line 9). For each sampled frame $f \in F_s$, we update its score and mark it as visited:

$$S_f = C_f, \quad N_{v,f} = 0 \quad (6)$$

To capture temporal locality, we employ a window-based update for high-confidence frames:

$$S_{f \pm \delta} = \max(S_{f \pm \delta}, \frac{S_f}{|\delta| + 1}), \quad \delta \in [-w, w] \quad (7)$$

where w is the window size. The probability distribution P is then updated using spline interpolation and normalized.

The search process continues iteratively until either all target objects are found or the search budget B is exhausted. Finally, the algorithm returns the top K frames based on their final scores (line 10).

Method	Frames↓	HAYSTACK-EGO4D						HAYSTACK-LVBENCH					
		Temporal			Visual			Temporal			Visual		
		Precision ↑	Recall ↑	F_1 ↑	Precision ↑	Recall ↑	F_1 ↑	Precision ↑	Recall ↑	F_1 ↑	Precision ↑	Recall ↑	F_1 ↑
Baselines: Static Frame Sampling													
Uniform [72]	8	1.0	3.4	1.6	58.0	63.0	60.2	1.4	6.3	2.2	56.0	72.0	62.7
Uniform [72]	32	1.1	14.8	2.0	58.5	65.6	61.5	1.4	24.9	2.7	58.7	81.6	67.3
Baselines: Adaptive Temporal Search													
VideoAgent [68]	10.1	1.7	5.8	2.7	58.0	62.4	59.9	1.2	8.5	2.1	58.8	73.2	64.7
Retrieval-based	8	1.2	4.2	1.9	58.5	61.7	59.9	1.5	6.3	2.3	63.1	65.5	64.1
Retrieval-based	32	1.0	13.8	1.9	58.5	65.4	61.4	1.3	21.8	2.4	59.9	80.8	67.8
Ours: T^* for Zooming In Temporal Search													
Attention-based	8	<u>2.2</u>	<u>7.5</u>	<u>3.3</u>	58.4	<u>62.5</u>	<u>60.2</u>	1.5	6.6	2.4	<u>63.6</u>	68.6	<u>65.7</u>
Training-based	8	1.4	4.9	2.1	58.0	61.5	59.6	1.5	6.6	2.3	59.8	71.1	64.5
Detector-based	8	1.7	5.8	2.7	<u>63.8</u>	70.1	66.8	<u>1.6</u>	<u>7.1</u>	<u>2.5</u>	58.4	<u>72.7</u>	64.3
Detector-based	32	1.8	26.3	3.4	62.9	76.2	68.9	1.7	28.2	3.1	58.3	83.2	67.8

Table 2. Search utility results on LV-HAYSTACK. 8-frame setting bests are underlined, 32-frame setting bests are in **bold**. We show that more searched frames consistently improves recall but reduces precision in retrieval methods. Detector-based T^* achieves best performance in 32-frame setting across metrics, demonstrating the effectiveness of visual grounding and iterative temporal search. Attention-based T^* performs well in 8-frame setting but requires larger foundation models, thereby reducing efficiency.

Method	Search Efficiency				Overall Task Efficiency		
	Grounding	Matching	TFLOPs ↓	Latency (sec) ↓	TFLOPs ↓	Latency (sec) ↓	Acc ↑
Baselines: Static Frame Sampling							
Uniform-8 [72]	N/A	N/A	N/A	0.2	139.3	3.8	45.9
Baselines: Adaptive Temporal Search							
VideoAgent [68]	GPT4×4	CLIP-1B×840	536.5 [†]	30.2	690.7 [†]	34.9	49.2
Retrieval-based	N/A	YOLO-world-110M×840	216.1	28.6	355.4	32.2	50.3
Ours: T^* for Efficient Temporal Search							
Attention-based	LLaVA-72B×3	N/A	88.9	13.7	228.2	17.3	49.6
Detector-based	LLaVA-7B×1	YOLO-world-110M×49	33.3	7.5	172.6	11.1	50.8
Training-based	LLaVA-7B×1	YOLO-world-110M×38	30.3	6.8	169.6	10.4	51.0

Table 3. Efficiency results on the full LV-HAYSTACK, including search efficiency and overall (search+downstream) efficiency. We report the search models used and their avg. call frequency (e.g., VideoAgent calls GPT-4 four times for grounding). T^* achieves high performance with significantly less computation and lower latency. VideoAgent’s FLOPs ([†]) exclude GPT-4 costs due to its closed-source nature. All training and inference operations are carried out on a cluster of 8×H800 Nvidia GPUs.

3.3. Downstream Task Completion

The final keyframes are selected using TopK operation on the score distribution (Algorithm 1, line 10), which returns K frames with timestamps for downstream tasks, ensuring both relevance and temporal coverage.

4. Experimental Setup

4.1. Evaluations on Search Utility and Efficiency

Datasets and models. We evaluate on LV-HAYSTACK (Sec. 2.2). For downstream task efficiency evaluation, 8 searched frames are passed to LLaVA-OneVision-72B for all methods. We implement the spatial search model H with three complementary ways: (1) attention-based using VLM’s attention matrix, (2) detector-based using object detector like YOLO-world [8], (3) training-based using custom trained models. More details can be found in the codebase.

Evaluation Metrics. We report search performance metrics from §2.3 and §2.4 with a 5-second temporal threshold.

Baselines. We include three representative sampling or search strategies: **1) Uniform Sampling** following [28, 72]; **2) Temporal Search methods like VideoAgent [68]** which leverages LLM-based video keyframe selection; **3) Retrieval-based methods** that score and rank all frames instead of T^* search methods with iterative frame sampling.

4.2. Evaluations on Downstream Tasks: Video QA

Datasets. We evaluate QA performance on a diverse set of video understanding tasks: LongVideoBench [72], VideoMME [15], EgoSchema [43], NExT-QA [77] and Ego4D LongVideo QA, which we extended from Ego4D NLQ task [19].

The videos range from brief clips (15 seconds) to extensive narratives (up to 60 minutes), covering tasks like

LongVideoBench						Video-MME					
Model and Size	#Frame	Video Length				Model and Size	#Frame	Video Length			
		XLong 15-60min	Long 2-10min	Medium 15-60s	Short 8-15s			Long 41min	Medium 9min	Short 1.3min	Total 17min
GPT4o	8	47.1	49.4	67.3	69.7	GPT4o	8	51.4	54.3	55.7	53.8
GPT4o + T^*	8	51.9	52.4	72.7	70.0	GPT4o + T^*	8	55.9	57.3	56.4	56.5
LLaVA-OneVision-72B	8	53.7	57.4	74.1	73.0	LLaVA-OneVision-72B	8	52.6	55.5	59.6	55.9
LLaVA-OneVision-72B + T^*	8	55.5	63.7	76.3	73.5	LLaVA-OneVision-72B + T^*	8	57.7	57.5	61.7	59.0
GPT4o	32	50.5	57.3	73.5	71.4	GPT4o	32	56.3	60.7	68.3	61.8
GPT4o + T^*	32	53.1	59.4	74.3	71.4	GPT4o + T^*	32	59.3	63.5	69.5	64.1
LLaVA-OneVision-72B	32	56.5	61.6	77.4	74.3	LLaVA-OneVision-72B	32	60.0	62.2	76.7	66.3
LLaVA-OneVision-72B + T^*	32	62.4	64.1	79.3	74.6	LLaVA-OneVision-72B + T^*	32	61.0	66.6	77.5	68.3
GPT-4o (0513)	256	61.6	66.7	76.8	71.6	Gemini-1.5-Pro (0615)	1/0.5 fps ^{1*}	67.4	74.3	81.7	75.0
Aria-8x3.5B	256	60.1	64.6	76.6	69.4	Qwen2-VL-72B	768 ^{3*}	62.2	71.3	80.1	71.2
LLaVA-Video-72B-Qwen2	128	59.3	63.9	77.4	72.4	GPT-4o (0615)	384 ^{2*}	65.3	70.3	80.0	71.9
Gemini-1.5-Pro (0514)	256	59.1	65.0	75.3	70.2	LLaVA-Video-72B	64	61.5	68.9	81.4	70.6
Qwen2-VL-7B	256	52.5	56.7	67.6	60.1	Aria-8x3.5B	256	58.8	67.0	76.9	67.6

Table 4. Downstream task evaluation results show T^* effectiveness as a temporal search module for VLMs on LongVideoBench and Video-MME (without subtitles for fair comparison). Using QA accuracy (%) as the metric, we compare with top leaderboard models (shown in gray), noting these typically use substantially more frames, making direct comparisons challenging. Models are ranked by XLong video performance on LongVideoBench and total score on Video-MME, with frame counts indicated. All baseline figures are directly cited from their original publications. Standard deviations and more detailed analysis are available in Appendix C.

temporal action reasoning, causal inference, and egocentric understanding.

Evaluation Metrics. We adopt accuracy on downstream QA tasks, following [32, 53, 65, 72, 93].

Baselines. We test various open/closed-source VLMs, comparing T^* and uniform frame selection with 8/32 frames. Implementation details can be found in Appendix D.

5. Experimental Results

5.1. Results on LV-HAYSTACK Search Performance

For search utility results (Table 2), attention-based T^* achieves the best temporal metrics with higher precision, recall, and F1 scores with 8 frames. For 32 frames, detector-based T^* has best performance across both temporal and visual metrics. Results show more frames improve recall but reduce precision in retrieval methods, demonstrating the effectiveness of visual grounding and iterative temporal search over retrieval-based methods or uniform sampling.

For search efficiency results, as shown in Table 3, T^* achieve competitive accuracy with significantly fewer TFLOPs and lower latency than baselines. Training-based T^* is particularly efficient (169.6 TFLOPs, 10.4s latency, 60.3% accuracy) compared to VideoAgent (690.7 TFLOPs, 34.9s latency, 49.2% accuracy). While uniform sampling has no search cost, it requires more frames to achieve similar performance, leading to more computational costs.

Model	Frames	NExT-QA 0.7min	EgoSchema 3min
Baselines using Static Uniform Sampling			
InternVideo [69]	90	49.1	32.1
MVU [52]	16	55.2	60.3
LLoVi [86]	90	67.7	57.6
LangRepo [23]	180	60.9	66.2
LLaVA-OneVision-7B [28]	32	79.4	65.4
Baselines using Adaptive Frame Selecting			
SeViLA [83]	32	63.6	25.7
VideoAgent [67]	8.4	71.3	60.2
LVNet [49]	12	72.9	66.0
VideoTree [70]	63.2	73.5	66.2
VidF4 [37]	8	74.1	-
Ours: Plug in T^* for Efficient Temporal Search			
LLaVA-OneVision-7B	8	76.4	63.6
+Detector-based T^*	8	80.4	66.6

Table 5. Downstream task evaluation results by plugging in T^* as an additional temporal search method for VLMs on NExT-QA and EgoSchema. The video length is shorter than Table 4. Baseline results are directly cited from respective publications.

5.2. Results on Downstream Tasks: Long Video QA

We evaluate T^* on four QA datasets by integrating it as a lightweight plugin into proprietary (GPT-4o) and open-source (LLaVA-OneVision-72B) vision-language models. For long-form videos, as shown in Table 4, T^* enhances VLM performance on LongVideoBench and VideoMME consistently across various frame budgets, video lengths, and

Model	Frames	Tiny		Test	
		Clip	Video	Clip	Video
Baselines using Static Uniform Sampling					
GPT4o	8	45.5	41.7	45.9	48.0
GPT4o	32	41.5	43.2	46.7	48.3
QWen2.5VL 7B	8	24.1	21.6	22.3	20.7
QWen2.5VL 7B	16	25.0	22.3	26.7	23.7
QWen2.5VL 72B	8	25.7	22.4	23.8	21.4
QWen2.5VL 72B	16	25.9	25.0	25.0	21.0
Ours: Plug in T^* for Efficient Temporal Search					
GPT4o + T^*	8	49.5	42.2	49.4	46.7
GPT4o + T^*	32	50.5	49.5	50.0	48.0
QWen2.5VL 72B + T^*	8	26.2	24.5	25.1	23.8
QWen2.5VL 72B + T^*	16	27.1	26.6	27.8	25.5

Table 6. Downstream evaluation results on the [Ego4D Longvideo QA dataset](#). We extend the Ego4D NLQ task by including answer options and responses, and report performance for both clip-level and full video inputs using vision-language models.

VLMs. For short videos, Table 5 demonstrates that on NExT-QA and EgoSchema, T^* outperforms other frame selection methods while using the least number of frames.

Notably, T^* is particularly effective for longer videos and smaller frame budgets. On the LongVideoBench XLong subset with an 8-frame constraint, T^* increases the SOTA models with a large margin, boosting GPT-4o performance from 47.1% to 51.9% with 8 frames, and LLaVA-OneVision-OV-72B from 56.5% to 62.4% with 32 frames.

5.3. Results on Ego4D LongVideo QA

In the original Ego4D [19] NLQ task, each sample consists of a text query, an hours-long video, and a recommended video clip (approximately 10 minutes) that provides context for the query. In LVHaystack, we recruited seven annotators to answer the queries from the Ego4D NLQ test set and to generate corresponding answer options, resulting in a new long-video QA dataset from an ego-centric perspective. The dataset is partitioned into three subsets: tiny, dev, and test.

We report the performance of two mainstream open-source models, QWen2.5-VL [2] and GPT4o. To facilitate future research, we provide results using both the full-length videos (hours-long video) and shorter clips (minutes-long video). The results are shown in Table 6.

6. Analysis

6.1. Time and Cost Complexity of T^*

T^* can be viewed as a quaternary search guided by a heuristic informed by an object detector. **In the worst case**, where the heuristic provides no useful information, T^* randoms upsampling frames into the image grid with a complexity of $\mathcal{O}(\log L)$. **In the best case**, the heuristic always identifies

the most relevant top cell in the grid. So T^* operates as a quaternary search with a complexity of $\mathcal{O}(\log L)$.

Therefore, T^* offers better efficiency compared to other methods that perform linear processing and examine all frames. And, the complexity for processing images in this scenario lies between $\mathcal{O}(L)$ and $\mathcal{O}\left(\frac{\log L}{P}\right)$, where P is the probability that the object-detector-based heuristic selects the target frame from among image cells.

The computational overhead C of T^* is:

$$C = \underbrace{N_{\text{VLM}} \cdot C_{\text{VLM}}}_{\text{Grounding Overhead}} + \underbrace{N_{\text{YOLO-world}} \cdot C_{\text{YOLO-world}}}_{\text{Matching Overhead}}, \quad (8)$$

Where, the overhead includes the frequency of reasoning and processing by the VLM and the cost associated with YOLO-world processing for each image grid. Empirical measurements of C_{VLM} and $C_{\text{YOLO-world}}$ are provided in Section 4.1.

6.2. Sampling Iteration Dynamics

We show the dynamics of temporal focus over multiple iterations of temporal search for three example videos in Figure 3. As one can observe, the results show that our method progressively aligns sampling weights with ground truth frames across iterations, enhancing the model’s ability to focus on relevant frames. Notably, even for distantly separated frames (e.g., around 50s and 100s in the top video), the model can simultaneously increase the sampling weights, demonstrating its ability to capture multiple critical frames in videos. This iterative refinement allows the model to identify and emphasize key frames accurately, improving overall long-form video understanding performance.

6.3. Effect of Search Frame Count on Accuracy

This section explores how the number of search frames influences the performance of our Visual Language Models (VLMs) on LongVideoBench.

Figure 4 illustrates the impact of different numbers of search frames on the performance of VLMs on LongVideoBench. The results show that T^* consistently outperforms the baseline model across varying frame counts and closely approaches human selection (oracle) accuracy as the frame count increases. Notably, with 64 frames, T^* achieves performance on par with human-selected frames, indicating that our method effectively captures the essential information with fewer frames.

7. Related Work

Long-form Video Understanding. Recent attention mechanisms [3, 10, 11, 29, 40, 42, 58, 62, 85, 90, 92] and video transformers [38, 88] improve temporal processing [21, 39, 48, 50] but struggle with long-range dependencies [60]. Current solutions use compression [22, 57] or frame

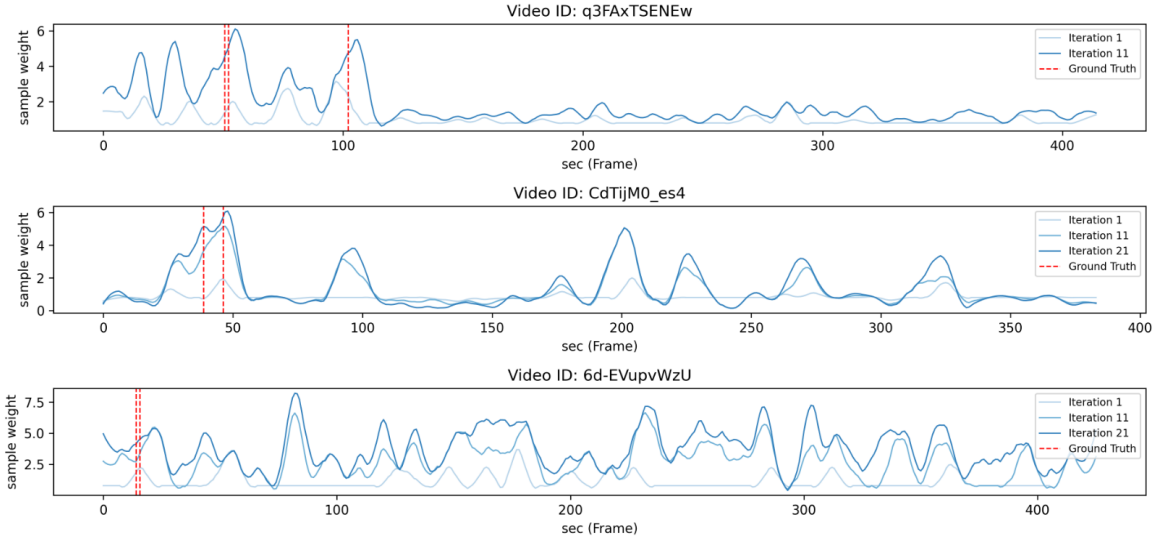


Figure 3. **Sampling weight dynamics over iterations for example videos.** Ground truth frames are marked in red. Sampling weights progressively focus on ground truth frames across iterations (1, 11, and 21), indicating improved model alignment with keyframes over time. Notably, due to the efficient sampling in temporal search, our model can simultaneously zoom in and focus on distantly located key frames (e.g., around 50s and 100s in the top plot).

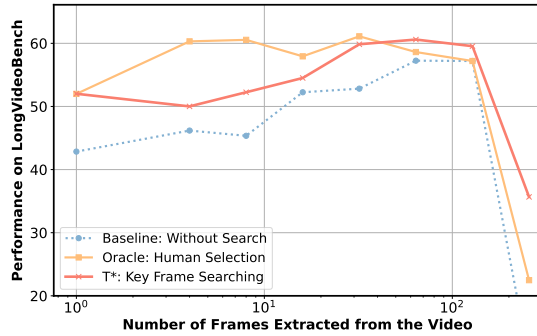


Figure 4. Performance improvement with increasing search frames. T^* consistently enhances accuracy and reaches near-human oracle performance at 64 frames.

selection [16, 33, 54, 56, 79, 83], while existing benchmarks [65, 93] focus on long videos, but are only evaluated on downstream QA while we focus on temporal search evaluation.

Temporal Localization and Temporal Search. While temporal localization [1, 17, 27, 55, 61, 78, 80, 81, 87] struggles with boundary detection, recent keyframe selection advances from “glance annotation” [9] to caption-based [24] and fine-grained approaches [7, 27]. Our work focus on a more challenging problem with longer videos.

Needle in a Haystack. Needle in a Haystack approaches span text [25, 45] and multimodal [4, 13, 63, 74, 89] domains but rely on synthetic data, while our Long Video Haystack focuses on real-world natural video contexts.

8. Conclusion

In this work, we revisit temporal search paradigms for long-form video understanding, studying a fundamental issue pertaining to all SOTA long-context vision-language models (VLMs). First, we formulate temporal search as a Long Video Haystack problem, i.e., finding a minimal set of relevant frames among tens of thousands of frames from real-world long videos given specific queries. To validate our formulation, we create **LV-HAYSTACK**, the first benchmark containing 15,092 human-annotated instances with a set of fine-grained evaluation metrics for assessing temporal search quality and computational efficiency. Empirical results on **LV-HAYSTACK** under SOTA temporal search methods reveal a significant gap in temporal search capabilities. Next, we re-think temporal search in long-form videos and propose a lightweight temporal search framework, T^* , which casts the expensive temporal search as a spatial search problem. Extensive experiments show that when integrated with video understanding models, T^* significantly improves SOTA performance. We hope that **LV-HAYSTACK** and T^* framework will drive meaningful advancements in developing efficient long-form video understanding systems.

Limitations

A potential limitation of our work lies in the assumption that most problems can be addressed with a few keyframes, which may not fully extend to more complex tasks requiring a broader context or dense reasoning. Additionally, our approach focuses primarily on visual cues, without leveraging other modalities such as audio or subtitles, which can be explored in future work to enhance multi-modal understanding

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