

# THINK-CLIP-SAMPLE: SLOW-FAST FRAME SELECTION FOR VIDEO UNDERSTANDING

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## ABSTRACT

Recent progress in multi-modal large language models (MLLMs) has significantly advanced video understanding. However, their performance on long-form videos remains limited by computational constraints and suboptimal frame selection. We present Think-Clip-Sample (TCS), a training-free framework that enhances long video understanding through two key components: (i) **Multi-Query Reasoning**, which generates multiple queries to capture complementary aspects of the question and video; and (ii) **Clip-level Slow-Fast Sampling**, which adaptively balances dense local details and sparse global context. Extensive experiments on MLVU, LongVideoBench, and VideoMME demonstrate that TCS consistently improves performance across different MLLMs, boosting up to 6.9% accuracy, and is capable of achieving comparable accuracy with 50% fewer inference time cost, highlighting both efficiency and efficacy of TCS on long video understanding.

**Index Terms**— Multi-modal LLMs, long video understanding

## 1. INTRODUCTION

Understanding long-form videos has become a central challenge in advancing multi-modal large language models (MLLMs) [1, 2, 3]. A long video often consists of thousands of frames, even with a low frame-per-second (FPS) sampling rate, leading to prohibitive computational costs. Mainstream MLLMs typically adopt uniform frame sampling [4, 5, 6], but this strategy treats all frames equally, regardless of their informativeness, thus resulting in subpar performance.

To mitigate this issue, several methods have been proposed to select more informative frames, e.g., Q-Frame [7] introduces adaptive frame selection and multi-resolution scaling tailored to the video content and the specific query. It proposes a CLIP-based [8] similarity with the Gumbel-Max trick for efficient selection, allowing Video-LLMs to process more relevant frames without exceeding computational limits. AKS [9] formulates selection as an optimization problem balancing query relevance and video coverage, and provides an adaptive algorithm to approximate the optimal solution.

Despite these advances, existing approaches face two fundamental challenges. First, they rely solely on direct question-frame similarity, assuming the question adequately represents all information needs. However, questions are often abstract and incomplete. For instance, a question like “Which team won in the end? (A) Team in black clothes; (B) Team in white clothes” only mentions subjects while omitting crucial details about actions and context. Directly feeding such questions to CLIP often retrieves frames showing players without capturing game-decisive moments. Second, similarity

based sampling tends to produce unbalanced frame distributions. Algorithms may duplicate spikes of high similarity frames, while neglecting informative regions with moderate similarity scores and global context. This results in sparse coverage that misses important information for comprehensive video understanding.

In this paper, we propose **Think-Clip-Sample (TCS)**, a training-free method designed to address these challenges. (1) To enhance diversity and ensure broader coverage, TCS first **thinks** of multiple queries [10, 11, 12, 13]. Instead of relying on a single question, we prompt the MLLM to generate multiple queries from different perspectives (e.g., objects, scenes, actions). These multi-view queries encourage the MLLM to capture complementary information for answering the question across diverse video segments. (2) To avoid sparse and uneven sampling, we propose a Clip-level Slow-Fast Sampling strategy: Given a total frame budget  $K$ , TCS first identify high-similarity **clips** rather than isolated frames. Then, a larger portion of  $K$  is allocated to these compact yet informative clips, denoted as slow **sampling**, while the remaining frames are uniformly sampled from non-clipped regions (fast sampling) to provide global coverage. This balanced allocation ensures both fine-grained detail and a global context.

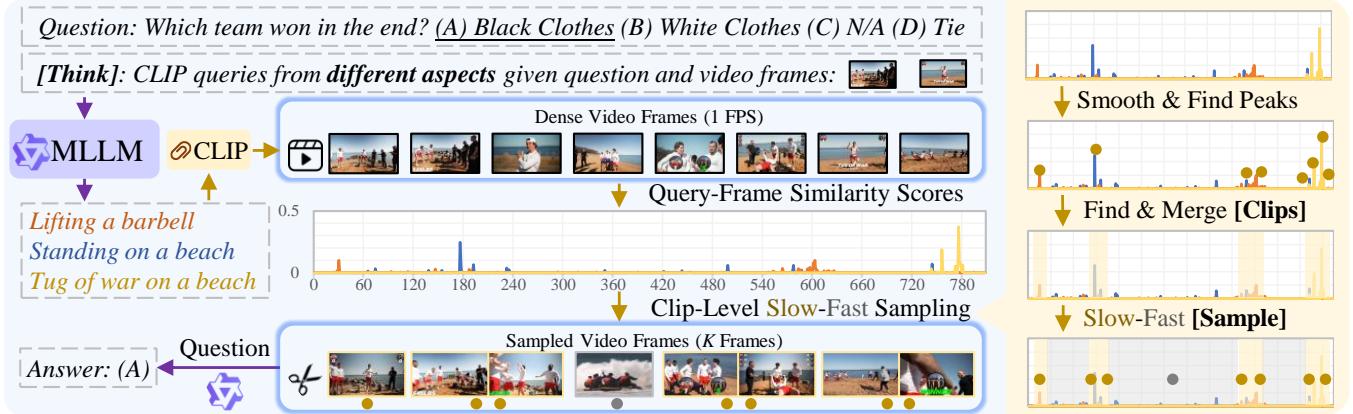
We evaluate TCS on two base MLLMs, Qwen2-VL-7B [4] and MiMo-VL-7B [14], across three challenging benchmarks: LongVideo-Bench [15], MLVU [16], and VideoMME [17]. Experimental results demonstrate that TCS consistently improves performance of the base MLLMs under the same sampling budget, achieving up to 6.9% accuracy improvement on MLVU, while reducing computation time by over 50% on Qwen2-VL-7B with comparable performance, highlighting both efficiency and efficacy of TCS for long video understanding.

Our main contributions are threefold:

- We propose **Multi-Query Reasoning**, to automatically generate multiple queries from the question and video, enabling the retrieval of diverse and complementary frames from different perspectives such as objects, actions, and scenes.
- We introduce **Clip-level slow-fast sampling** strategy, which first identifies high-similarity clips and allocates a larger portion of the frame budget to these regions, and uniformly sampling the remainder from non-clipped regions, to ensure both fine-grained detail and global coverage.
- Experimental results demonstrate that TCS significantly improves long video understanding across multiple MLLMs and benchmarks, achieving up to 6.9% accuracy gain, and reducing inference time by over 50% with comparable performance, demonstrating both efficiency and efficacy.

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**Fig. 1.** Overview of our proposed method Think-Clip-Sample (TCS): (i) Given a question on a long video, TCS first **thinks** of queries from different perspectives, which are used with CLIP to retrieve frames with both high relevance and broad coverage. (ii) Instead of sampling frames with highest similarity scores, TCS identifies high-relevance **clips**, and then (iii) applies Slow-Fast **Sampling** to allocate more frames on informative clips (yellow) and distribute the remainder across non-clip regions (gray), preserving both local detail and global context.

## 2. METHOD

### 2.1. Overview

This work focuses on video understanding through video question answering tasks. Given a video  $V \in \mathbb{R}^{T \times H \times W \times 3}$  with  $T$  frames and  $(H \times W)$  resolution, and a multi-option question  $Q$ , the goal of the MLLM is to select the correct answer among the options.

For long videos (e.g., longer than 10 minutes),  $T$  can be very large and infeasible to process directly. Thus, selecting a subset of  $K$  frames, where  $K \ll T$ , is crucial for efficient video understanding. A straightforward approach is to uniformly sample  $K$  frames across the video. Although this ensures temporal coverage, it often results in sparse observations that miss crucial visual evidence.

To address this, a common strategy is to compute similarity scores  $\mathbf{s} = \{\mathbf{s}_i\}_{i=1}^T$  between the question and frames using a pre-trained vision-language models (VLMs) [18, 19, 20, 21, 22], such as CLIP [8], and then sample frames according to  $\mathbf{s}$ . However, this pipeline presents two key challenges: (1) how to obtain better similarity scores  $\mathbf{s}$ , and (2) how to design an effective sampling strategy given  $\mathbf{s}$ . We address these in Section 2.2 and 2.3, respectively.

### 2.2. Reasoning for Multi-Perspective Queries

Previous work typically computes similarity scores directly between the **question** and video frames  $V$  with VLMs such as CLIP. However, these VLMs are designed to compare visual descriptions with images, rather than natural language questions. Furthermore, a single question may only highlight one aspect of the visual content, resulting in incomplete frame retrieval. For example, given a question such as “Which team won in the end? (A) Team in Black Clothes (B) Team in White Clothes”, CLIP would retrieve all the frames where the players are present, lacking core relevance to the question.

To overcome these limitations, we propose **Multi-Query Reasoning**. As shown in Figure 1 (left), instead of feeding the question directly into the CLIP model, we first provide the question to the MLLM with a small set of sparsely sampled low-resolution frames to provide necessary semantics. Then, the MLLM is prompted to generate multiple queries  $\mathbf{q} = \{q_i\}_{i=1}^{N_q}$ , each from a different perspective, such as objects, scenes, or actions potentially relevant to

the question. To balance coverage and efficiency, we limit the maximum number of queries to  $N_q = 4$ . Each query is then passed to CLIP to compute similarity scores  $\mathbf{s}_{mq} \in \mathbb{R}^{N_q \times T}$  with frames sampled in 1 FPS. Finally, we aggregate across queries using average pooling to obtain  $\mathbf{s}$ , yielding frame-level similarity scores enriched by multi-perspective evidence.

### 2.3. Clip-level Slow-Fast Sampling

With the similarity scores  $\mathbf{s}$ , a naive method is top-k sampling, which selects frames with the highest scores. However, as  $\mathbf{s}$  is aggregated from multiple perspectives, it naturally follows a **multimodal distribution**. Using top-k sampling may overly focus on sharp score spikes, neglecting other informative regions and global observation.

To address this, we propose a **Clip-level Slow-Fast Sampling** strategy, as illustrated in Figure 1 (right). The core idea is to identify short but informative clips and allocate a majority of frames (the **slow** path) within these clips, while dedicating a smaller portion of frames (the **fast** path) to uniformly sample the remaining video, thus maintaining global context.

Concretely, we first obtain smoothed similarity scores  $\mathbf{s}$  with a Gaussian filter to reduce noise:

$$\mathbf{s}_{\text{smoothed}}[i] = \frac{1}{\sqrt{2\pi}\sigma} \sum_{j=-r}^r \mathbf{s}[i+j] \cdot \exp\left(-\frac{j^2}{2\sigma^2}\right), \quad (1)$$

where we use default values of kernel radius  $r = 4$  and  $\sigma = 1$ .

We then compute a dynamic threshold  $\tau_s = \mu_s + \alpha\sigma_s$ , where  $\mu_s$  and  $\sigma_s$  are the mean and standard deviation of  $\mathbf{s}_{\text{smoothed}}$ , and  $\alpha$  is a hyperparameter. Local maxima above  $\tau_s$  are detected as peaks, and we expand around each peak with decreasing scores to form candidate clips. Finally, we merge overlapping clips to avoid duplication.

Then we devide the budget of  $K$  frames into  $K_{\text{slow}}$  and  $K_{\text{fast}}$  (e.g.,  $K_{\text{slow}} = 3K/4$ ,  $K_{\text{fast}} = K/4$ ), and proceed as follows:

- **Slow sampling.** We uniformly sample  $K_{\text{slow}}$  frames from all frames within the detected clips (in yellow). This ensures dense and uniform coverage of locally informative regions. If the total number of clip frames is smaller than  $K_{\text{slow}}$ , indicating too short high-relevance clips, we divide the peak threshold  $\alpha$  by 2 to enlarge the clips, and re-process the clipping.

**Table 1.** Comparison of MLLMs and baseline methods against our method TCS on three benchmarks. We bold the best and underline the second best results. The performance of baseline methods are reported according to original papers.

	#Frames	MLVU	LongVideoBench	Overall	VideoMME (w/o sub.)		
					Short	Medium	Long
<b>Long-form Video-LLMs</b>							
Video-XL-7B ( <i>CVPR 2025</i> )	128	<u>64.9</u>	-	55.5	64.0	53.2	<b>49.2</b>
LongVILA-8B ( <i>ICLR 2025</i> )	128	-	-	49.2	60.2	48.2	38.8
<b>Frame-Sampling Methods</b>							
Qwen2-VL-7B	32	58.1	55.5	57.6	-	-	-
w/ AKS ( <i>CVPR 2025</i> )	32	-	<u>60.5</u>	<b>59.9</b>	-	-	-
w/ Q-Frame ( <i>ICCV 2025</i> )	4+8+32	<b>65.4</b>	<u>58.4</u>	<u>58.3</u>	<b>69.4</b>	57.1	<u>48.3</u>
w/ TCS ( <i>Ours</i> )	32	61.2	<b>60.9</b>	58.0	<u>69.2</u>	<b>57.4</b>	47.9
MiMo-VL-7B	32	60.9	64.3	62.4	75.2	60.7	51.3
w/ TCS ( <i>Ours</i> )	32	<b>67.8</b> (6.9↑)	<b>67.2</b> (2.9↑)	<b>65.0</b> (2.6↑)	<b>76.3</b> (1.1↑)	<b>65.9</b> (5.2↑)	<b>52.7</b> (1.4↑)

- **Fast sampling.** We uniformly sample  $K_{\text{fast}}$  frames from the remaining non-clipped regions (in gray). This guarantees that frames outside high-similarity regions still contribute to the overall context. If the non-clip regions contain fewer than  $K_{\text{fast}}$  frames, denoting too many high-relevance clips, we multiply the peak threshold  $\alpha$  by 2 and re-clip.

Finally, we merge the slow and fast sampled frames to construct the final set of  $K$  frames. This hybrid allocation ensures that key segments are well-represented without sacrificing global video coverage, balancing local detail and global understanding.

### 3. EXPERIMENTS

#### 3.1. Experimental Setup

**Baseline Methods.** To evaluate the effectiveness and efficiency of TCS, we implement and compare our method on two base MLLMs: **Qwen2-VL-7B** [4] and **MiMo-VL-7B** [14]. We also include two long-form Video-LLMs and two training-free frame selection methods: (i) **Video-XL** [23] leverages MLLMs’ inherent key-value (KV) sparsification capacity to condense the visual input; (ii) **LongVILA** [24] introduces long-context Multi-Modal Sequence Parallelism for high efficiency long video input training; (iii) **AKS** [9] adopts adaptive keyframe selection by detecting saliency peaks across temporal similarity distributions; (iv) **Q-Frame** [7] integrates semantic relevance into dynamic-resolution frame selection.

**Benchmarks.** We evaluate on three widely used long video understanding benchmarks: (i) **MLVU** [16], consisting of 2,593 questions across nine categories, with average video duration of 12 minutes. (ii) **LongVideoBench** [15], a benchmark targeting long video comprehension, with 1,337 questions and similar average video duration. (iii) **VideoMME** [17], which covers Short (1.3 min), Medium (9 min), and Long (41 min) subsets, each with 900 questions from 300 videos. To focus on pure visual understanding, we run all benchmarks without subtitles.

**Implementation Details.** For Multi-Query Reasoning, we uniformly sample  $K/4$  frames with minimum resolution (up to  $224 \times 224$ ) for lightweight visual prompts. CLIP-ViT-Large-FP16 [8] is adopted as the query-frame similarity scorer. For Clip-level Slow-Fast Sampling, the peak threshold  $\alpha$  is set to 0.5 and the ratio of fast frames is set to 1/4 across all the benchmarks. All experiments are conducted on vLLM backend [25].

#### 3.2. Main Results

Table 1 reports the performance of TCS against baseline methods on both Qwen2-VL-7B and MiMo-VL-7B. Several key observations can be made:

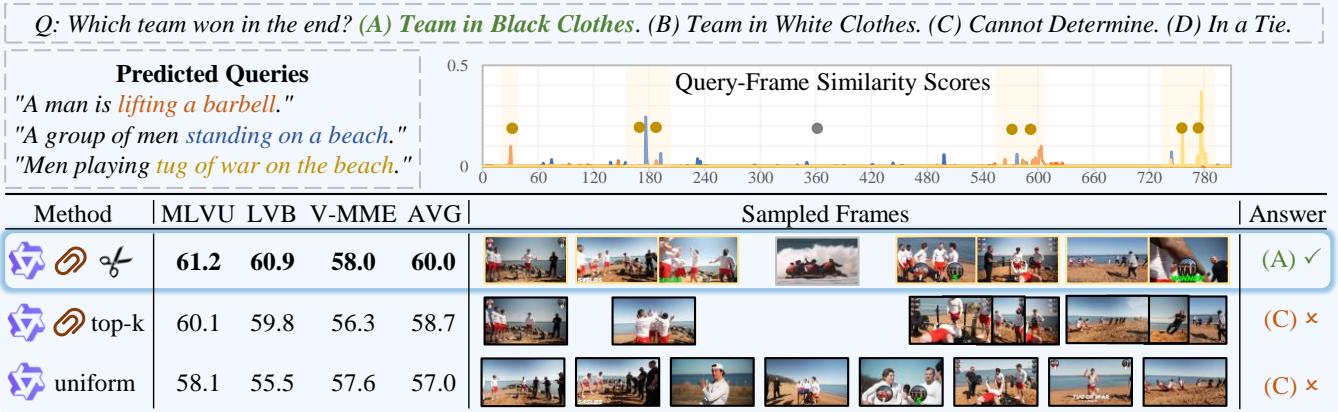
- (1) Compared to long-form Video-LLMs, frame-sampling based methods achieves higher average performance with fewer input frames, highlighting the efficiency and efficacy of key frame sampling in long video understanding.
- (2) Compared to AKS and Q-Frame, TCS achieves the best performance on LVBench and VideoMME-Medium. We mainly attribute this to our multi-query design, which provides comprehensive cues to answer the question, along with our clip-level slow-fast sampling strategy that captures both local and global information.
- (3) TCS consistently improves performance of the two base MLLMs across all the benchmarks: Qwen2-VL-7B and MiMo-VL-7B gain an average of 3.0% and 4.1% accuracy improvement, respectively. These gains validate the effectiveness and generalizability of the Multi-Query and Slow-Fast designs. Moreover, we notice that TCS expresses more significant performance gain with MiMo-VL-7B (6.9% on MLVU, 2.9% on LVBench, and 5.2% on VideoMME-Medium). This could be attribute to the fact that MiMo-VL is fundamentally a “*reasoning model*” [10, 12], i.e., it was originally trained on complex reasoning tasks, which enables more efficient multi-query reasoning, producing more comprehensive queries that better leverage our framework’s capabilities.

#### 3.3. Qualitative and Quantitative Ablation Study

In this section, we answer the question: “*How does our proposed components influence model performance qualitatively and quantitatively?*”. The experiments are conducted on Qwen2-VL-7B and the results are shown with Figure 2.

**Quantitatively**, comparing line 2 vs. line 3 shows that Multi-Query Reasoning boosts accuracy by an average of 1.7%. Comparing line 2 vs. line 1 shows that Slow-Fast Sampling further improves accuracy by 1.3%. Together, these results confirm that both components contribute complementary benefits.

**Qualitatively**, for a question such as “*which team won in the end*”, Multi-Query Reasoning successfully identifies key event queries (*lifting, standing on the beach, tug-of-war*), allowing CLIP to retrieve highly relevant frames. Without it, retrieval would degenerate to semantically sparse frames (*people in black/white clothes*). In the second stage, Slow-Fast Sampling captures critical sequences



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