



VIDEO LLAMB: LONG-CONTEXT VIDEO UNDERSTANDING WITH RECURRENT MEMORY BRIDGES

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ABSTRACT

Recent advancements in large-scale video-language models have shown significant potential for real-time planning and detailed interactions. However, their high computational demands and the scarcity of annotated datasets limit their practicality for academic researchers. In this work, we introduce **VideoLLaMB**, a novel framework that utilizes temporal memory tokens within bridge layers to allow for the encoding of **entire video sequences** alongside historical visual data, effectively preserving **semantic continuity** and enhancing model performance across various tasks. This approach includes recurrent memory tokens and a SceneTilling algorithm, which segments videos into independent semantic units to preserve semantic integrity. Empirically, VideoLLaMB significantly outstrips existing video-language models, demonstrating a 5.5 points improvement over its competitors across three VideoQA benchmarks, and 2.06 points on egocentric planning. Comprehensive results on the MVBench show that VideoLLaMB-7B achieves markedly better results than previous 7B models of same LLM. Remarkably, it maintains robust performance as PLLaVA even as video length increases up to $8\times$. Besides, the frame retrieval results on our specialized **Needle in a Video Haystack (NIAVH)** benchmark, further validate VideoLLaMB’s prowess in accurately identifying specific frames within lengthy videos. Our SceneTilling algorithm also enables the generation of streaming video captions directly, *without necessitating additional training*. In terms of efficiency, VideoLLaMB, trained on 16 frames, supports up to 320 frames on a single Nvidia A100 GPU with linear GPU memory scaling, ensuring both high performance and cost-effectiveness, thereby setting a new foundation for long-form video-language models in both academic and practical applications.



Web <https://VideoLLaMB.github.io>



Code <https://github.com/bigai-nlco/VideoLLaMB>

1 INTRODUCTION

The recent advances of large-scale video language models, represented with GPT4-o¹ and Project Astra², have amazed the world by their potential for nuanced interaction with the real world environment, particularly for real-time planning that demands the ability to observe the current state and draw from long-term memory. However, training such super-scale video-language foundational models is infeasible to academic researchers because of the massive computational cost required by the complex, high-dimensional nature of long video data, coupled with a scarcity of well-annotated, public

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¹<https://openai.com/index/hello-gpt-4o/>

²<https://deepmind.google/technologies/gemini/project-astra/>

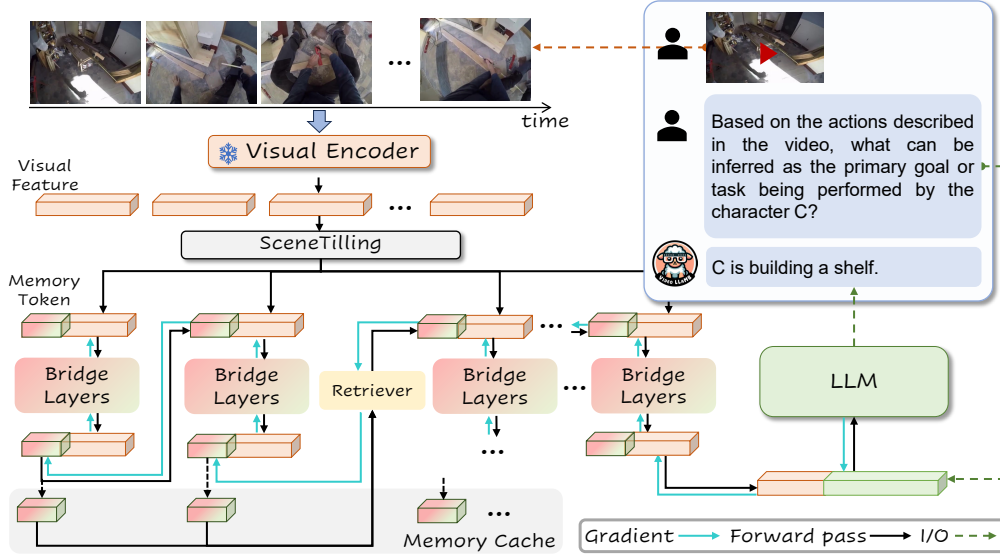


Figure 1: **Overview of VideoLLaMB.** We first extract the video features using an off-the-shelf vision encoder, then apply SceneTilling to segment the video into semantic segments (§2.1). Next, we use recurrent memory on these semantic segments to store video information within memory tokens (§2.2). We further employ a retrieval mechanism to update the memory tokens and address long-dependency issues (§2.3). Finally, we project the memory-token-augmented features from the current video segment into the LLM.

video-language datasets, which poses significant challenges for extensively scaling video-language models akin to those observed with large language models (LLMs).

To circumvent these challenges, the community has witnessed a growing interest in developing computationally efficient multimodal large language models (MLLMs). Traditional methods resort to *video compression* strategies, such as sampling (Zhang et al., 2023b; Lin et al., 2023), aggregation (Xu et al., 2024b), semantic consolidation (Song et al., 2023b), and resampling (Ma et al., 2023; He et al., 2024), in order to temporally reduce the length of the video. Yet, these methods often lead to the **loss of critical visual cues**, undermining the model’s ability to capture essential cues. Some other approaches employ a *sliding window* mechanism (Qian et al., 2024b), segmenting videos into shorter clips to mitigate the computational load of processing long videos. However, segmentation can **disrupt the semantic flow of content**, complicating the encoding process and potentially impacting the general understanding of the video narrative. Lastly, prevalent video understanding benchmarks, primarily based on linguistic question-answering pairs, exhibit **static** (Lei et al., 2023) and/or **language biases** (Ruggeri & Nozza, 2023; Zhou et al., 2022). These biases favor models that rely more on static imagery or textual elements, respectively, and fail to provide a comprehensive assessment of a model’s capability on extended video sequences. Refer to §4 for detailed discussions.

To address these multifaceted limitations, we introduce **VideoLLaMB**, an innovative framework that learns temporal **Memory** tokens within **Bridge** layers that recursively encode the entire video content, ensuring that no visual information is discarded deliberately (Figure 1; §2). Specifically, we devise Memory Bridge Layers, equipped with recurrent memory tokens, function without altering the architecture of the visual encoder and LLM. Furthermore, to mitigate the risk of vanishing gradients, we maintain long-term dependencies by preserving recurrent memory tokens in a memory cache, which is periodically refreshed through a retrieval process. To compensate for the limitations of the sliding window technique, we propose SceneTilling algorithm that divides the video into relatively independent sequences of semantic segments. This reduces the dimensions within each semantic unit without sacrificing semantic details. By constructing our recurrent memory with a retrieval mechanism based on these semantic segments, our method strikes a balance between effective and efficient comprehension of the current state and long-term memory retention.

In §3, we highlight the empirical advantages of VideoLLaMB in comparison with prior arts as:

- **Comprehensive long video understanding.** We demonstrate the effectiveness of VideoLLaMB using two long-form video QA benchmarks: EgoSchema (Mangalam et al., 2023) and NextQA (Xiao et al., 2021). Our results show an average improvement of 5.5 accuracy points over PLLaVA (Xu et al., 2024b), a model with the same initialization and training video dataset. Furthermore, VideoLLaMB maintains its performance even when the video length extends to 8 times longer than the original. Additionally, performance on MVBench (Li et al., 2023b) indicates that VideoLLaMB significantly outperforms prior models like PLLaVA using the same training data and LLM baseline.
- **Training-free streaming captioning.** By employing the SceneTiling algorithm, our method can automatically predict the end of a caption in streaming video without relying on special tokens during the training phase.
- **Memory-based egocentric planning.** To evaluate our model’s performance in video planning tasks, we used the planning dataset EgoPlan (Chen et al., 2023). Our method achieves the best performance among all 7B video-language models, showing an improvement of 2.06 accuracy points over PLLaVA.
- **Enhanced frame retrieval in long videos.** To evaluate our model’s ability in frame retrieval for long videos, we propose a multimodal Needle in a Video Haystack (NIAVH) test. This test requires the model to predict the true answer about an inserted image in a long video. In our NIAVH pressure test, which ranges from 1 to 320 seconds in length, VideoLLaMB consistently retrieves the correct image needles at various depths, outperforming other methods as video length increases.

2 VIDEOLLaMB

VideoLLaMB is an extensible framework designed to enhance long video understanding, composed of three key modules: semantic-based segmenter (§2.1), recurrent memory layer (§2.2), and memory retriever (§2.3). Each of these components will be detailed in the subsequent sections. Figure 1 depicts the overall framework.

2.1 SCENETILING: SEGMENTATION WITH SEMANTICS

Semantic segmentation along temporal sequence has long been recognized as an important task because it preserves the non-linear structure of context and greatly aids in compressing extensive context (Rao et al., 2020; Chen et al., 2021; Mun et al., 2022; Huang et al., 2020; Wang et al., 2023d). To address the disruption of semantic flow (see §1), we introduce SceneTiling, a model-free scene segmentation algorithm inspired by TextTiling (Hearst, 1997). SceneTiling divides the entire video sequence into segments that are semantically distinct, ensuring inter-segment coherence.

Formally, given a sequence of n frames $\{v_1, v_2, \dots, v_n\}$, the SceneTiling algorithm is as follows.

1. Compute the cosine similarity $S_C(\cdot, \cdot)$ between adjacent frame pairs using the [CLS] token from ViT, resulting in a sequence of similarity scores $\{c_1, c_2, \dots, c_{n-1}\}$, where $c_i = S_C(\text{ViT}(v_i), \text{ViT}(v_{i+1}))$.
2. Calculate the depth score for each point as $d_i = (cl_i + cr_i - 2c_i) / 2$, where cl_i and cr_i are the highest score to the left and right of c_i , respectively. A higher depth score indicates that the surrounding similarity is greater than at the point itself.
3. Calculate the expectation μ and variance σ of the depth scores $\{d_1, d_2, \dots, d_{n-1}\}$. Set the segmentation threshold as $\mu + \alpha \cdot \sigma$, where α is a hyperparameter controlling the likelihood of segmenting the video. Select the $K - 1$ depth scores that exceed the threshold to divide the video into K semantic segments $\{s_1, s_2, \dots, s_K\}$. Each segment represents a relatively independent semantic unit consisting of a sequence of frames.

Aside from temporal semantic segmentation, SceneTiling enables streaming video captioning without requiring training with special tokens (Chen et al., 2024b; Zhou et al., 2024; Fu et al., 2024) (Figure 4).

2.2 RECURRENT MEMORY BRIDGE LAYERS

Traditional recurrent memory-based Transformers (Bulatov et al., 2022; 2023; Kuratov et al., 2024) incur significant computational costs when scaled up, *i.e.*, $\mathcal{O}(LK)$, where L is the context length and K is the number of segment, primarily due to its recurrent mechanism over the whole language

model. More recently, some works empirically identify that linear projection best withstands visual information within MLLMs (Liu et al., 2023b;a; Zhang et al., 2024b), albeit with high space complexity, whereas the resampler has strong compressing ability on semantic information (Li et al., 2022), though it tends to miss detailed information (Xu et al., 2024a).

In this work, we devised a novel Recurrent Memory Bridge Layer, implemented as a multi-layer Transformer block, that integrates recurrent memory tokens within bridge layers to enhance the linear layer’s memorization ability. Formally, for each video segment s_i , we prepend a fixed number of memory tokens, denoted as $[m_i; s_i]$, where m_i represents the memory tokens. Subsequently, we apply standard self-attention to this sequence, yielding $[m_{i+1}; o_i] = \text{BridgeLayer}([m_i; s_i])$. Here, m_{i+1} is the updated memory token, and o_i is the visual representation from the bridge layers. This process is carried out recursively, traversing the semantic video segments while updating the memory tokens. After a total of k steps, this output represents the condensed visual summary of the video sequence and will be used as the input for the LLM. As such, the Memory Bridge can **compress past video into memory tokens while preserving current video scenes through projection without losing detailed information by compressing**.

2.3 MEMORY CACHE WITH RETRIEVAL

One of the primary challenges associated with recurrent memory bridge layers is the potential for gradient vanishing, which can impede the model’s ability to learn long-range dependencies. To mitigate this issue, we propose the incorporation of a memory cache with a retrieval strategy designed to preserve previous states of memory.

Memory Attention At each timestep i , the system stores all previous memory tokens in a memory cache, denoted as $M_i = [m_1, \dots, m_i]$. We employ a self-retrieval mechanism to update the current memory token m_i . Specifically, we treat m_i as a query and the concatenated memory cache M_i as key and value. The model performs a standard multi-head cross-attention operation to integrate information from previous timesteps into the current memory state, yielding the updated memory token

$$m_{i+1} = \text{Softmax} \left(\frac{W_i^Q m_i (W_i^K M_i)^\top}{\sqrt{d_k}} \right) W_i^V M_i, \quad (1)$$

where W_i^Q, W_i^K, W_i^V are weight matrices for query, key and value, respectively.

Computational Complexity For bridge layers, we consider three main components for the theoretical complexity: (i) the self-attention within each segment, which scales as $\mathcal{O}((C + M)^2)$, where C is the segment length and M is the length of memory tokens; (ii) the memory retrieval, which scales as $\mathcal{O}(MK)$; and (iii) the recurrent processing. Consequently, the overall time complexity of our approach is $\mathcal{O}(K^2)$, and the space complexity is $\mathcal{O}(K)$. For the LLM, the complexity is $\mathcal{O}(M^2)$. In practice, the segment length C is a constant that depends on the constraint of LLM. K is one M -th of L , thus our segmentation approach effectively compresses semantic units to an extreme degree, thereby striking a favorable balance between computational efficiency and model efficacy. Moreover, The number of segments can be fixed to accommodate the constraints of the environment.

3 EXPERIMENTS

3.1 SETUP

We utilize Vicuna-7B-v1.5³ as the LLM and ViT-L/14 as the visual backbone following VideoLLaVA (Lin et al., 2023). Each frame is resized and cropped to a dimension of 224×224 . The Memory Bridge Layers are based on a single-layer Transformer. Our model is trained with 16 frames and 4 segments, following the same video data protocol as PLLaVA. For the NIVAH test, we use the memory tokens as input to LLMs to evaluate their memory capabilities. For additional implementation details, please refer to **Appendix B**.

³<https://huggingface.co/lmsys/vicuna-7b-v1.5>

3.2 LONG-FORM VIDEO UNDERSTANDING

Baselines We compare two model types: retrieval-based methods and generative video-language models, as discussed in Section 4. For fairness, we primarily compare against SOTA models LLaVA-NeXT-Video-DPO (Zhang et al., 2024b) and PLLaVA (Xu et al., 2024b), which use the same base model and video datasets as ours. Other works like MovieChat (Song et al., 2023b) and MA-LMM (He et al., 2024) are excluded due to inconsistent model configurations and benchmark settings (see Appendix B.3).

Model	LLM	Frames	Accuracy
GPT4-o	OpenAI API	16	72.2
<i>Retrieval-based Video-Language Models</i>			
LongViViT* 2023	-	256	56.8
MC-ViT-L* 2024	-	128	62.5
<i>Generative Video-Language Models</i>			
SeViLA 2023	Flan-T5-XL	32	25.8
mPLUG-Owl 2023	LLaMA-7B	5	33.8
VideoLLaVA 2023	Vicuna-7B	8	40.2
LLaVA-NeXT-Video-DPO 2024b	Vicuna-7B	32	41.6
PLLaVA 2024b	Vicuna-7B	16 (16)	45.6
PLLaVA 2024b	Vicuna-7B	32 (16)	43.8
VideoLLaMB (Ours)	Vicuna-7B	32 (8)	53.8

Table 1: **Results on Subset of EgoSchema under zero-shot setting.** * indicates that the model has been fine-tuned using the training data from EgoSchema.

Model	Temporal	Causal	Description	All
GPT4-o	70.3	78.0	80.8	76.0
<i>Retrieval-based Video-Language Models</i>				
AIO* 2023a	48.0	48.6	63.2	50.6
VQA-T* 2021	49.6	51.5	63.2	52.3
ATP* 2022	50.2	53.1	66.8	54.3
VGTT* 2022	52.3	55.1	64.1	55.0
MIST-CLIP* 2023	56.6	54.6	66.9	57.1
<i>Generative Video-Language Models</i>				
SeViLA 2023	61.5	61.3	75.6	63.6
LLaMA-VID 2023d	53.8	60.0	73.0	59.5
VideoLLaVA 2023	56.9	61.0	75.0	61.3
LLaVA-NeXT-Video-DPO 2024b	55.6	61.0	73.9	61.3
PLLaVA* 2024b	62.2	68.5	79.7	68.2
VideoLLaMB (Ours)*	66.8	71.6	78.4	71.1

Table 2: **Comparison accuracy on NExT-QA.** * indicates that the instruction data includes the training data from NExTQA.

Results on EgoSchema EgoSchema (Mangalam et al., 2023) consists of egocentric videos, each averaging **180 seconds** in length. This video QA dataset focuses on aspects such as understanding, reasoning, and long-term memory. In our experiment, we follow the precedent set by previous studies and use the public subset for evaluation. The results are presented in Table 1. Overall, our method significantly outperforms current generative video language models trained on similar data, demonstrating robust performance compared to other approaches and confirming its efficacy. Specifically, we compare our method with PLLaVA Xu et al. (2024b), which shares the same training data, LLM backbones, and input number of frames. Our method shows significant improvements over PLLaVA, indicating its superiority in understanding long egocentric videos. While our method does not yet match the performance of fine-tuned retrieval-based methods, we plan to apply our approach to larger language models to bridge this performance gap.

Length Extrapolation The model is trained on 16-frame sequences, divided into 4 segments. However, in real-world scenarios, videos can be significantly longer than this training configuration. To demonstrate VideoLLaMB’s ability to extrapolate to longer videos, we conducted experiments on EgoSchema under two conditions: 1) dynamic segments, which adaptively control the number of segments based on the SceneTilling threshold, and 2) static segments, fixed at 4 segments. Results in Figure 2 reveal that dynamic segments are more effective than static segments, especially for shorter videos, indicating that our method can effectively maintain an appropriate number of segments. However, as video length increases, the performance of dynamic segments declines, notably at the 32-frame mark, where both strategies use four segments. Beyond this point, increasing the number of segments results in diminishing returns, likely due to the domain gap from training on shorter videos. To address this issue, we plan to fine-tune our models on longer videos for more substantial improvements. Overall, compared to PLLaVA, our method maintains consistent performance as the input length increases. In summary, our approach effectively extracts key information from videos, outperforming the simple pooling strategies used for memory consolidation in existing methods.

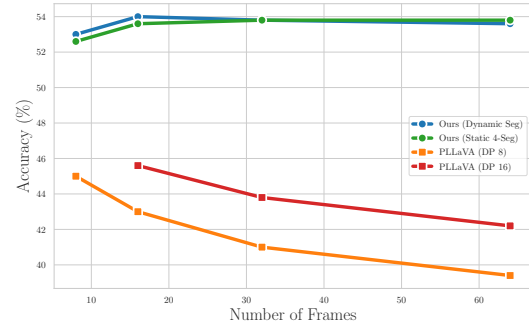


Figure 2: **Length extrapolation results on EgoSchema dataset.**

Method	Vision Encoder	LLM Size	AS	AP	AA	FA	UA	OE	OI	OS	MD	AL	ST	AC	MC	MA	SC	FP	CO	EN	ER	CI	Avg.
GPT-4V	GPT-4V	/	55.5	63.5	72.0	46.5	73.5	18.5	59.0	29.5	12.0	40.5	83.5	39.0	12.0	22.5	45.0	47.5	52.0	31.0	59.0	11.0	43.5
mPLUG-Owl-I 2023	VIT-L	7B	25.0	20.0	44.5	27.0	23.5	36.0	24.0	34.0	23.0	24.0	34.5	34.5	22.0	31.5	40.0	24.0	37.0	25.5	21.0	37.0	29.4
LLaMA-Adapter 2023d	VIT-B	7B	23.0	28.0	51.0	30.0	33.0	53.5	32.5	33.5	25.5	21.5	30.5	29.0	22.5	41.5	39.5	25.0	31.5	22.5	28.0	32.0	31.7
BLIP2 2022	VIT-G	2.7B	24.5	29.0	33.5	17.0	42.0	51.5	26.0	31.0	25.5	26.0	32.5	25.5	30.0	40.0	42.0	27.0	30.0	26.0	37.0	31.0	31.4
Otter-I 2023a	VIT-L	7B	34.5	32.0	39.5	30.5	38.5	48.5	44.0	29.5	19.0	25.5	55.0	20.0	32.5	28.5	39.0	28.0	27.0	32.0	29.0	36.5	33.5
MiniGPT-4 2023	VIT-G	7B	16.0	18.0	26.0	21.5	16.0	29.5	25.5	13.0	11.5	12.0	9.5	32.5	15.5	8.0	34.0	26.0	29.5	19.0	9.9	3.0	18.8
InstructBLIP 2023	VIT-G	7B	20.0	16.5	46.0	24.5	46.0	51.0	26.0	37.5	22.0	23.0	46.5	42.5	26.5	40.5	32.0	25.5	30.0	25.5	30.5	38.0	32.5
LLaVA 2023b	VIT-L	7B	28.0	39.5	63.0	30.5	39.0	53.0	41.0	41.5	23.0	20.5	45.0	34.0	20.5	38.5	47.0	25.0	36.0	27.0	26.5	42.0	36.0
Video-LLaMA 2023b	CLIP-G	7B	27.5	25.5	51.0	29.0	39.0	48.0	40.5	38.0	22.5	22.5	43.0	34.0	22.5	32.5	45.5	32.5	40.0	30.0	21.0	37.0	34.1
LLaMA-Adapter 2023d	VIT-B	7B	23.0	28.0	51.0	30.0	33.0	53.5	32.5	33.5	25.5	21.5	30.5	29.0	22.5	41.5	39.5	25.0	31.5	22.5	28.0	32.0	31.7
Video-ChatGPT 2023	VIT-L	7B	23.5	26.0	62.0	22.5	26.5	54.0	28.0	40.0	23.0	20.0	31.0	30.5	25.5	39.5	48.5	29.0	33.0	29.5	26.0	35.5	32.7
VideoChat 2023c	CLIP-G	7B	33.5	26.5	56.0	33.5	40.5	53.0	40.5	30.0	25.5	27.0	48.5	35.0	20.5	42.5	46.0	26.5	41.0	23.5	23.5	36.0	35.5
VideoChat2 2023b	UMT-L	7B	66.0	47.5	83.5	49.5	60.0	58.0	71.5	42.5	23.0	23.0	88.5	39.0	42.0	58.5	44.0	49.0	36.5	35.0	40.5	65.5	51.1
PLLaVA 7B 2024b	VIT-L	7B	58.0	49.0	55.5	41.0	61.0	56.0	61.0	36.0	23.5	26.0	82.0	39.5	42.0	52.0	45.0	42.0	53.5	30.5	48.0	31.0	46.6
PLLaVA 13B 2024b	VIT-L	13B	66.0	53.0	65.5	45.0	65.0	58.0	64.5	35.5	23.5	30.0	85.0	39.5	45.5	57.0	47.5	49.5	49.0	33.0	53.0	37.0	50.1
VideoLLaMB α (Ours)	VIT-L	7B	52.0	50.5	85.5	42.5	51.0	69.5	56.0	38.5	41.0	24.0	69.5	40.0	48.0	71.5	43.5	34.5	41.5	29.5	38.0	60.0	49.33
VideoLLaMB β (Ours)	VIT-L	7B	54.5	47.0	86.5	44.5	52.0	79.0	58.5	32.0	47.0	33.0	82.5	40.5	52.0	82.0	40.5	37.5	43.0	31.0	42.5	60.0	52.5

Table 3: **Results on MVBench (Li et al., 2023b) multi-choice question answering.** We list GPT-4V in the first row group as a reference. The second row group includes image-based MLLMs. The third row group includes video-based MLLMs. We highlight top-3 results among all 7B models of each category in purple. α : training data from Xu et al. (2024b). β : training with data from Li et al. (2023b).

Results on NExTQA (Xiao et al., 2021) NExTQA (Xiao et al., 2021), featuring daily-life videos that average 45 seconds in length, is designed to test a variety of question types, specifically temporal, causal, and descriptive questions. We applied our method to NExTQA to evaluate its temporal grounding ability. To maintain consistency with established benchmarks, we used the validation set for evaluation. In Table 2, we present the comprehensive results of our analysis. For a fair comparison, our primary benchmark is against PLLaVA, which includes instruction data from the NExTQA training set. Our method surpasses PLLaVA by 2.9 points. Notably, our approach demonstrates a significant enhancement in the temporal setting, achieving a 4.6 point improvement over PLLaVA. These results indicate that our scene-segment aware method effectively improves the model’s temporal grounding ability by compressing abundant information within scenes that share high semantic similarity.

Results on Comprehensive Video Understanding Benchmark We also evaluate our method on a comprehensive video understanding benchmark MVBench (Li et al., 2023b). In Table 3, our results could reveal that our mechanism will reserve the comprehensive video understanding ability over general video understanding tasks. Notably, our method with the same training data as PLLaVA, could achieve similar performance as 13B level model. We believe our method could obtain more information whether for short or long videos. To further validate the scalability of our model, we trained our method on the VideoChat2 (Li et al., 2023c) dataset. The results, illustrated at the bottom of Table 3, show that when trained on larger video datasets, VideoLLaMB improves accuracy on MVBench by 3.17 points and surpasses VideoChat2, which was trained on the same dataset.

3.3 PLANNING TASKS

Baselines Given the relatively brief duration of the input videos of the current planning benchmark, our comparative analysis includes both image-language and video-language models. The original protocol dictated the selection of a single frame corresponding to each action. To refine this approach and enhance the evaluation process, we introduce a smoother method. This involves segmenting the entire video into intervals based on predefined timesteps. This revised method is applied in the evaluation of the PLLaVA, LLaVA-NeXT-Video-DPO, and VideoLLaMB.

Results on EgoPlan (Chen et al., 2023) The EgoPlan dataset (Chen et al., 2023) was developed as an egocentric question-answering benchmark tailored for embodied planning tasks, comprising 3,355 questions. The evaluation follows the framework established in the original study, utilizing the probability $p(a|v, l)$ to identify the most suitable answer candidates. In Table 4, we demonstrate that our model surpasses all other video-language models in performance. This suggests that our model’s use of memory significantly enhances its planning capabilities compared to methods focused on the current stage. While our approach does not outperform certain image-language models, we attribute this to the constraints of the current benchmark, which features brief action sequences and carefully curated frame-action pairs. Our goal is to develop more challenging benchmarks for

Model	LLM	Accuracy
GPT-4V	OpenAI API	37.98
<i>Image-Language Model</i>		
Qwen-VL-Chat (Bai et al., 2023)	Qwen-7B	26.32
LLaVA-1.5 (Liu et al., 2023a)	Vicuna-7B	26.80
SEED-LLaMA (Ge et al., 2023)	LLaMA2-Chat-13B	29.93
InternLM-Xcomposer (Zhang et al., 2023c)	InternLM-7B	34.4
<i>Video-Language Model</i>		
VideoChatGPT (Maaz et al., 2023)	LLaMA-7B	26.35
Valley (Luo et al., 2023)	LLaMA-13B	26.17
VideoLLaMA (Zhang et al., 2023b)	LLaMA2-Chat-7B	29.85
LLaVA-NeXT-Video (Zhang et al., 2024b)	Vicuna-7B	28.96
PLLaVA (Xu et al., 2024b)	Vicuna-7B	30.26
VideoLLaMB (Ours)	Vicuna-7B	32.32

Table 4: Results on EgoPlan under Zero-shot setting.

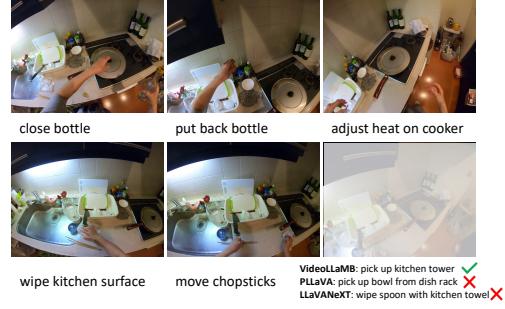


Figure 3: Qualitative results on EgoPlan.

egocentric planning and to adapt our method for real-time planning tasks. We are confident that our method holds great promise for generalizing to practical, real-world planning scenarios.

Qualitative Results We present the qualitative outcomes of various approaches on EgoPlan, as depicted in the Figure 3. The target goal is “clean and organize kitchen”. Our method showcases effective reasoning based on previous steps and the current state, in contrast to other methods that tend to make predictions based solely on the initial or final visual inputs. Consequently, our approach enhances the model’s capability in planning tasks.

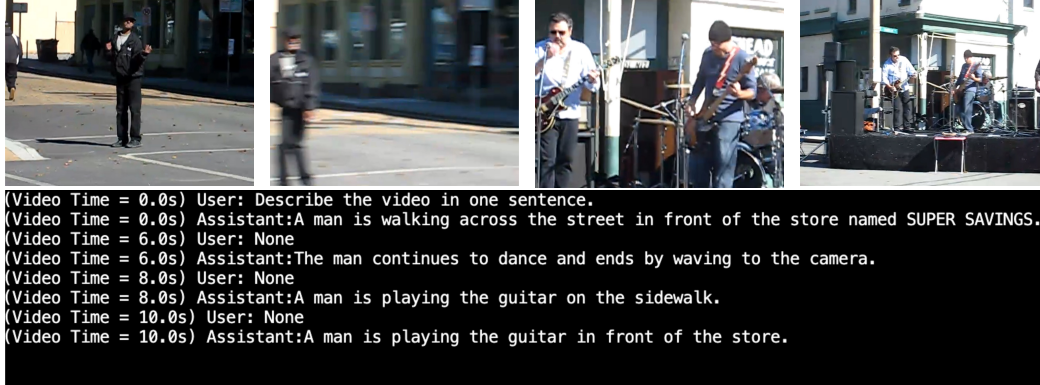


Figure 4: Qualitative results on streaming dense caption tasks. The video is randomly selected from the NExTQA validation set. Our method could accurately recognize the camera change and zoom out, and predict the corresponding captions.

3.4 STREAMING CAPTION

Streaming dense video captions (Chen et al., 2024b; Zhou et al., 2024) involves generating captions for videos in real-time, without the need to process the entire video sequence beforehand. The primary challenge in this task is determining the exact timestamps to predict event captions. Most existing methods rely on special tokens, annotated as the end of an action, for training. Our approach introduces the SceneTiling algorithm, which can automatically identify the break points in a streaming video and generate captions without requiring special training tokens. To enhance the efficiency of our method, we calculate the depth score using only the left similarity: $d_i = (cl(i) + s_i) / 2$. In Figure 4, we present qualitative results of our method applied to a streaming video. These results demonstrate that our method can effectively detect scene changes and automatically generate event captions.

3.5 STRESS TEST: “NEEDLE IN A VIDEO HAYSTACK”

To address existing limitations in long-form video language understanding benchmarks, our work takes inspiration from the latest developments in the field and develops a new benchmark specifically designed for the task of identifying specific content within extensive video material, a challenge we

Needle: *A young man is sitting on a piece of cloud in the sky, reading a book.*

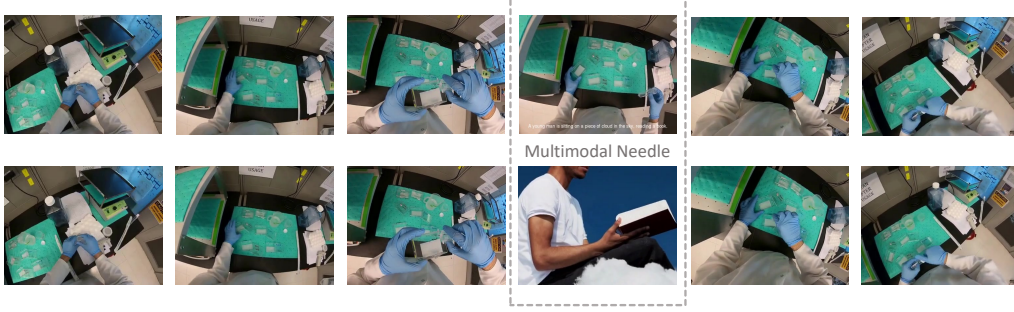


Figure 5: **Example of NIAVH.** For the text needle, the description is appended directly to the video; for the image and video needles, the corresponding image and video clips are inserted into the video haystack.

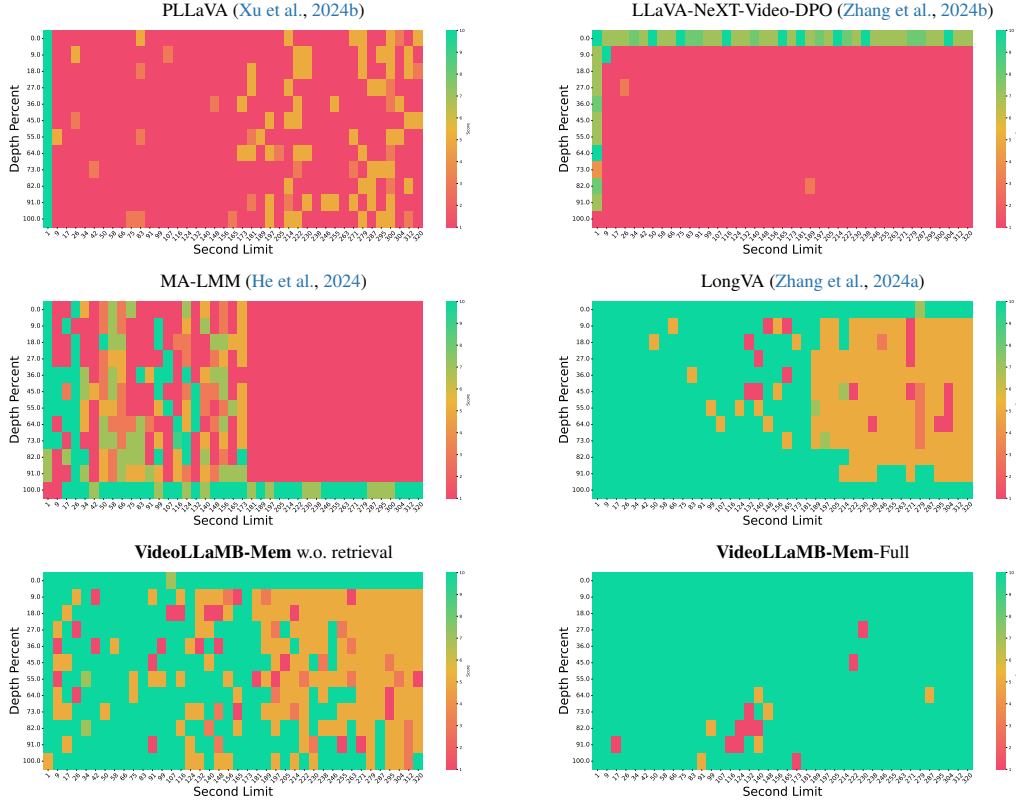


Figure 6: **Comparison of VideoLLaMB with two long video understanding models on Needle In A Video Haystack (NIAVH).** Currently, we set the context length to 320 seconds w.r.t. existing models’ ability and set the frame rate to 1 fps to ensure the input contains the needle. The X-axis indicates the video length, and the Y-axis is the depth of the insertion point.

refer to as the Needle In A Video Haystack (NIAVH). This benchmark is unique in that it supports queries in various modalities, including text, image, and video, allowing for a more comprehensive assessment of a model’s video understanding capability.

Benchmark Setting In NIAVH, we utilize ego-centric videos from the Ego4D (Grauman et al., 2022) dataset as the “haystack,” within which we seek to locate the “needle” provided in three distinct modalities: textual, image, and video. For the textual modality, we supply a crafted description; for

the image modality, we use DALL-E⁴ to create a corresponding image; and for the video modality, we employ Sora (Brooks et al., 2024) to generate a short video clip, all based on the same description. Each “needle” is set to a duration of 1 second and is inserted into the concatenated Ego4D videos at various depths and lengths. To evaluate the benchmark, a direct question about the details within the needles is set, and an LLM compares the response with the ground truth, providing a score from 1 to 10, with 10 indicating a perfect match. For quantitative results, we calculate the average scores for additional analysis.

Comparison with similar benchmarks Recent work proposes a multimodal needle-in-a-haystack benchmark MM-NIAH (Wang et al., 2024a), which focuses on a mixture of images and documents as the haystack and only supports text and image needles. In contrast, NIVAH focuses on streaming video stacks and supports text, image, and video needles.

Experiment Setup Given the limitations of current methods in understanding long videos, we designed an experiment where the “haystack” is a 320-second video. The “needle” is a 1-second video clip generated by Sora, prompted by the description, “the young man seated on a cloud in the sky is reading a book”. The associated question posed for the experiment is, “What is the young man seated on a cloud in the sky doing?”. We divided the context into 40 intervals and set the video depth at 12 intervals.

Results and Analysis In our experiment, we evaluate our approach with four distinct methods. These include (a) adaptive pooling (Xu et al., 2024b), (b) position extrapolation combined with sampling (Zhang et al., 2024b), and (c) the integration of resampler with memory retrieval and consolidation (He et al., 2024). (d) video alignment with long-context LLM without compression (Zhang et al., 2024a). For each model, we standardize the video frame rate to one frame per second, aligning the number of input frames with the duration of the video in seconds. This allows the inputs not to miss the needle information and all the models are in fair comparison. The outcomes of this evaluation are depicted in Figure 6. Our analysis leads to the following key observations:

- Methods utilizing an adaptive pooling strategy risk omitting crucial information, as the length of the source material (the “haystack”) is often many times greater than the target segment (the “needle”).
- Pooling strategies that incorporate position extrapolation are ineffective at predicting lengths that exceed those encountered during training or fine-tuning.
- Combining a resampler with a memory retrieval strategy markedly improves the encoding of extended information within a video. However, the length that can be encoded is ultimately constrained by the resampler’s compression capacity.
- VideoLLaMB with memory retrieval is the most efficient at preserving previously encountered information. Nevertheless, it still exhibits shortcomings: it tends to forget earlier information and is prone to hallucination issues, such as misidentifying “holding book” as “holding phone”.

3.6 PERFORMANCE ANALYSIS

Memory Cost Our model’s recurrent strategy maintains a consistent visual input length to the LLM, significantly reducing GPU memory usage. While a larger memory cache theoretically requires more memory, the impact is minimal due to shorter memory tokens compared to visual input tokens. The recurrent memory operates on the bridge layer, minimizing intermediate costs. In our experiments on the EgoSchema (Mangalam et al., 2023) dataset, we compared our model against three video-language model categories: vanilla, pooling-based, and sampling-based.

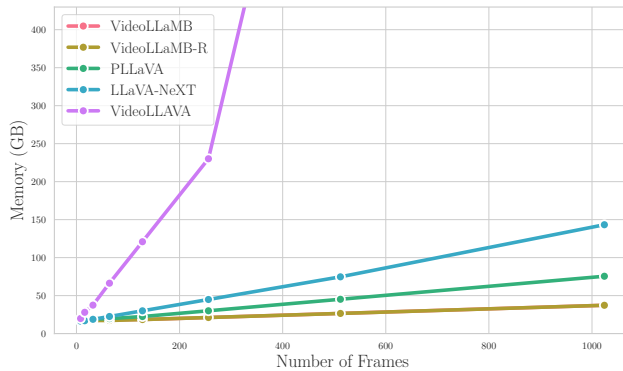


Figure 7: **GPU Memory Cost.** We apply all the experiments on a single NVIDIA A800 GPU.

⁴<https://openai.com/index/dall-e-3/>

Results in Figure 7 show that our methods and other fixed-length input models significantly cut memory usage, with our approach compressing input length more effectively. Our design’s efficiency is evident, as the memory cache incurs negligible additional memory cost.

Inference Time Our primary concern with our approach is the potential time expenditure associated with recurrent processes and memory retrieval. To address this, we conducted experiments to assess the efficiency of our method in comparison to others. The evaluation included all current methods capable of handling long videos. We tested each model on NIAVH with 300 second video cases to measure their performance for comparison. The results Table 5, demonstrate that our method not only outperformed the existing methods but did so even when compared to those employing a pooling strategy (Xu et al., 2024b). We attribute this improved performance to the efficient memory management mechanism integrated within the bridge layer of our method. This enables our approach to condense the visual input more effectively than others, resulting in shorter processing times of the LLM.

Methods	LLM	Inference Time (s) ↓	Score ↑
MovieChat	Vicuna-7B	143.7	-
MALMM	Vicuna-7B	14.5	3.39
LLaVA-NeXT-Video-DPO	Vicuna-7B	11.1	1.72
PLLaVA	Vicuna-7B	7.4	1.82
VideoLLaMB	Vicuna-7B	4.21	5.73

Table 5: **Average Inference Time** on the 300-second videos from NIAVH. The score is the average score on NIAVH.

3.6.1 ABLATION STUDY

In this section, we present an ablation study of our method, focusing on its individual components. We analysis our method the EgoSchema dataset. The corresponding results are detailed in Table 6. Initially, we assess the effectiveness of the recurrent mechanism. To do this, we replace this mechanism with two pooling strategies: mean pooling and adaptive pooling. For comparison purposes, we configure the adaptive pooling strategies to produce a target time sequence length of 4, matching our method’s settings. Our findings reveal that all pooling strategies cause a notable degradation in performance. Notably, the adaptive pooling strategy underperforms even mean pooling. We hypothesize that this discrepancy arises from differences in how training and inference are conducted; mean pooling, being more consistent, likely enhances the model’s generalizability. We then evaluate the memory retrieval mechanism and observe that it is indeed capable of preserving memory to a certain degree. Lastly, we examine the impact of our semantic segmentation strategy. Compared to a uniform segmentation approach, our method is more adept at dividing videos into semantic segments. This segmentation results in a more efficient preservation of information, mitigating the information loss typically associated with sampling strategies.

Method	Accuracy	Δ
w.o. recurrent memory (mean pooling)	51.61	-2.19
w.o. recurrent memory (adaptive pooling)	49.4	-4.4
w.o. memory retrieval	52.2	-1.6
w.o. semantic segment (uniform segment)	52	-1.8
w.o. mixture of images	49.8	-4.0
memory tokens only	50.4	-3.4
VideoLLaMB	53.8	

Table 6: **Ablated results on the effects of different modules.**

4 RELATED WORK

Long Video Language Understanding The evolution of LLMs has significantly enhanced our ability to understand lengthy videos in terms of their interaction with human language. Methods for long video analysis fall into three categories: scaling-up approaches, agent-based techniques, and length extrapolation strategies. Scaling-up approaches focus on enlarging model parameters and extending training data (Liu et al., 2024a), or creating more efficient architectures to replace computationally intensive transformers (Li et al., 2024; Chen et al., 2024a), though these may not always be practical. Agent-based techniques utilize LLMs’ strategic planning, involving various visual experts for comprehensive understanding (Wang et al., 2023b; Choudhury et al., 2023; Fan et al., 2024) or converting visual inputs into textual descriptions (Wang et al., 2023c; Zhang et al., 2023a; Yang et al., 2024; Wang et al., 2024b), but can face efficiency issues or out-of-domain content challenges. Length extrapolation extends image-language and short video-language modeling to longer durations using strategies like temporal embeddings (Qian et al., 2024a), prompts (Ren et al., 2023), position encodings (Wang et al., 2024c;d), frame condensation (Song et al., 2023b), visual

token compression (Korbar et al., 2023; Ma et al., 2023; Liu et al., 2024b), and retrieval-based methods with visual features (He et al., 2024), often through selective sampling which risks losing information. Our work introduces a recurrent memory strategy to encode entire video sequences and use a memory cache to preserve past memory, and project the memory-augmented current semantic segment into the LLM to maintain long video understanding ability.

Anticipatory Video Planning The field of planning, which entails the prediction of future actions based on past action sequences and the present context, has been substantiated as an effective approach within language models, as evidenced by several studies (Driess et al., 2023; Song et al., 2023a; Mu et al., 2023). This methodology has parallels in video understanding, where the task of action anticipation based on visual data has gained traction (Sener & Yao, 2019; Farha et al., 2020; Furnari et al., 2017). A burgeoning area of research is the intersection of action anticipation and goal-directed planning, which enhances the fundamental capabilities of artificial intelligence in the context of video understanding (Patel et al., 2023; Zhao et al., 2023; Chen et al., 2023). This challenge is particularly acute in real-time streaming environments, where the system must not only interpret the current state but also retain a relatively extensive memory of past events to inform decision-making. Therefore, our proposed method could naturally suit this problem.

5 CONCLUSION

In conclusion, VideoLLaMB offers an advancement in video-language models by enhancing computational efficiency and efficacy. Utilizing Memory Bridge Layers with recurrent memory tokens and the SceneTilling algorithm, VideoLLaMB preserves crucial visual information and semantic coherence in long videos. The NIAVH benchmark robustly evaluates this capability. Empirical results show VideoLLaMB outperforms existing methods in long video QA, egocentric planning, and frame retrieval. In the future, we would like to integrate part of the LLM memory with the memory in the bridge while keeping the whole system efficient.

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A PARAMETER ANALYSIS

# of Memory Tokens	# of Bridge Layer	Accuracy
32	1	53.8
64	1	53
32	3	54
64	3	54.6

Table 7: **Parameter Analysis** we apply analysis of different parameters of our framework

We conducted a detailed parameter analysis of our model, focusing on two primary aspects: the number of memory tokens and the number of bridge layers. This analysis was performed using the EgoSchema dataset, under the experimental settings in Appendix B.1. The outcomes of this analysis are presented in Table 7. From the results, we observed a clear trend: a simultaneous increase in the number of memory tokens and the number of bridge layers leads to a notable improvement in performance. This finding is significant as it provides valuable direction for future enhancements of our method. To optimize our model further, we propose expanding the capacity of the bridge layer by adding more parameters while concurrently exploring more efficient architectural designs.

B IMPLEMENTATION DETAILS

B.1 IMPLEMENTATION DETAILS

In our experiment, we configured the memory tokens to a capacity of 32 and employed a single transformer layer as the bridge layer. For the training process, we set the number of training frames to 16 and limited the number of segments to 4. In order to ensure the visual encoder’s plug-and-play functionality, we froze its parameters, focusing the training solely on the bridge layer and the LLMs. We utilized the Image Encoder and Video Encoder from VideoLLaVA (Lin et al., 2023). In alignment with the procedures of PLLaVA (Xu et al., 2024b), we initialized the LLM using the LLaVA-1.5 (Liu et al., 2023a) configuration. The training dataset was identical to that used in PLLaVA, leveraging the same video data. To maintain the model’s proficiency in static visual learning, we retained the fine-tuning image data from LLaVA-1.5. Our experiments were conducted on four Nvidia A800 GPUs. Regarding other hyperparameters, we adhered to the original settings specified in the initialized models

B.2 PARAMETER DETAILS

In this section, we will include more detailed implementation details. In Table 8, we demonstrate the implementation details of our method, including the details of the Bridge Layer, Retrieval Layer, and other hyperparameters of our initialized LLaVA.

B.3 BASELINE CLARIFICATION

This work miss two long-video understanding model in some benchmarks for the following reasons: (1) the MALMM is built on InstructBLIP, which limits the input query length and, therefore, can’t be applied to the EgoSchma and the NExTQA benchmark. (2) MovieChat requires reloading the model at each test and requires heavy I/O pressure. Therefore, we only include the MALMM on our NIAVH benchmark for comparison.

Table 8: Hyperparameters for VideoLLaMB.

Hyperparam	VideoLLaMB
Number of Bridge Layers	1
Number of Retrieval Layers	1
Bridge Layer Attention Heads	8
Retrieval Layer Attention Heads	8
Bridge Layer Hidden Size	1024
Retrieval Layer Hidden Size	1024
Vision Feature Select Layer	-2
Model Max Length	2048
Learning Rate	2e-4
Batch Size	8
Epoch	1
Warmup Ratio	0.03
Weight Decay	0.0
Patch Size	14
Image Size	224