MA-LMM: Memory-Augmented Large Multimodal Model for Long-Term Video Understanding

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https://boheumd.github.io/MA-LMM/

Abstract

*With the success of large language models (LLMs), integrating the vision model into LLMs to build vision-language foundation models has gained much more interest recently. However, existing LLM-based large multimodal models (*e.g.*, Video-LLaMA, VideoChat) can only take in a limited number of frames for short video understanding. In this study, we mainly focus on designing an efficient and effective model for long-term video understanding. Instead of trying to process more frames simultaneously like most existing work, we propose to process videos in an online manner and store past video information in a memory bank. This allows our model to reference historical video content for long-term analysis without exceeding LLMs' context length constraints or GPU memory limits. Our memory bank can be seamlessly integrated into current multimodal LLMs in an off-the-shelf manner. We conduct extensive experiments on various video understanding tasks, such as long-video understanding, video question answering, and video captioning, and our model can achieve state-of-the-art performances across multiple datasets.*

1. Introduction

Large language models (LLMs) have gained significant popularity in the natural language processing field. By pre-training on large-scaled textual data, LLMs (*e.g.* GPT [1–4], LLaMA [5, 6]) have demonstrated remarkable abilities to perform both generative and discriminative tasks with a unified framework. Recently, there has been a growing interest in utilizing LLMs on multimodal tasks. By integrating LLMs with visual encoders, they can take images and videos as input and show incredible capabilities in various visual understanding tasks, such as captioning, question answering [7–13], classification, detection, and segmentation [14–20].

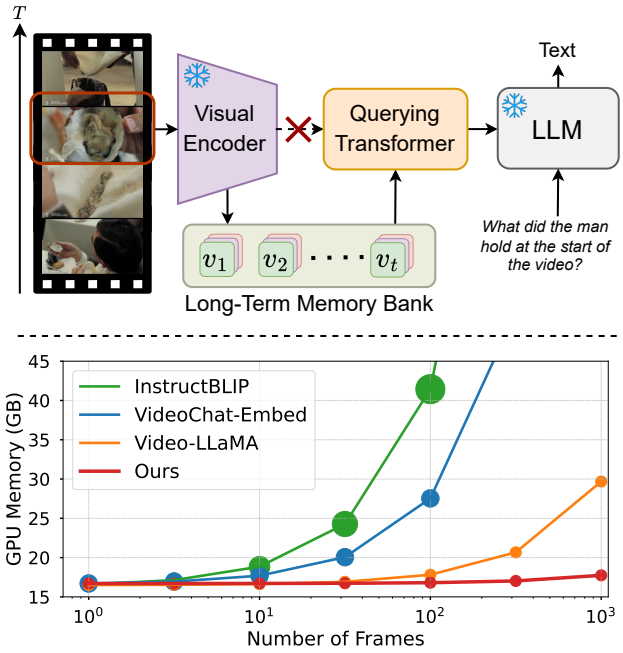

Figure 1. (a) We propose the long-term memory bank to auto-regressively store and accumulate past video information, different from previous methods directly feeding the visual encoder's outputs into the querying transformer. (b) GPU memory and token number v.s. video frame length of multimodal methods and MA-LMM during inference. Circle sizes represent the number of text tokens.

To handle video inputs, some prior large multimodal models [7, 9] directly feed the concatenated query embeddings of each frame along the temporal axis into LLMs. However, the inherent context length limitation of LLMs and GPU memory consumption restrict the number of video frames that can be processed. For example, LLaMA has a context length limitation of 2048 while large multimodal models like LLaVA [8] and BLIP-2 [7, 9] take in 256 and 32 tokens per image respectively. Therefore, this design is not practical and feasible when video duration is much longer (*e.g.* movies and TV shows). To address these issues, a naive solution is to apply average pooling along the temporal axis like Video-ChatGPT [21], but this leads to inferior performances as it

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lacks explicit temporal modeling. An alternative method involves adding a video modeling component to capture temporal dynamics, as seen in Video-LLaMA [12], which employs an extra video querying transformer (Q-Former) to obtain video-level representation. However, this design adds model complexities, increases the training parameters, and is not suitable for online video analysis.

With these in mind, we introduce a **M**emory-**A**ugmented **L**arge **M**ultimodal **M**odel (MA-LMM), aiming for efficient and effective long-term video modeling. MA-LMM adopts a structure similar to existing large multimodal models [7, 9, 12], which comprise a visual encoder to extract visual features, a querying transformer to align the visual and text embedding spaces, and a large language model. As illustrated in Figure 1(a), as opposed to directly feeding visual encoder outputs to the querying transformer, we opt for an online processing approach that takes video frames sequentially and stores the video features in the proposed long-term memory bank. This strategy of sequentially processing video frames and leveraging a memory bank significantly reduces the GPU memory footprint for long video sequences. It also effectively addresses the constraints posed by the limited context length in LLMs as demonstrated in Figure 1(b). Our design provides a solution for long-term video understanding with large multimodal models with great advantages over prior approaches [7, 9, 12, 13, 21] which consume huge GPU memory and require a large number of input text tokens.

The core contribution of our approach is the introduction of a long-term memory bank that captures and aggregates historical video information. Specifically, the memory bank aggregates past video features in an auto-regressive manner, which can be referenced during subsequent video sequence processing. Also, our memory bank is designed to be compatible with the Q-Former, where it acts as the key and value in the attention operation for long-term temporal modeling. As a result, it can be seamlessly integrated into existing large multimodal models in an off-the-shelf manner to enable long-term video modeling ability. To further enhance efficiency, we propose a memory bank compression method that maintains the length of the memory bank constant relative to the input video length. By selecting and averaging the most similar adjacent frame features, it can preserve all the temporal information while significantly reducing the temporal redundancies in long videos.

We summarize our main contributions as follows:

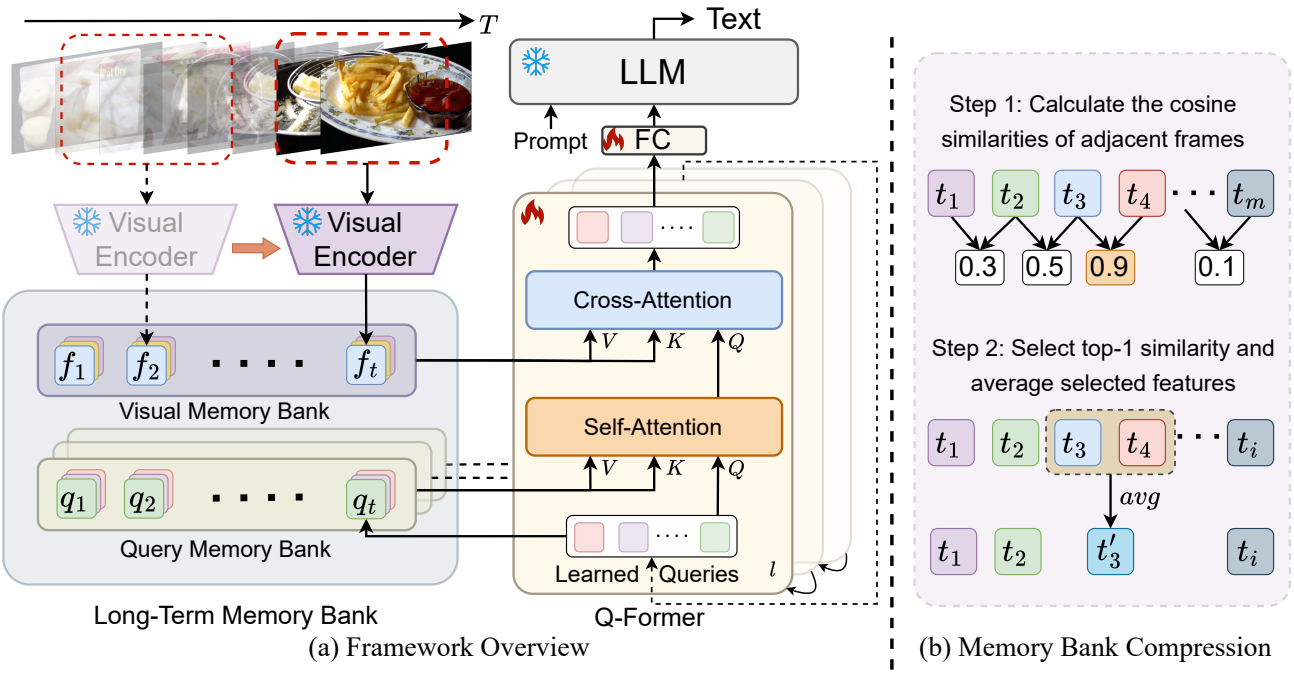
- We introduce a novel long-term memory bank design to enhance existing large multimodal models, equipping them with long-term video modeling capability.
- Our model significantly reduces the GPU memory usage and addresses LLMs' context length limitations by processing video sequences in an online fashion.
- Our approach has achieved new state-of-the-art performances on various downstreaming video tasks, including long-term video understanding, video question answering, and video captioning.

2. Related Work

Image-language models. Inspired by the success of powerful language models [1–6], recent image-language models tend to incorporate pre-trained language models with image encoders to support the multimodal reasoning ability [7–10, 22]. Flamingo [22] proposes to connect powerful pre-trained vision-only and language-only models and achieve state-of-the-art performance in few-shot learning tasks. BLIP-2 [7] introduces a lightweight querying transformer to bridge the modality gap between the frozen pre-trained image encoder and frozen LLMs. Despite having significantly fewer trainable parameters, it performs well on various multimodal tasks. LLaVA [8] employs a simple linear layer to project image features into the text embedding space and efficiently finetunes LLMs [23] for better performance. Building upon BLIP-2, MiniGPT-4 [10] collects a large-scale high-quality dataset of image-text pairs and achieves better language generation ability. VisionLLM [15] leverages the reasoning and parsing capacities of LLMs, producing strong performance on multiple fine-grained object-level and coarse-grained reasoning tasks.

Video-language models. Previous image-language models such as Flamingo [22] and BLIP-2 [7, 9] can also support video inputs. They simply flattened the spatio-temporal features into 1D sequences and then fed them into the language models for video inputs. However, these approaches can not effectively capture the temporal dynamics of videos. Based on this motivation, Video-LLaMA [12] enhances BLIP-2 structure by adding an additional video querying transformer to explicitly model the temporal relationship. Similarly, building on LLaVA [8], Video-ChatGPT [21] simply average pools the frame-level features across spatial and temporal dimensions to generate video-level representation. VideoChat [13] utilizes perception models to generate action and object annotations, which are then forwarded to LLMs for further reasoning. Despite the advancements, these models are primarily designed for short videos. Inspired by the Token Merging [24] which averages highly similar tokens to reduce the computation cost, we propose an extension of this idea to video data, specifically along the temporal axis. This extension aims to mitigate the challenges posed by extensive token numbers and computational cost associated with processing long video inputs. Several concurrent works [25–27] have also explored similar strategies of merging akin tokens for video inputs. Please refer to the supplementary material for more detailed discussions.

Long-term video models. Long-term video understanding methods focus on capturing long-range patterns in long videos, which typically exceed 30 seconds. To mitigate



(a) Framework Overview (b) Memory Bank Compression

Figure 2. (a) Framework overview. MA-LMM auto-regressively processes video frames in an online manner. Two long-term memory banks are designed to store the raw visual features and learned queries at each timestep, which are used for future reference. The Q-Former is composed of several cascaded blocks, indexed by l. LLM outputs text for various video understanding downstream tasks. The snowflake icon indicates components with fixed parameters, while the flame icon denotes parts of the model that are fine-tuned. (b) Illustration of the memory bank compression technique, which is applied to maintain the length of the memory bank constant.

the computational demands of processing long videos, a prevalent approach involves using pre-extracted features, sidestepping the need for joint training of backbone architectures [28–32]. Alternatively, some research works aim to devise sparse video sampling methods [33, 34], reducing the number of input frames by only preserving salient video content. Other works like Vis4mer [35] and S5 [36] leverage the streamlined transformer decoder structure of S4 [37] to enable long-range temporal modeling with linear computation complexity. Inspired by the memory bank design [38–41], we propose to integrate the long-term memory bank with large multimodal models to enable efficient and effective long-term temporal modeling capabilities.

3. Method

We introduce MA-LMM, a memory-augmented large multimodal model for long-term video understanding. Instead of processing more frames simultaneously as most video understanding methods [31, 42–49], we propose to auto-regressively process video frames in an online manner, which draws inspiration from the online processing fashion with long-term memory design presented in MeMViT [41]. Figure 2(a) illustrates the overview of our MA-LMM framework. Following similar practices of large multimodal models [7–9, 12], the overall model architecture can be divided into three parts: (1) visual feature extraction with a frozen visual encoder (Sec. 3.1), (2) long-term temporal modeling with a trainable querying transformer (Q-Former) to align the visual and text embedding spaces (Sec. 3.2), and (3) text decoding with a frozen large language model (Sec. 3.3).

3.1. Visual Feature Extraction

This design draws inspiration from the cognitive processes humans use to handle long-term visual information. Instead of concurrently processing extensive duration of signals, humans process them in a sequential manner, correlate current visual inputs with past memories for comprehension, and selectively retain salient information for subsequent reference [41]. Similarly, our MA-LMM processes video frames sequentially, dynamically associating new frame input with historical data stored in the long-term memory bank, ensuring that only discriminative information is conserved for later use. This selective retention facilitates a more sustainable and efficient approach to video understanding, which further allows the model to automatically support online video reasoning tasks.

Formally, given a sequence of T video frames, we pass each video frame into a pre-trained visual encoder and obtain the visual features $V = [v_1, v_2, .., v_T], v_t \in \mathbb{R}^{P \times C}$, where P is the number of patches for each frame and C is the channel dimension for the extracted frame feature. Then we inject temporal ordering information into the frame-level features by a position embedding layer (PE) as

$$f_t = v_t + PE(t), f_t \in \mathbb{R}^{P \times C}. \quad (1)$$

3.2. Long-term Temporal Modeling

For aligning the visual embedding to the text embedding space, we use the same architecture as the Querying Transformer (Q-Former) in BLIP-2 [7, 9]. Q-Former takes in the learned queries $z \in \mathbb{R}^{N \times C}$ to capture video temporal information, where N is the number of learned queries, and C is the channel dimension. In our experiments, Q-Former outputs 32 tokens for each image, which is more efficient than 256 tokens produced by LLaVA [8]. Each Q-Former block consists of two attention submodules: (1) cross-attention layer, which interacts with the raw visual embedding extracted from the frozen visual encoder, and (2) self-attention layer, which models interactions within the input queries. Different from the original Q-Former in BLIP-2 that only attends to the current frame's embedding, we design a long-term memory bank consisting of the visual memory bank and the query memory bank, which accumulates the past video information and augments the input to cross- and self-attention layers for effective long-term video understanding.

Visual Memory Bank. The visual memory bank stores the raw visual features of each frame extracted from the frozen visual encoder. Specifically, for the current time step t, the visual memory bank contains the concatenated list of past visual features $F_t = \texttt{Concat}[f_1, f_2, .., f_t], F_t \in \mathbb{R}^{tP \times C}$. Given the input query z_t, the visual memory bank acts as the key and value as:

$$Q = z_t W_Q,\ K = F_t W_K,\ V = F_t W_V. \tag{2}$$

Then we apply the cross-attention operation as:

$$O = Attn(Q, K, V) = \text{Softmax}\left(\frac{QK^T}{\sqrt{C}}\right) V. \tag{3}$$

In this way, it can explicitly attend to past visual information through the cached visual memory bank with long-term context. Since all the cross-attention layers in the Q-Former attend to the same visual feature, there is only one visual memory bank that is shared across all the Q-Former blocks.

Query Memory Bank. Different from the fixed visual memory bank which stores the raw and static visual features, the query memory bank accumulates input queries of each timestep, represented as $Z_t = \texttt{Concat}[z_1, z_2, .., z_t], Z_t \in \mathbb{R}^{tN \times C}$. By storing these queries, we maintain a dynamic memory of the model's understanding and processing of each frame up to the current timestep via the Q-Former. The query memory bank also acts as key and value as:

$$Q = z_t W_Q,\ K = Z_t W_K,\ V = Z_t W_V. \tag{4}$$

similar to the Eq 2. Then we apply the same attention operation as Eq. 3. At each time step, z_t contains the learned important information specifically for each video till the current timestep t. Different from the static visual memory bank, the input queries z_t evolve through cascaded Q-Former blocks during the model training, capturing distinct video concepts and patterns at increasing levels of abstraction. As a result, each self-attention layer has a unique query memory bank, where the contained input queries are updated during the training time.

Memory Bank Compression. Given that our model directly stores past video information in the memory banks, the GPU memory and computational cost increase linearly as the number of past video frames. This becomes particularly challenging for long videos, and thus it is essential to further compress the memory bank to a smaller size. One conventional approach to managing temporal sequences involves employing a first-in-first-out queue. Here, features from the earliest time step are removed when the memory bank reaches a predefined limit, a strategy utilized in MeMViT [41]. However, it results in the loss of earlier historical information as new frames are added and old features are popped to maintain memory bank capacity. Alternatively, MeMViT employs learnable pooling operators to compress the spatio-temporal size of stored feature in the memory bank, albeit at the cost of introducing additional trainable parameters.

Drawing inspiration from the effectiveness of token merging and pruning techniques showcased in works such as [24, 50–52], we introduce a novel Memory Bank Compression (MBC) technique to exploit temporal redundancies inherent in videos. Our proposed method aggregates and compresses video information over time by leveraging the similarity between adjacent features, thereby retaining early historical information. This approach effectively compresses repetitive information within the memory bank while preserving discriminative features. Notably, several concurrent works [25–27] have similarly embraced the token merging strategies to reduce video redundancies.

Same as MeMViT [41], which applies feature compression at each iteration, our method applies the compression algorithm at each auto-regressive step if the current length of the memory bank exceeds the predefined threshold M. Formally, given the visual memory bank containing a list of $[f_1, f_2, .., f_M], f_t \in \mathbb{R}^{P \times C}$, when a new frame feature f_{M+1} comes in, we need to compress the memory bank by reducing the length by 1. At each spatial location i, we first calculate the cosine similarity between all the temporally adjacent tokens as

$$s_t^i = \cos(f_t^i, f_{t+1}^i), t \in [1, M], i \in [1, P]. \tag{5}$$

Then we select the highest similarity across time, which can be interpreted as the most temporally redundant features:

$$k = \text{argmax}_t(s_t^i). \tag{6}$$

Next, we simply average the selected token features at all the spatial locations to reduce the memory bank length by 1:

$$\hat{f}_k^i = (f_k^i + f_{k+1}^i)/2. \tag{7}$$

In this way, we can still preserve the most discriminative features while keeping the temporal ordering unchanged as depicted in Figure 2(b). The same procedure is adopted to compress the query memory bank.

3.3. Text Decoding

As we process video frames in an auto-regressive manner, the Q-Former output at the final timestep contains all historical information, which is then fed into the LLM. Therefore, we can significantly reduce the number of input text tokens from $N * T$ to N, addressing the context length limitation of the current LLMs and substantially easing the GPU memory requirements. During training, given a labeled dataset consisting of video and text pairs, our model is supervised with the standard cross entropy loss as:

$$\mathcal{L} = -\frac{1}{S}\sum_{i=1}^{S} \log P(w_i|w_{<i}, V). \tag{8}$$

in which V represents the input video, and w_i is the i-th ground-truth text token. During training, we update the parameters of the Q-Former while keeping the weights of both the visual encoder and the language model frozen.

4. Experiments

4.1. Tasks and Datasets

To validate the effectiveness of the proposed MA-LMM, we mainly focus on the long-term video understanding task. We also extend the evaluation to standard video understanding tasks (*e.g.*, video question answering, video captioning) to further compare with existing multimodal methods.

Long-term Video Understanding. We conduct experiments on three widely used long-term video datasets including LVU [32], Breakfast [56], and COIN [57]. We report the top-1 classification accuracy as the evaluation metric. The LVU dataset contains ∼30K videos extracted from ∼3K movies, with each video lasting 1 to 3 minutes. Given that current large multimodal models generally perform text generation and lack regression capability, we limit our experiments to seven classification tasks: relationship, speaking style, scene, director, genre, writer, and release year. The Breakfast [56] dataset includes videos related to breakfast preparation, which consists of 1712 videos with an average length of around 2.7 minutes. COIN [57] is a large-scale dataset for comprehensive instructional video analysis, which comprises 11827 instructional videos from YouTube, covering 180 distinct tasks in 12 domains related to daily life. The average length of a video is 2.36 minutes.

Video Question Answering. We conduct evaluation on three open-ended video question answering datasets including MSRVTT-QA [62], MSVD-QA [62], and ActivityNet-QA [63]. ActivityNet-QA contains long videos with average durations of 2 minutes, while MSRVTT-QA and MSVD-QA consist of short videos with 10-15 seconds duration.

Video Captioning. We report the video captioning results of METEOR [64] and CIDEr [65] metrics on three popular datasets: MSRVTT [66], MSVD [67] and Youcook2 [68].

Online Action Prediction. We further evaluate the online prediction capability of our model by conducting experiments on the EpicKitchens-100 [69] dataset, which consists of 700 long videos of cooking activities with 100 total hours. It includes 97 verbs, 300 nouns, and 3807 action types. Following the same experimental setting in [70], we report the top-5 accuracy and recall results on the validation dataset.

4.2. Implementation Details

For the visual encoder, we adopt the pre-trained image encoder ViT-G/14 [71] from EVA-CLIP [72], it can be further changed to other clip-based video encoders. We use the pre-trained Q-Former weights from InstructBLIP [9] and adopt Vicuna-7B [73] as the LLM. All the experiments are conducted on 4 A100 GPUs. More details about training and evaluation are described in the supplementary material.

4.3. Main Results

Long-term Video Understanding. We compare MA-LMM with previous state-of-the-art (SOTA) methods on the LVU benchmark [32] in Table 1. Notably, MA-LMM outperforms existing long-term video models (S5 [36], ViS4mer [35], VideoBERT [55], and Object Transformer [32]) in both content understanding and metadata prediction tasks. This results in significant improvement in most tasks, enhancing the average top-1 accuracy by 3.8% compared to the S5 [36] model. Unlike previous video-based models which process all video frames simultaneously in an offline manner and predict probabilities for each class, our MA-LMM processes video frames in an online fashion and directly outputs the text label for each class type.

We also evaluate our MA-LMM on the Breakfast [56] and COIN [57] datasets that pose a challenge for the long-term video activity classification task. We show the results in Table 2. Our method improves upon the previous best method, S5[36], by 2.3% and 2.4% respectively on the top-1 accuracy metric. This result further proves the superior long-term video understanding capability of our approach.

Video Question Answering. To compare with existing multimodal video understanding methods, we conduct experiments on the open-ended video question answering datasets in Table 3 to demonstrate the generalization ability of our model. Given that these are mostly short videos, it is expected that our memory bank will be less effective. Interestingly, we observe that our MA-LMM achieves new state-of-the-art performances on the MSRVTT and MSVD datasets while falling short of VideoCoCa's performance on the Ac-

Table 1. Comparison with state-of-the-art methods on the LVU [32] dataset. **Bold** and underline represent the top-1 and top-2 results.

Model	Content			Metadata				Avg
	Relation	Speak	Scene	Director	Genre	Writer	Year	
Obj_T4mer [32]	54.8	33.2	52.9	47.7	52.7	36.3	37.8	45.0
Performer [53]	50.0	38.8	60.5	58.9	49.5	48.2	41.3	49.6
Orthoformer [54]	50.0	38.3	66.3	55.1	55.8	47.0	43.4	50.8
VideoBERT [55]	52.8	37.9	54.9	47.3	51.9	38.5	36.1	45.6
LST [35]	52.5	37.3	62.8	56.1	52.7	42.3	39.2	49.0
VIS4mer [35]	57.1	40.8	67.4	62.6	54.7	48.8	44.8	53.7
S5 [36]	**67.1**	42.1	73.5	67.3	**65.4**	51.3	48.0	59.2
Ours	58.2	**44.8**	**80.3**	**74.6**	61.0	**70.4**	**51.9**	**63.0**

Table 2. Comparison on the Breakfast [56] and COIN [57] datasets. The top-1 accuracy is reported here.

Model	Breakfast	COIN
TSN [58]	-	73.4
VideoGraph [59]	69.5	-
Timeception [31]	71.3	-
GHRM [60]	75.5	-
D-Sprv. [61]	89.9	90.0
ViS4mer [35]	88.2	88.4
S5 [36]	90.7	90.8
Ours	**93.0**	**93.2**

Table 3. Comparison with state-of-the-art methods on the video question answering task. Top-1 accuracy is reported.

Model	MSRVTT	MSVD	ActivityNet
JustAsk [74]	41.8	47.5	38.9
FrozenBiLM [75]	47.0	54.8	43.2
SINGULARITY [76]	43.5	–	44.1
VIOLETv2 [77]	44.5	54.7	–
GiT [78]	43.2	56.8	–
mPLUG-2 [79]	48.0	58.1	–
UMT-L [80]	47.1	55.2	47.9
VideoCoCa [81]	46.3	56.9	**56.1**
Video-LLaMA [12]	46.5	58.3	45.5
Ours	**48.5**	**60.6**	49.8

Table 4. Comparison with state-of-the-art methods on the video captioning task. METEOR (M) and CIDEr (C) results are reported.

Model	MSRVTT		MSVD		YouCook2	
	M	C	M	C	M	C
UniVL [82]	28.2	49.9	29.3	52.8	–	127.0
SwinBERT [83]	29.9	53.8	41.3	120.6	15.6	109.0
GIT [78]	32.9	73.9	**51.1**	**180.2**	17.3	129.8
mPLUG-2 [79]	**34.9**	**80.3**	48.4	165.8	–	–
VideoCoca [81]	–	73.2	–	–	–	128.0
Video-LLaMA	32.9	71.6	49.8	175.3	16.5	123.7
Ours	33.4	74.6	51.0	179.1	**17.6**	**131.2**

tivityNet dataset. On the latter, it is not surprising, since VideoCoCa [81] leverages large-scale video-text datasets for pre-training (*e.g.*, HowTo100M [84] and VideoCC3M [85]) while our MA-LMM uses model weights only pre-trained on the image-text datasets.

Notably, our MA-LMM significantly outperforms the recent LLM-based model Video-LLaMA [12] on all three datasets. Video-LLaMA concatenates all the query embeddings from the frozen image Q-Former and trains an additional video Q-Former from scratch to model temporal dependencies, consuming too much GPU memory to be feasible for long video inputs. In contrast, our MA-LMM simply fine-tunes the weights from the pre-trained image Q-Former without introducing an additional video Q-Former, yet is able to effectively capture temporal relationships by virtue of the long-term memory bank. This result strongly justifies the superiority of our design on the general video question answering task, and reveals that even a few frames and queries captured in the memory banks can have significant beneficial effects.

Video Captioning. To further evaluate the capabilities of our MA-LMM in generating free-form text, we conduct experiments on the standard video captioning datasets including MSRVTT [66], MSVD [67] and YouCook2 [68] in Table 4. Although these datasets only consist of videos with short duration and our model is initially pre-trained merely on image-text dataset pairs, our MA-LMM exhibits outstanding performances across all the metrics. It consistently ranks among the top-2 positions compared to current leading methods. Remarkably, our results also surpass the recent Video-LLaMA [12] on these datasets, highlighting the significant improvements our model offers in both video captioning and question-answering tasks.

Table 5. Action anticipation results on EpicKitchens-100.

Model	Accuracy@Top-5			Recall@Top-5		
	Verb	Noun	Act.	Verb	Noun	Act.
Video-LLaMA	73.9	47.5	29.7	**26.3**	27.3	11.7
Ours	**74.5**	**50.7**	**32.7**	25.9	**29.9**	**12.2**

Online Action Prediction. Since our model can naturally support the online video understanding task, we compare our MA-LMM with Video-LLaMA on the EpicKitchens-100 [69] dataset to investigate the online action prediction capability. In Table 5, our MA-LMM outperforms Video-LLaMA, achieving more accurate results in both top-5 accuracy and recall measures. This highlights our model's

Table 6. Contribution of visual and query memory banks.

Visual	Query	LVU	Breakfast	COIN
✗	✗	48.3	74.6	72.3
✓	✗	61.5	91.8	92.4
✗	✓	58.0	81.4	88.5
✓	✓	**63.0**	**93.0**	**93.2**

Table 7. Contribution of the long-term memory bank (MB) under off-the-shelf evaluation without training.

MB	MSRVTT	MSVD	ActivityNet	LVU
✗	19.5	38.8	29.9	23.6
✓	**20.3**	**40.0**	**37.2**	**32.8**

Table 8. Ablation of different temporal modeling methods.

Method	#Frame	#Token	GPU	LVU	Breakfast	COIN
Concat	60	1920	49.2	62.6	90.4	93.0
Avg Pool	100	32	21.2	57.6	80.6	87.6
ToMe	100	200	22.2	61.5	91.3	91.5
FIFO	100	32	19.1	61.3	88.5	90.4
MBC	100	32	19.1	**63.0**	**93.0**	**93.2**

Table 9. The comparison of using different LLMs.

LLM	MSRVTT	MSVD	ActivityNet	LVU
FlanT5-XL	46.5	57.6	48.2	62.0
Vicuna-7B	**48.5**	**60.6**	**49.8**	**63.0**

superior capacity to anticipate actions in an online manner, showcasing its effectiveness for applications that require real-time analytical capabilities.

4.4. Ablation Studies

Contribution of each component. To further investigate the contribution of the visual memory bank and query memory bank, we conduct ablation studies in Table 6. Initially, we observe that without any memory bank module, the performances across all three datasets are notably worse, due to the lack of temporal context. The introduction of either memory bank results in substantial improvements, confirming their roles in enhancing the model's ability to understand temporal sequences. We also find that the visual memory bank achieves better performance than the query memory bank. We hypothesize that the explicit method of storing historical raw video features in the visual memory bank is more effective than the query memory bank which implicitly captures video information through the input learned queries. And two memory banks are complementary to each other. When incorporating two memory banks together, our approach can boost the final performance by 14.7%, 18.4%, and 20.9% on the LVU, Breakfast, and COIN, respectively.

Long-term temporal modeling ablation. We compare different temporal modeling approaches in Table 8. In our setup, the Q-Former outputs 32 text tokens per frame. The most straightforward approach for temporal feature integration is either concatenating or averaging frame-level features. However, they resulted in inferior performances. Notably, concatenation requires a significantly higher number of text tokens and computational cost compared to other variants, which also introduces higher GPU memory consumption since they need to takes in all the video frames simultaneously. In addition, we conduct experiments using ToMe [24] to reduce the number of text tokens per frame from 32 to 2. However, without our auto-regressive strategy, it still requires 200 text tokens for 100-frame input. The second part

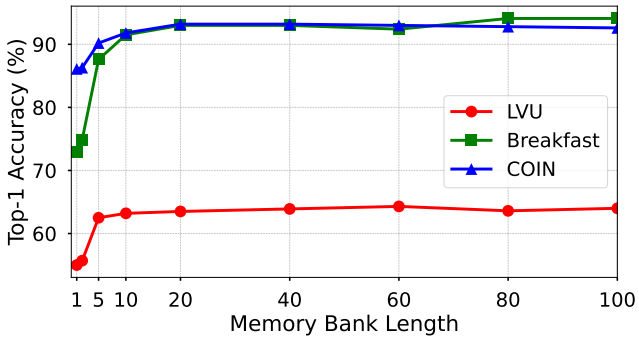


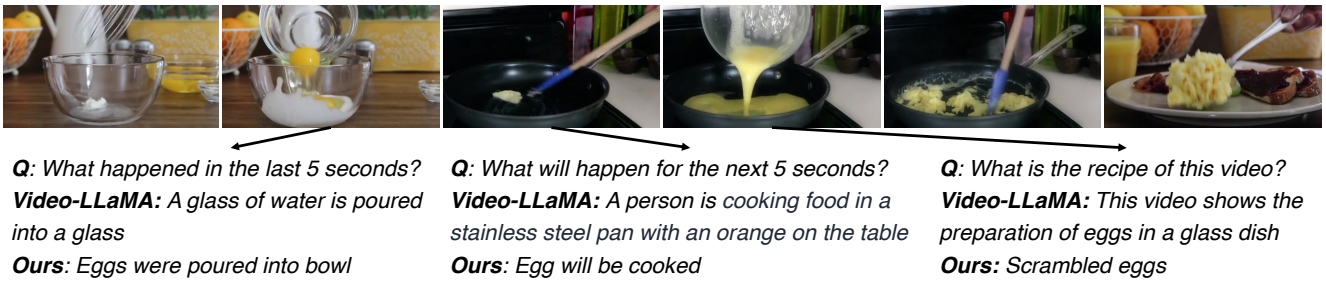
Figure 3. Impact of different memory bank lengths.

of this table presents the performances of different memory bank compression approaches. The first-in-first-out (FIFO) technique removes the oldest features to main the length of the memory bank fixed, while the memory bank compression (MBC) strategy merges temporally consecutive features with the highest similarity, effectively reducing the most redundant information while keeping the temporal ordering unchanged. With this design that theoretically keeps all historical information, MBC outperforms FIFO by 1.7%, 4.5%, and 2.8% accuracy across three datasets. This experimental result validates the superior efficiency and effectiveness of our approach in modeling long-term temporal information.

Off-the-shelf evaluation. A key advantage of MA-LMM is that our long-term memory bank can be inserted into existing large multimodal models in an off-the-shelf manner, thereby endowing them with effective temporal modeling capabilities without retraining. As presented in Table 7, MA-LMM can consistently boost the final performance when incorporating the long-term memory bank to the baseline method [9]. Particularly, on long-term video datasets like ActivityNet and LVU, MA-LMM can largely improve the results by 7.3% and 9.2%. This highlights the robustness of long-term memory banks in temporal modeling under the off-the-shelf setting.

Different language model architectures. Our MA-LMM

(a) Video question answering Task (ActivityNet-QA)



(b) Online off-the-shelf setting with custom questions

Figure 4. Visualization results on the video question answering task and the online off-the-shelf setting.

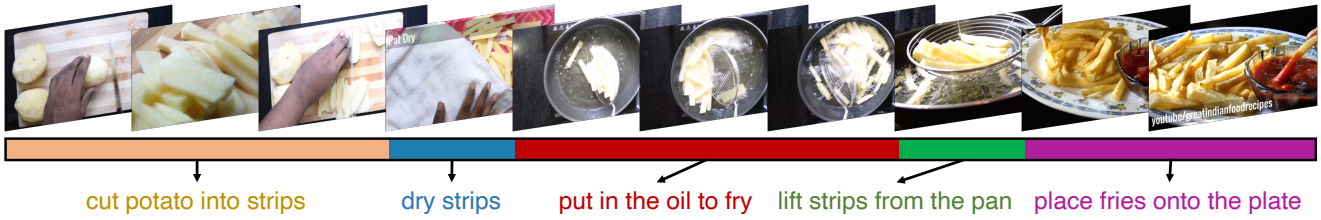


Figure 5. Visualization of the compressed visual memory bank.

can utilize different language model architectures including but not limited to encoder-decoder models and decoder-only models. We experimented with two popular models FlanT5-XL [86] and Vicuna-7B [73], and show the results in Table 9 that the Vicuna-7B marginally outperforms the FlanT5-XL on these video tasks.

Memory bank length ablation. In Figure 3, we conduct experiments to evaluate the effect of varying the memory bank length. Given an input of 100 video frames, the top-1 accuracy first increases as the feature bank length becomes larger. This rise can be attributed to the augmented storage capacity of the memory bank, which can preserve more historical data and consequently boost the final performance. However, we observe that performances begin to saturate when the memory bank length is around 10 to 20. This supports our hypothesis that there are prevalent temporal redundancies in long videos, and we can significantly reduce the frame length without sacrificing the performance.

4.5. Visualization

In Figure 4, we provide a comprehensive visual comparison between MA-LMM and Video-LLaMA [12]. In the video question answering task, MA-LMM exhibits superior memorization and recognition capabilities. Specifically, it can accurately memorize historical information and recognize fine-grained information, such as the color of the man with No.7, and precisely count the number of goalkeepers who appeared in the video. With the auto-regressive design, our model supports online reasoning directly. This capability is further exemplified in our experiments on off-the-shelf evaluations using custom questions. MA-LMM can correctly anticipate the next step of the video (*"egg will be cooked"*) and predict the correct recipe (*"scrambled egg"*). More visualization examples are shown in the supplementary material.

Figure 5 provides a visualization of the compressed visual memory bank. We set the memory bank length to 5 for this illustration. The compressed visual memory bank appears to group consecutive frames with similar visual content. For instance, in the presented video, the video frames are effectively grouped into five clusters, each capturing a distinct yet semantically consistent activity, which is similar to the effect of temporal segmentation.

5. Conclusion

In this paper, we introduce a long-term memory bank designed to augment current large multimodal models, equipping them with the capabilities to effectively and efficiently

model long-term video sequences. Our approach processes video frames sequentially and stores historical data in the memory bank, addressing LLMs' context length limitation and GPU memory constraints posed by the long video inputs. Our long-term memory bank is a plug-and-play module that can be easily integrated into existing large multimodal models in an off-the-shelf manner. Experiments on various tasks have demonstrated the superior advantages of our method. We believe our MA-LMM offers valuable insights for future research in the long-term video understanding area.

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Appendix

We present additional ablation experiments in Section A and further qualitative results for the video captioning task in Section B. Next, in Section C, we discuss the relations to concurrent works [25–27] in details. And in Sec. D, we show more dataset-specific implementation details and hyper-parameter settings. Finally, we address some limitations and outline directions for future research in Section E.

A. Additional Experiments

Memory bank compression at different spatial levels. In Table 10, we show comparison results of compressing the memory bank at different spatial levels (frame-level vs. token-level) on the LVU [32], Breakfast [56] and COIN [57] datasets. For the frame-level compression, we calculate the cosine similarity between adjacent frame features and average the frame-level features with the highest similarity. For the token-level compression, the cosine similarity is calculated between tokens at the same spatial location across the entire temporal axis, given that each frame-level feature contains multiple tokens at different spatial locations. The results indicate that token-level compression consistently surpasses frame-level compression in performance. Particularly, on the Breakfast dataset, the token-level surpasses the frame-level by 6.5% in top-1 accuracy. This superiority can be attributed to the importance of recognizing the object type of breakfast in videos. And token-level compression can help preserve much more fine-grained spatial information and details.

Inference time v.s. video frame lengths. In Figure 6, the inference time of MA-LMM increases linearly with respect to the frame lengths, due to its auto-regressive design of processing video frames sequentially. In contrast, directly concatenating frame-level features takes much longer time and higher GPU memory consumption, since it needs to process all video frames simultaneously.

B. More Qualitative Results

Our model's enhanced capabilities in video captioning are further showcased through additional visualization results in Figure 7. Here, our MA-LMM significantly outperforms Video-LLaMA [12] in generating detailed and accurate sentence descriptions. For instance, in the first video, our model precisely describes the action as "remove the onion rings and place them on the paper towel," capturing the entire action steps, while Video-LLaMA's description lacks this completeness, notably missing the crucial action of removing the onion rings. In the second video example, our model distinguishes itself by accurately identifying subtle details such as specific ingredients: chili powder, salt, and garlic powder, which Video-LLaMA overlooks. This highlights the enhanced capability of our MA-LMM in recognizing and describing fine-grained details.

Table 10. Memory bank compression at different spatial levels.

Spatial Level	LVU	Breakfast	COIN
Frame-level	61.8	86.5	91.1
Token-level	**63.0**	**93.0**	**93.2**

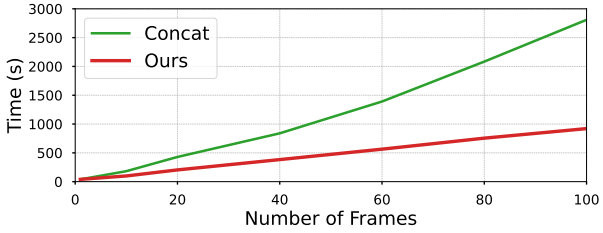

Figure 6. Inference time vs. input frame length.

C. Relations to Concurrent Works

In this section, we compare and discuss the relations between our MA-LMM with the concurrent works including TESTA [25], MovieChat [26] and Chat-UniVi [27]. All of these methods focus on utilizing the idea of token merging [24] to reduce video redundancies.

Temporal Modeling. Temporal modeling across these methodologies falls into three categories. Chat-UniVi [27] directly feed visual tokens into large language models (LLMs) without explicit temporal modeling, utilizing LLMs' inherent sequence processing for video understanding. In contrast, TESTA [25] and MovieChat [26] employ global self-attention; TESTA captures interactions along spatial and temporal dimensions, whereas MovieChat processes long videos in segments, compresses these into short-term memories, then concatenates and models global temporal interactions using a video Q-Former. Differently, our MA-LMM adopts causal self-attention, restricting each frame's feature access to prior video information only. Such a design naturally endows our MA-LMM with the capability to support online video applications in robotics, AR/VR, and video streaming.

Token Merging Application. Building on the token merging [24] strategy, four methodologies have adopted and modified this approach to reduce video data redundancy. Each uses the core concept of merging similar tokens but differs in implementation. TESTA [25] utilizes a cascaded module for spatial and temporal aggregation, progressively shortening video length and decreasing tokens per frame. In contrast, Chat-UniVi's [27] modules operate in parallel, merging tokens across both dimensions before LLM reasoning. MovieChat [26] employs a selective strategy to merge similar adjacent frames, reducing the number of video

Ground-Truth: *remove the onions and place on paper towel*
Video-LLaMA: *fry the onion rings in oil*
Ours: *remove the onion rings from the oil and place them on a paper towel*

Ground-Truth: *add garlic powder chili powder paprika salt cayenne pepper buffalo wing sauce to the wings and mix*
Video-LLaMA: *coat the chicken wings with the sauce*
Ours: *add chili powder salt garlic powder onion powder and paprika to the chicken and mix*

Figure 7. Visualization results on the video captioning task.

frames. Similarly, our MA-LMM conducts token merging along the temporal dimension to condense video length but at a more fine-grained spatial level. It independently compresses visual and query tokens across different spatial areas, enhancing performance as evidenced in Table 10.

Based Model. Both TESTA [25] and Moviechat [26] are built upon the video-based multimodal model. TESTA integrates TimeSFormer [47] as its video encoder, facilitating long-range video modeling. Meanwhile, MovieChat adopts the Video-LLaMA [12] framework, combining an image Q-Former with a video Q-Former to effectively manage long-term temporal relationships. On the contrary, another group involves adapting image-based multimodal models for video understanding. Chat-UniVi [27] leverages the LLaVA [8] architecture, feeding concatenated visual tokens along the temporal axis into LLMs. Our MA-LMM builds on InstructBLIP [9] as a plug-and-play module that significantly boosts long-term temporal modeling. Demonstrated in Table 7, our memory bank module greatly excels over InstructBLIP under the off-the-shelf setting without video-specific pre-training or introducing additional parameters.

Memory Bank Design. The integration of memory banks to enhance long-term video understanding has been thoroughly explored [38, 39, 41, 87, 88]. Building on these studies, MovieChat [26] and our MA-LMM both employ memory bank designs. MovieChat primarily uses memory banks to consolidate raw and static visual features. In contrast, our MA-LMM innovates with an additional query memory bank that captures dynamic memory, reflecting the evolving understanding of past video frames. The effectiveness of our query memory bank is evidenced in Table 6.

D. Experiment Details

We build our MA-LMM on top of InstructBlip [9], following the codebase [89]. We show the details of hyper-parameters in the following table for different tasks and datasets. For all the experiments, we use a cosine learning rate decay. Table 11 shows the hyper-parameters for the long-term video understanding task. For the LVU dataset, we follow the same practice in [35, 36], we sample 100 frames of 1 fps for each video clip. For the Breakfast [56] and COIN [57], we uniformly sample 100 frames from the whole video. Table 12 shows the hyper-parameters on the MSRVTT-QA [62], MSVD-QA [62], and ActivityNet-QA [63] datasets for the video question answering task while Table 13 presents the hyperparameters on the MSRVTT [66], MSVD [67], YouCook2 [68] datasets for video captioning.

E. Limitation and Future Work

Since our model takes in video frames in an online manner, leading to reduced GPU memory usage, but at the cost of increased video processing time. This trade-off becomes particularly noticeable with extremely long videos, where processing times can become significantly prolonged. To mitigate this issue, we suggest a hierarchical method to process extremely long-term video sequences. This strategy involves dividing extensive videos into smaller segments and then processing each segment sequentially in an auto-regressive fashion as we present in the main paper. Then we can employ additional video modeling techniques to model inter-segment relationships. This method aims to strike a balance between memory efficiency and processing speed, making it a practical solution for long-term video understanding.

For the future work, there are several potential aspects to further enhance the model's capabilities. First, replacing the existing image-based visual encoder with a video or clip-based encoder can naturally enhance the model's ability to capture short-term video dynamics. This provides a better representation of the video's temporal dynamics. Second, the model's overall performance in understanding videos can substantially benefit from the pre-training stage on large-scale video-text datasets. This approach is a common practice in existing research and has proven effective in enhancing generalization capabilities. Finally, the flexibility inherent in our model's architecture allows for the incorporation of a more advanced LLM as the language decoder. This integration offers a clear opportunity for boosting the final performance, making our model more effective in interpreting and responding to complex video content.

Table 11. Hyperparameters of different datasets on the long-term video understanding task.

Dataset	**LVU**	**Breakfast**	**COIN**
LLM	Vicuna-7B		
Epochs	20		
Learning rate	1e-4		
Batch size	64		
AdamW β	(0.9, 0.999)		
Weight decay	0.05		
Image resolution	224		
Beam size	5		
Frame length	100		
Memory bank length	20		
Prompt	"What is the {task} of the movie?"	"What type of breakfast is shown in the video?"	"What is the activity in the video?"

Table 12. Hyperparameters of different datasets on the video question answering task.

Dataset	**MSRVTT**	**MSVD**	**ActivityNet**
LLM	Vicuna-7B		
Epochs	5		
Learning rate	1e-4		
Batch size	128		
AdamW β	(0.9, 0.999)		
Weight decay	0.05		
Image resolution	224		
Beam size	5		
Frame length	20		
Memory bank length	10		
Prompt	"Question: {} Short Answer:"		

Table 13. Hyperparameters of different datasets on the video captioning task.

Dataset	**MSRVTT**	**MSVD**	**YouCook2**
LLM	Vicuna-7B		
Epochs	10		
Learning rate	1e-5	1e-5	1e-4
Batch size	128		
AdamW β	(0.9, 0.999)		
Weight decay	0.05		
Beam size	5		
Image resolution	224		
Frame length	80		
Memory bank length	40		
Prompt	"what does the video describe?"		