

MovieChat: From Dense Token to Sparse Memory for Long Video Understanding

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<https://reself.github.io/MovieChat>

Abstract

Recently, integrating video foundation models and large language models to build a video understanding system can overcome the limitations of specific pre-defined vision tasks. Yet, existing systems can only handle videos with very few frames. For long videos, the computation complexity, memory cost, and long-term temporal connection impose additional challenges. Taking advantage of the Atkinson-Shiffrin memory model, with tokens in Transformers being employed as the carriers of memory in combination with our specially designed memory mechanism, we propose the MovieChat to overcome these challenges. MovieChat achieves state-of-the-art performance in long video understanding, along with the released MovieChat-1K benchmark with 1K long video and 14K manual annotations for validation of the effectiveness of our method.

1. Introduction

Recent advances in Large Language Models (LLMs) [13, 19, 47, 62, 64] achieve great success in Natural Language Processing (NLP). It is a natural progression to introduce multi-modality [16] into LLMs and turn it into Multi-modal Large Language Models (MLLMs), which is able to conduct multimodal rationalization and understanding. MLLMs have shown incredible emergent capabilities in various multimodal tasks such as perception (e.g., existence, count, position, OCR) [1, 33, 34, 43, 69, 85], commonsense reasoning [26, 28, 33, 34, 36, 43, 61, 85], and code reasoning [21, 24, 26, 39, 41, 78], resulting in a potential path to Artificial General Intelligence (AGI). Compared to LLMs and other task-specific models, MLLMs provide a

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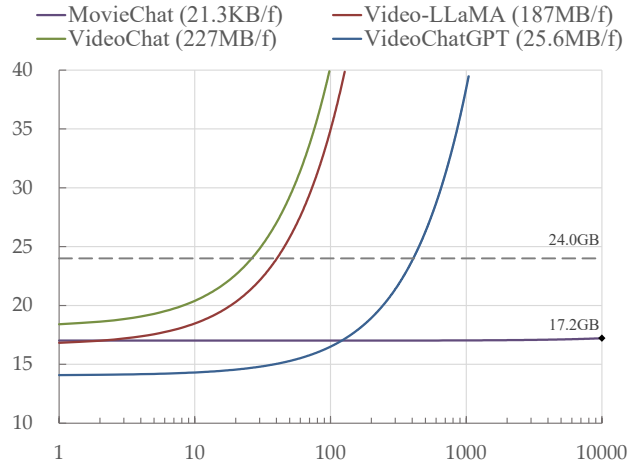


Figure 1. VRAM cost under gigabyte (GB) (y-axis) v.s. frame number (x-axis) comparison. We test the visual-only inference of all methods at a resolution of 224×224 without frame sampling. While the previous method can only support around 100 frames of inference, MovieChat can handle videos with $>10K$ frames on a 24GB graphics card. MovieChat has a $10000\times$ advantage over other methods in terms of the average increase in VRAM cost per frame (21.3KB to ~ 200 MB per frame).

more human-like interpretation of the scenarios, a user-friendly interface for interaction, and a broader range of capabilities.

Existing vision-centric MLLMs follow the paradigm that utilizing pre-trained LLMs and visual encoder with additional learnable modules (Q-former [21, 34, 36, 82] or simple projection layer [22, 39, 43, 61]). In video field, some previous works [43, 82] follow this paradigm to build video MLLMs, while works in the other paradigm [37, 67] combine existing visual perception tools (e.g., tracking and classification) and LLMs through Application Programming In-

terface (API) to build a system without training. Yet, previously, there is no exploration of a model or system based on long videos (over one minute), and there is also a lack of a standardized benchmark to evaluate the capabilities of these systems.

In this paper, we present MovieChat, a novel framework that integrates vision models and LLMs to conduct long video understanding tasks. We claim that the computation complexity, memory cost, and long-term temporal connection are the main challenges for long video understanding. Atkinson-Shiffrin memory model [5] proposes that short-term memory functions as a buffer of long-term memory, serving as a processor for the encoding of information into long-term memory. Inspired by this, we propose a memory mechanism to deal with long video understanding tasks, which includes a rapidly updated short-term memory and a compact thus sustained long-term memory. We use a sliding window approach to extract video features and represent them in token form, which are then sequentially fed into the short-term memory frame by frame. The short-term memory has a fixed length, and when it reaches its set limit, the earliest tokens are popped and consolidated into the long-term memory. After passing through a projection layer, the video representation is inputted into a large language model for interaction with the user. As shown in Fig. 1, our proposed MovieChat mechanism outperforms other existing methods in terms of Video Random Access Memory (VRAM) cost. We also release a new benchmark, MovieChat-1K, with 1K long videos and 13K manual question-answering pairs for validation of the effectiveness of our proposed MovieChat.

The contributions of this work are summarized as:

- We present MovieChat, a novel framework that integrates vision models and LLMs, which is the first to support long video (>10K frames) understanding tasks.
- We propose an effective memory management mechanism to reduce the computation complexity and memory cost, while enhancing the long-term connection.
- We release the first long video understanding benchmark, MovieChat-1K, with manual annotations and conduct extensive quantitative evaluation and case studies to evaluate the comparable performance of both understanding capability and inference cost.

2. Related Works

2.1. Multi-modal Large Language Models

LLMs [13, 19, 47, 62, 64, 65] have achieved great success in natural language processing (NLP) tasks recently. Many works try to build MLLMs [1, 21, 26, 28, 33, 34, 43, 69, 78, 85]

by combining models of other modalities. Flamingo [1] bridges powerful pre-trained vision-only and language-only models and achieves state-of-the-art performance with few-shot learning. BLIP-2 [34] proposes a generic and efficient pre-training strategy that bootstraps vision-language pre-training from an off-the-shelf frozen pre-trained image encoders and a frozen large language model. MiniGPT-4 [85] also aligns a frozen visual encoder with a frozen LLM, Vicuna [19], using just one projection layer to realize the system. Otter [33] showcases improved instruction-following ability and in-context learning. In video field, ChatVideo [67] treats tracklets as the basic video unit and allows users' interacting with the LLMs. VideoChat [37] integrates video foundation models and LLMs via a learnable neural interface, excelling in spatiotemporal reasoning, event localization, and causal relationship inference. VideoLLaMA [82] further leverages pre-trained models ImageBind [27] and LLaMA [64], bootstrapping cross-modal training in videos following BLIP-2. Yet, these methods fail to handle long video understanding because of high computation complexity, large memory cost, and weak long-term temporal connection. Therefore, our main effort is to introduce an effective memory mechanism to overcome these challenges.

2.2. Long Video Understanding

Understanding long videos is a challenging task in computer vision. Prior arts use 3D CNN for long-term feature bank [70], object/human-centric motion [50, 71], or other forms [54, 72] as video representations. MIST [25] decomposes dense self-attention into a cascade segment and region selection module to increase the computation efficiency for understanding minutes of long videos. Building long-form video understanding datasets is challenging and rarely explored. [57] captures large scale data from Kinetics-400 [15], but only for generic event boundary detection tasks. [58] creates a language grounding benchmark from audio descriptions of movies, but it lacks long-term understanding evaluation. [63] successfully builds a benchmark contains multiple sources of information (*e.g.*, video clips, plots, and DVS) for question-answering tasks in the movie field. There are also several datasets of video-caption/description pairs among various domains, such as cooking (*e.g.*, MPII Cooking [51–53] and TACoS [48, 49]), instruction (*e.g.*, HowTo100M [45] and HiREST [80]), Ego [44], and movie (*e.g.*, MovieQA [63] and MovieNet [31]) from different sources such as YouTube [17, 45, 81], Twitter [6–9], and Internet [10]. Yet, those datasets lack diverse and fine-grained dense captioning for long videos.

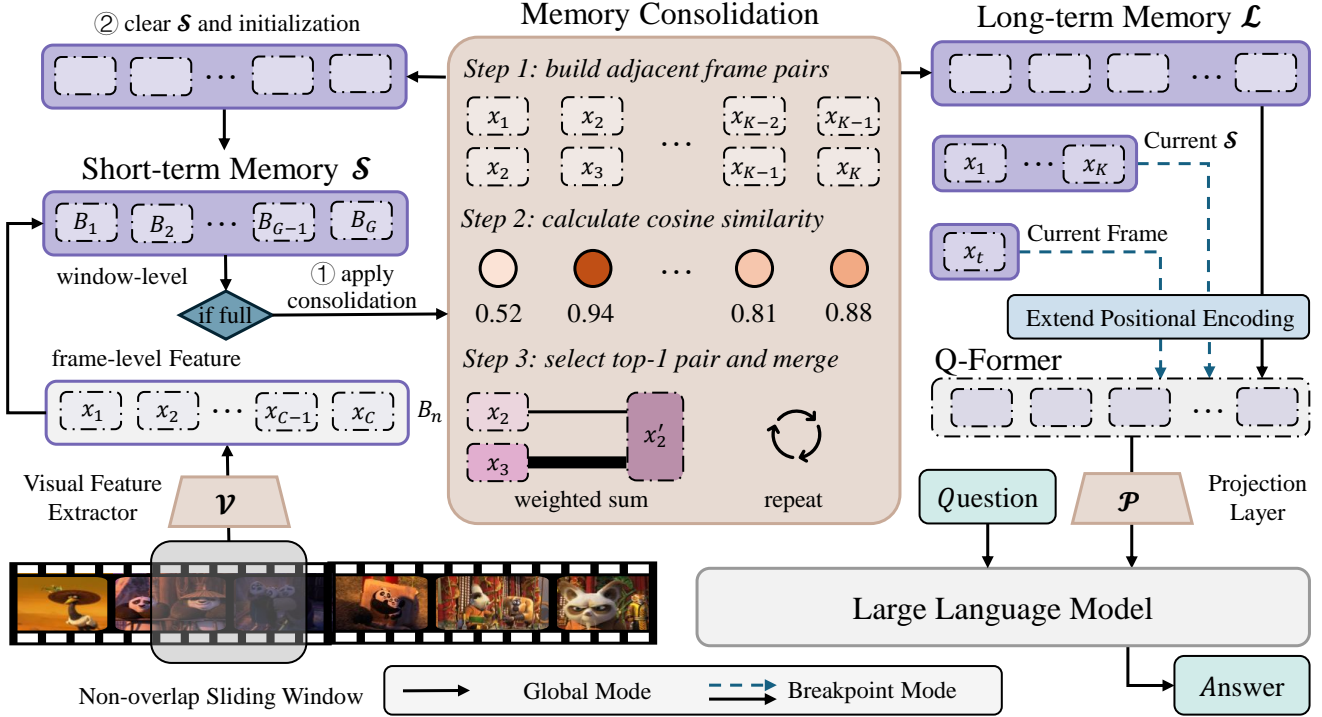


Figure 2. **Illustration of MovieChat.** MovieChat extracts video features with a sliding window and represents them in token form, which are then sequentially fed into the short-term memory frame by frame. When the fixed-length short-term memory reaches its preset limit, the earliest tokens are popped and consolidated into the long-term memory. MovieChat incorporates two distinct inference modes: the global mode, which exclusively utilizes the long-term memory, and the breakpoint mode, which additionally incorporates the current short-term memory as part of the video representation. The breakpoint mode allows for understanding the video at a specific moment in time. After passing through a projection layer, the video representation is inputted into a large language model for interaction with the user.

2.3. Memory Models in Vision Tasks

There are some prior works exploring memory models [59] in various vision tasks in videos, such as video object segmentation (VOS) [18, 30, 55, 56], multi-object tracking (MOT) [2, 14, 29, 73], visual object tracking (VOT) [38, 42, 77, 84], and action understanding [68]. MeMOT [14] builds a large spatiotemporal memory that stores the past observations of the tracked objects. XMem [18] develops an architecture that incorporates multiple independent yet deeply-connected feature memory storage to handle long videos with thousands of frames. We learn from the experience of those prior arts and further adopt an effective memory mechanism in combination with LLMs.

Our method focuses on reducing the redundancy of visual tokens in the video and building a memory mechanism to pass the information among a large temporal range.

3. MovieChat

3.1. Overview

Our proposed method, MovieChat, comprises several key components, including the frame-wise visual feature

extractor, the short-term and long-term memory modules, the video projection layer, and the Large Language Model (LLM), as illustrated in Fig. 2. MovieChat is designed for ultra-long videos (>10K frames) understanding through interactive dialogue with the user. To address the impractical storage demands of concurrently storing a vast number of frames in both GPU memory and RAM, we employ a sliding window approach to efficiently process the video. The short-term memory module embeds dense tokens with sliding window and the long-term memory module periodically updates. MovieChat supports two inference modes: Breakpoint mode is used to understand a specific moment in the video, providing insights and answers based on that particular frame or scene; Global mode, on the other hand, is employed to comprehend the entire video as a whole, enabling a comprehensive understanding of the overall content and context.

3.2. Visual Feature Extraction

For visual feature extraction, instead of utilizing video-based foundational models such as ViViT [4] or VideoSwin [40], we simply use an image-based model to get

frame-wise feature in the form of tokens. To be specific, we utilize pre-trained models as our visual feature extractor, including the ViT-G/14 from EVA-CLIP [23] and the Q-former from BLIP-2 [35]. This is mainly because 1) there is few video foundation model that makes good alignment with text, and 2) our proposed memory mechanism can effectively capture temporal features. Given a raw video, the visual input $\mathbf{v} \in \mathbb{Z}^{T \times 3 \times H \times W}$ is a sequence of T RGB frames of size $H \times W$ sampled from the video. The visual features are extracted in a sliding window manner, which could be formulated as

$$B_n = \{\mathbf{x}_i = \mathcal{V}(\mathbf{v}_i) \mid \forall i = 1, \dots, C\}, n = 1, \dots, \lceil \frac{T}{C} \rceil, \quad (1)$$

where B_n is the n -th video clip feature within the sliding window spanning C frames. $\mathcal{V}(\cdot)$ is the visual feature extractor, taking as input a single frame $\mathbf{v}_i \in \mathbb{Z}^{3 \times H \times W}$. $\mathbf{x}_i \in \mathbb{R}^{N \times D}$ denotes N extracted visual tokens with respect to each frame, and D is the feature dimension of each token.

3.3. Short-term Memory

Short-term memory stores the frame tokens in a temporary fixed-length buffer. The previously extracted visual features by sliding window G times without further processing are used to construct short-term memory, which can be formulated by:

$$\mathcal{S} = \bigcup_n B_n = \{\mathbf{x}_i \mid \forall i = 1, \dots, K\}, n = 1, \dots, G, \quad (2)$$

where \mathcal{S} is short-term memory, and K is equal to $C \times G$. Note that we set short-term memory to contain a fixed length of K frames since the role of short-term memory is to assist in video understanding based on previous short-term contextual information.

The update strategy for short-term memory is based on the First-in-First-out (FIFO) queue. As a new batch of visual tokens enters, when the short-term memory reaches its capacity, we pop the currently stored frames to the memory consolidation module and clear the short-term memory. The output video feature obtained from the consolidation module augments the long-term memory; on the other hand, it reinitializes the short-term memory with this feature. The initialization aims at communicating the information between different sliding windows, thereby achieving more efficient compression.

3.4. Long-term Memory

Long-term memory can effectively avoid the problem of catastrophic knowledge forgetting, which is crucial for handling long video understanding tasks. The features stored in short-term memory are dense tokens, but due to the limitations of GPU memory and computation cost, storing all the tokens dropped from short-term memory into long-term

Algorithm 1 Memory consolidation

Require: \mathcal{S} ▷ short-term memory
1: **while** $len(\mathcal{S}) > R_L$ **do** ▷ iterative merge
2: **for** \mathbf{x}_i in \mathcal{S} **do**
3: $s \leftarrow sim(\mathbf{x}_i, \mathbf{x}_{i+1})$ ▷ tokens similarity
4: **end for**
5: $m \leftarrow max(s)$ ▷ the maximum value index
6: $\mathbf{x}_m \leftarrow merge(\mathbf{x}_m, \mathbf{x}_{m+1})$ ▷ merge
7: **del** \mathbf{x}_{m+1}
8: **end while**

memory buffer in sequence is infeasible. Besides, we observe significant temporal redundancy in videos, where activities span multiple frames with minimal visual changes. To this end, we propose a method to merge adjacent similar frames to simplify video feature representation and accelerate video encoding. This method transforms the dense tokens to the sparse memories, which are stored in long-term memory.

To be specific, as shown in Algorithm 1, we conduct memory consolidation by merging the most similar tokens in the adjacent frames following ToMe [12] periodically. We find that the token embedding in Transformer already summarize the information of each frame for using in calculating the average cosine similarity s of N embedded tokens:

$$s = \frac{1}{N} \sum_{j=1}^N [\cos(\mathbf{x}_i^j, \mathbf{x}_{i+1}^j)]. \quad (3)$$

Our goal is to keep R_L frames after every merge operation, which also embeds rich information stored in the long-term memory. R_L is the hyper-parameter to control the trade-offs between performance and efficiency. Therefore, we greedily merge each set of adjacent frames with the highest similarity via weighted averaging. The merge operation is iteratively conducted until the token count reaches the predefined value set R_L for each consolidation operation, resulting in the output video feature $\mathbf{v}' \in \mathbb{Z}^{R_L \times 3 \times H \times W}$ (operational details in appendix). The above algorithm is parameter-free, and can be easily plugged into a frame-based video encoder. Although the frame similarity calculation brings additional computing overhead, it is negligible compared to the efficiency gained by reducing stored frames.

Extend positional encoding. For long-term memory, the number of tokens exceeds the maximum length of the positional encoding from the pre-trained model. Thus, our model utilizes the positional encoding mechanism following BERT [32], which results in a portion exceeding the length threshold n without available positional encoding. In order to handle long enough long memory, we adopt the hi-

Method	MSVD-QA		MSRVTT-QA		ActivityNet-QA	
	Accuracy	Score	Accuracy	Score	Accuracy	Score
FrozenBiLM [76]	32.2	–	16.8	–	24.7	–
Video Chat [37]	56.3	2.8	45.0	2.5	26.5	2.2
LLaMA Adapter [83]	54.9	3.1	43.8	<u>2.7</u>	34.2	2.7
Video LLaMA [82]	51.6	2.5	29.6	1.8	12.4	1.1
Video-ChatGPT [43]	<u>64.9</u>	<u>3.3</u>	<u>49.3</u>	2.8	<u>35.2</u>	<u>2.7</u>
MovieChat (<i>Ours</i>)	75.2	3.8	52.7	2.6	45.7	3.4

Table 1. Quantitative evaluation for short video question answering with GPT-3.5 [46]. MovieChat achieves comparable performance even it is not specifically designed for short video question-answering tasks. The best result is highlighted in bold, and the second best is underlined.

Method	CI	DO	CU	TU	CO
Video Chat [37]	2.23	2.50	2.53	1.94	2.24
LLaMA Adapter [83]	2.03	2.32	2.30	1.98	2.15
Video LLaMA [82]	1.96	2.18	2.16	1.82	1.79
Video-ChatGPT [43]	<u>2.40</u>	<u>2.52</u>	<u>2.62</u>	<u>1.98</u>	<u>2.37</u>
MovieChat (<i>Ours</i>)	2.76	2.93	3.01	2.24	2.42

Table 2. Quantitative evaluation for short video generation performance with GPT-3.5 [46]. CI stands for correctness of information, DO stands for detail orientation, CU stands for contextual understanding, TU stands for temporal understanding, and CO stands for consistency. The best result is highlighted in bold, and the second best is underlined.

tamps for breakpoint mode. Fig. 3c illustrates the distribution of question types in MovieChat-1K. Note that MovieChat-1K is specifically designed for long video comprehension tasks, the majority of questions are open-ended, with only a quarter classified as multiple-choice questions, marked by initiators such as ‘Do,’ ‘Does,’ ‘Is,’ or ‘Are.’ We also compute the word distributions of our provided question-answer pairs. As illustrated in Fig. 4, which includes common objects (people, clothes, etc.), time (day, night, etc.), scenes (indoor, outdoor, etc.), and so on. More statistics information can be found in appendix.

5. Experiments

We conduct quantitative and qualitative evaluations between MovieChat and previous methods. Additionally, we perform ablation studies to investigate MovieChat. Experimental settings and analyses can be found in appendix.

5.1. Quantitative Evaluation

Short video question-answering. We use several widely used open-ended datasets: MSVD-QA [74], MSRVTT-QA [75], and ActivityNet-QA [79] for short video question-answering tasks. The evaluation process is under the assistance of LLM with the default hyper-parameter settings. The accuracy and relative scores on a scale of 0 to 5 are

Method	# Frames	Global Mode		Breakpoint Mode	
		Accuracy	Score	Accuracy	Score
Video Chat [37]	32	<u>57.8</u>	<u>3.00</u>	46.1	2.29
Video LLaMA [82]	32	51.7	2.67	39.1	2.04
Video-ChatGPT [43]	100	47.6	2.55	<u>48.0</u>	<u>2.45</u>
MovieChat (<i>ours</i>)	2048	62.3	3.23	48.3	2.57

Table 3. Quantitative evaluation for long video question answering on MovieChat-1K test set in global mode with the average of GPT-3.5 [46], Claude [3] and human blind rating. HBR stands for human blind rating. The best result is highlighted in bold, and the second best is underlined.

reported. Compared to previous methods [37, 43, 82, 83], MovieChat achieves comparable performance even it is not specifically designed for short video question-answering tasks, as shown in Tab. 1.

Short video generative performance. Following [43], we employ GPT-assisted evaluation to conduct a more comprehensive comparison of the text generation performance between MovieChat and previous methods [37, 43, 76] on processed ActivityNet-QA [79]. The evaluation pipeline covers crucial metrics (including *Correctness of Information*, *Detailed Orientation*, *Contextual Understanding*, *Temporal Understanding* and *Consistency*) and assigns relative scores to the generated predictions on a scale of 1-5. We present the results of the generation performance evaluation in Tab. 2. The results reveal its competitive performance across all key aspects compared to previous methods.

Long video question-answering. We evaluate the long video question-answering performance of MovieChat with our proposed MovieChat-1K. We split 1,000 videos into training set (800), test set (100), validation set (100) and only use test set for final performance evaluation. We select three recent LLM-based video understanding models (e.g. Video Chat [37], Video LLaMA [82], and Video-ChatGPT [43]) as the baselines. Yet, none of those methods can support such long video (>10K frames). Therefore, to accommodate their length limitations in global questions, we uniformly sample from the original video up to the maximum frame count which can be officially supported by each individual model. For breakpoint questions, we extend half of the maximum frame count before and after the breakpoint (*i.e.*, placing the breakpoint at the center frame).

To enhance the robustness of the results, we simultaneously employ GPT-3.5 [46] and Claude [3] as LLM assistants, with the additional support of human blind rating. We observe a discrepancy between the accuracy and relative score generated by the previously LLM-assisted evaluation method [43] for video question-answering tasks. However,

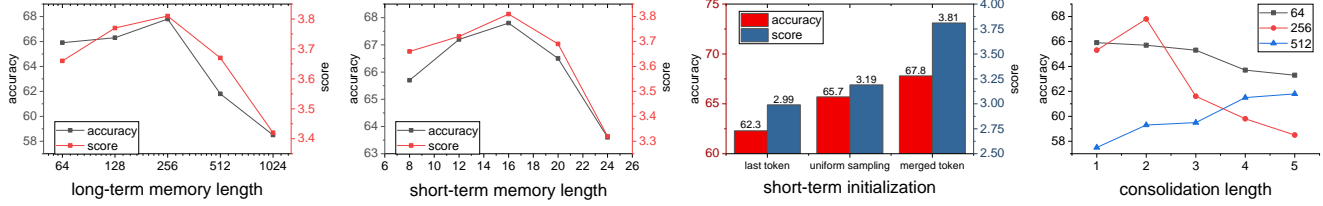


Figure 5. Hyperparameter ablation studies on how length of long-term memory buffer l_{length} , short-term memory buffer l_{short} , consolidation length l_{merge} and short-term initialization affect the performance of MovieChat on long video understanding. We set $l_{short} = 16$, $l_{merge} = 2$ in ablation study of long-term memory, $l_{long} = 256$, $l_{merge} = 2$ in ablation study of short-term memory and $l_{short} = 16$ in ablation study of consolidation length and short-term initialization.

Method	CI	DO	CU	TU	CO
Video Chat [37]	3.04	2.75	3.09	3.00	3.21
Video LLaMA [82]	2.75	2.24	2.83	2.62	2.97
Video-ChatGPT [43]	2.37	2.30	2.58	2.49	2.69
MovieChat (Ours)	3.11	2.93	3.24	3.17	3.25

Table 4. Quantitative evaluation for long video generation performance in global mode with the average of GPT-3.5 [46], Claude [3] and human blind rating. CI stands for correctness of information, DO stands for detail orientation, CU stands for contextual understanding, TU stands for temporal understanding, and CO stands for consistency. The best result is in bold, and the second best is underlined.

merely adjusting the prompt for the LLM cannot effectively address this issue. Therefore, after obtaining the accuracy and score from the LLM-assisted evaluation method, we implement manual filtering to remove results with inconsistent values, thus improving the reliability of our outcomes.

As shown in Tab. 3, compared to previous methods [37, 43, 82], MovieChat reads more video frames. In both global mode and breakpoint mode, our method maintains a performance gain in terms of the average accuracy and score provided by LLM assistants and human blind rating. We comprehensively evaluate MovieChat’s question-answering performance across different question types compared to baselines. The results indicate that our approach outperforms the baselines in both open-ended and true-false questions.

Long video generative performance. We compare the quality of answers generated by MovieChat and previous methods [37, 43, 82] in long video question-answering on MovieChat-1K. As shown in Tab. 4, with the average score provided by GPT-3.5 [46], Claude [3] and human blind rating, our approach continues to generate higher-quality answers even as the video contents become more extensive.

5.2. Ablation Study

Short-term and long-term memory buffers. As MovieChat incorporates a memory mechanism including

Method	Global Mode		Breakpoint Mode	
	Accuracy	Score	Accuracy	Score
w/o MM	51.4	3.10	38.2	2.31
base	67.8	3.81	50.4	2.96

Table 5. Ablation study on how memory mechanism (MM) affects the long video question answering. The best result is in bold.

Method	Global Mode					Breakpoint Mode				
	CI	DO	CU	TU	CO	CI	DO	CU	TU	CO
w/o MM	3.30	2.53	3.28	2.77	3.42	2.42	2.85	2.87	2.00	2.87
base	3.32	3.28	3.40	2.97	3.48	2.97	3.24	3.31	2.70	3.45

Table 6. Ablation study on how memory mechanism (MM) affects the long video generative performance. CI stands for correctness of information, DO stands for detail orientation, CU stands for contextual understanding, TU stands for temporal understanding, and CO stands for consistency. The best result is in bold.

short-term memory and long-term memory, it is imperative to evaluate how the proposed memory mechanism influences the performance. Tab. 5 and Tab. 6 provide the memory-dependent performance of MovieChat for long video question-answering and generative tasks with the average results of GPT-3.5 [46], Claude [3], and human blind rating. MovieChat with the memory mechanism significantly outperforms the memory-independent variant, which signifies the importance of memory mechanisms.

Hyper-parameter ablations. We perform a series of hyperparameter ablations based on the MovieChat-1K dataset to better understand MovieChat. Fig. 5 shows the performance when ablating the length of memory buffers, consolidation length and short-term initialization with the average results of GPT-3.5 [46], Claude [3], and human blind rating. The performance of MovieChat degrades when all four are significantly changed, showing the validity of our empirically chosen hyperparameters. Fig. 5 demonstrates that information obtained from the video expands with the growing length of memory buffers, while the loss of finer details intensifies with the fixed length of consolidation. Further-



Q#1 at 4250

Question #1

What may happen next step?

Breakpoint Mode

Video Chat Based on the video, it appears that the person is cooking meat and vegetables on a stove top using different utensils and ingredients such as onions, garlic, mustard, and olive oil. It is likely that the person will continue cooking the meat until it is fully cooked, and then serve it to their family or friends. Additionally, they may add other ingredients such as mushrooms or potatoes to the dish. It is possible that they will use different types of cooking methods such as sautéing or grilling to ensure the meat is cooked evenly and to perfection.

Video LLaMA At frame 4250, the video shows the hand of a man cutting meat on a cutting board. It's not clear what happens next, but it is possible that the man continues cutting the meat.

Video-ChatGPT The next step in the video is to place the cooked meat on a plate and serve it. The person in the video is seen cutting the meat into smaller pieces and placing it on a plate. The person then takes a fork and begins to eat the meat.

MovieChat I think the man will prepare the food in the kitchen. It seems like he is going to cook it with spices and herbs. He has a large wooden board on the kitchen counter and a large white pot on the stove, and he will probably use some tools to prepare the food. He might also use his hands or a spatula to cook the meat.

Question #2

Which step took the longest to complete this dish?

Global Mode

Video Chat Based on the video, it appears that the longest step in making the dish is preparing the pan for cooking the steak. Specifically, the man takes the pan out of the oven and starts cleaning it by wiping it with a rag, then rubbing it with olive oil, and finally heating the pan to high heat. It is also mentioned that the man has to wait for the pan to heat up before putting the steak in the pan.

Video LLaMA The dish that this video portrays took several minutes to complete. However, the most time-consuming task seems to have been preparing the ingredients on the white kitchen counter. The man in the video is seen chopping vegetables and using a sharp knife to prepare a meal. Finally, he will sit down to enjoy the meal, savoring each bite and reflecting on the process that led to this culinary creation.

Video-ChatGPT The longest step in preparing the dish was the time it took to cook the meat. The man in the video cooks the meat on a stove for a long time, which is a crucial step in the process. The video shows the man cooking the meat on a stove for a considerable amount of time, which indicates that it took a considerable amount of effort and patience to achieve the desired result.

MovieChat The longest step to complete this dish would be the preparation of the food on the cutting board. It requires chopping the meat and adding other ingredients like broccoli and carrots, and mixing them together before putting them in the pan. The chef had to carefully chop and arrange the ingredients before cooking the dish.

Figure 6. Question and answer about a clip from *YouTube*, which is a tutorial on how to cook steak. The entire instructional process begins with marinating the steak, followed by pan-searing it, preparing side dishes, and ultimately plating the meal. Green (Red) highlights the correct (wrong) answer and yellow indicates that the model is hallucinating.

more, using merged tokens for short-term initialization outperforms last few tokens and uniform sampling. Additionally, the length of merged tokens and the memory buffer size have a combined effect on MovieChat’s performance.

5.3. Case Study

We perform an extensive case study of MovieChat on a variety of open-ended long video (such as cartoon movie and TV series) for long video question-answering, including the ■ breakpoint mode (Q#1) and the ■ global mode

(Q#2). The evaluation is conducted between MovieChat and previous methods [37, 43, 83] as shown in Fig. 6. For Q#1 in breakpoint mode, we mark the timestamp when the question is asked. For long videos over 10K frames, MovieChat is still capable of providing excellent responses to questions regarding both the current moment and the entire video content with less hallucination. More examples to show long video scene understanding and temporal understanding ability of MovieChat are available in appendix.

6. Limitation

Although MovieChat has demonstrated impressive abilities in long video understanding, it is still an early-stage prototype and has some limitations, including: 1) Limited perception capacities. MovieChat’s performance is hindered by the pretrained short video understanding model. 2) Inadequate Time Processing. MovieChat provides only rough estimates of the duration proportions of events within long videos, lacking precision in temporal details.

7. Conclusion

Conclusively, we presents an innovative video understanding system integrating video foundation models and large language models. By incorporating a memory mechanism represented by tokens in Transformers, our proposed system, MovieChat overcomes challenges associated with analyzing long videos. MovieChat achieves state-of-the-art performance in long video understanding, surpassing existing systems limited to handling videos with few frames.

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MovieChat: From Dense Token to Sparse Memory for Long Video Understanding

Supplementary Material

The supplementary material is structured as follows:

1. We first present schematic diagram of the memory consolidation algorithm of MovieChat in Section A.
2. We provide detailed supplementary statistical information for MovieChat-1K in Section B.
3. The prompt template we use for LLM-Assisted Evaluation is shown in Section C.
4. We also list the hyperparameter settings of MovieChat in Section D.
5. We mention the specific LLM-Assisted Evaluation method employed for the assessment of short video generative performance in Section E.
6. In comparison to the LLM currently used by MovieChat, we switch to a different LLM and compare the results in Section F.
7. To avoid the impact of misjudgments by LLM assistants on the results, we introduce the manual filtering strategy in Section G.
8. The performance of MovieChat varies across different categories of questions, and we present the results in Section H.
9. We add the result of quantitative evaluation for long video generative performance in breakpoint mode in Section I.
10. To demonstrate the outstanding performance of MovieChat across a wide range of categories, we calculate the Pearson correlation coefficient of different score methods in Section J.
11. We then list the evaluation results with GPT-3.5 [46], Claude [3] and human blind rating in Section K.
12. We conduct result analyses for the ablation study on hyperparameter settings in Section L.
13. Lastly, we give more examples for scene understanding and temporal understanding of MovieChat in Section M.

A. Memory consolidation algorithm of MovieChat.

As shown in Fig. A1, for each sampled frame x_i , we calculate its similarity with adjacent frames. After that, we select the pair with the greatest similarity, merge and replace these two frames, resulting in a new sequence. We conduct the merge operation repeatedly until the count of existing frames in short-term memory reaches the predefined value.

B. MovieChat-1K Statistics Information

Distribution of video categories. MovieChat-1K contains videos from 15 popular categories with varying distribution. As shown in Tab. B1, every video comprises multiple alternating scenes.

Category	Percentage
Documentary Film	21.80%
Animation Film	17.00%
Detective Film	15.10%
Epic Film	11.40%
Action Film	6.70%
Family Film	4.90%
Crime Film	3.80%
Science Fiction Film	3.70%
War Film	3.70%
Adventure Film	3.50%
Romance Film	3.30%
History Film	2.10%
Suspense Film	1.30%
Fantasy	0.90%
School Film	0.80%

Table B1. Distribution of video categories in MovieChat-1K.

Video information and visual question-answer data format.

To the best of our knowledge, a long video understanding dataset has not yet been established. Our work represents the initial step in creating and making it publicly available. We create MovieChat1K, containing 1k long videos and corresponding 1k dense captions, and 13k visual question-answer pairs. One visual example of these arrangements is provided in Figure B2.

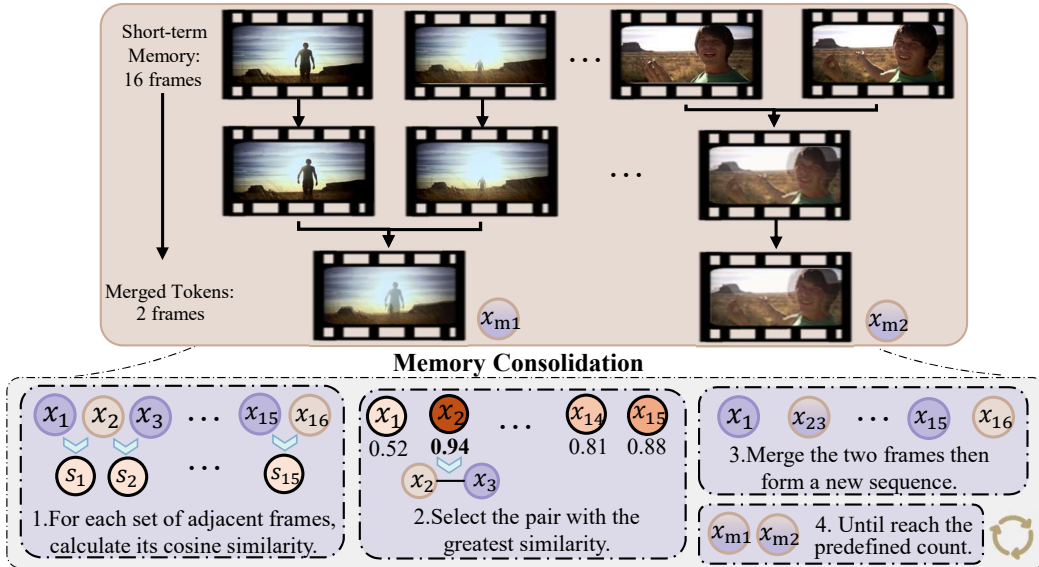


Figure A1. Question and answer about clips from *YouTube*, which is a tutorial on how to cook steak. The entire instructional process begins with marinating the steak, followed by pan-searing it, preparing side dishes, and ultimately plating the meal.

Sentence length distribution of question-answer pairs. MovieChat1K exhibits diverse lengths of question-answer pairs in the segmented clip level. Fig. B3 and Fig. B4 demonstrate the length distribution of question-answer pairs in different modes. Despite the distribution of question-answer pairs varies between the global mode and breakpoint mode, the majority of questions tends to concentrate between 5-15 words in length, while the length of answers generally have fewer than 10 words.

Stastics information of dense captions. To facilitate a more detailed understanding of long videos, we provide a dense caption for each video. As shown in Fig. B5, MovieChat-1K exhibits diverse caption lengths in the segmented clip level. Approximately two-thirds of the clips have captions with 100-149 words, while one-fifth of the clip captions have fewer than 100 words. About 11% of clips have long captions with more than 150 words.

To analyze the word distribution of our generated captions, we compute their distributions. The resulting word distribution of the captions is presented in Fig. B6, which includes common objects (man, woman, people, girl, etc.), attributes (detective, various, small, white, etc.), locations (inside, behind, south, next, etc.), scenes (room, house, building, office, etc.), actions/events (talk, enter, leave, take, etc.), and more.

In terms of actionness, MovieChat-1K captions contains nearly the same number of verbs as with the WebVid10M dataset [11]. To evaluate this, we use the NLTK toolkit to

analyze the number of verbs in captions, focusing on extracting and tagging all unique verbs. We find a total of 109,485 verbs in the WebVid10M caption dataset, while the MovieChat-1K captions contain 102,988 unique instances of verbs. While these counts may not be entirely accurate due to our simple counting method, we believe they provide a rough indication of the actionness of the two datasets.

Comparison between MovieChat-1K and other benchmarks. MovieChat-1K provides a large-scale benchmark for long video understanding, which contains 1K movies, 1K dense captions and 13k question-answer pairs. The comparison between different datasets are shown in Tab. B2. It is evident that MovieChat-1K provides the longest average duration for movie clips. MovieQA [63] exclusively offers question-answer pairs related to movies, while MovieGraphs [66] supplies captions associated with movies. Unlike other datasets, MovieNet [31] encompasses three main types of texts: subtitle, synopsis, and script, excluding question-answer pairs. Additionally, the synopsis category is designed for the entire movie rather than video clips. Consequently, MovieChat-1K is more suitable for studying long video comprehension compared to other datasets.



```

"info": {
  "video_path": "MI6-19.mp4",
  "url": "",
  "class": "action film",
  "w": 720,
  "h": 480,
  "num_frame": 10500,
  "fps": 25
},
"caption": "It is a part of a movie. The theme of the movie is spy and agent. The helicopter is crashed on the snow land on the cliff. At the same time, in a room, a man is tied on the rope, and another man is trying to kill a woman. The fight against each other. The man tied on the rope helps the woman, but then he is nearly killed by the rope. Luckily, the woman finally kills the man and saves the man who is nearly killed by the rope. At the cliff, a man is kicked down the cliff by another man. ",
"global": [
  {
    "question": "When does the things in the video happens, ancient age, modern age or future?",
    "answer": "Modern age."
  },
  ...
  {
    "question": "Does it happen during day or night?",
    "answer": "Day."
  }
],
"breakpoint": [
  {
    "time": 750,
    "question": "What are the people doing?",
    "answer": "Fighting."
  },
  ...
  {
    "time": 9750,
    "question": "Are there any plants?",
    "answer": "Yes."
  }
]

```

Figure B2. Video information and visual question-answer data format in MovieChat1K.

Dataset	Avg. Duration (min)	Number of Captions	Avg. Caption Length	Number of Question-Answer Pairs	Avg. Question Length	Avg. Answer Length
MovieQA [63]	3.5	-	-	14.9K	9.3	5.1
MovieGraphs [66]	0.73	15K	35	-	-	-
MovieNet [31]	2.1	2.5K	-	-	-	-
MovieChat-1K	9.4	1K	121	13K	7.8	2.3

Table B2. Comparison between MovieChat-1K and other benchmarks.

C. LLM-Assisted Evaluation for the short video question-answering task.

Following [43], we use LLM-Assisted Evaluation for the short video question-answering task in Section 5.1. Given


```

openai.ChatCompletion.create(
  model="gpt-3.5-turbo",
  messages=[
    {
      "role": "system",
      "content":
        "You are an intelligent chatbot designed for evaluating the correctness of generative outputs for question-answer pairs. "
        "Your task is to compare the predicted answer with the correct answer and determine if they match meaningfully. Here's how you can accomplish the task:"
        "-----"
        "##INSTRUCTIONS: "
        "- Focus on the meaningful match between the predicted answer and the correct answer.\n"
        "- Consider synonyms or paraphrases as valid matches.\n"
        "- Evaluate the correctness of the prediction compared to the answer."
    },
    {
      "role": "user",
      "content":
        "Please evaluate the following video-based question-answer pair:\n\n"
        f"Question: {question}\n"
        f"Correct Answer: {answer}\n"
        f"Predicted Answer: {pred}\n\n"
        "Provide your evaluation only as a yes/no and score where the score is an integer value between 0 and 5, with 5 indicating the highest meaningful match. "
        "Please generate the response in the form of a Python dictionary string with keys 'pred' and 'score', where value of 'pred' is a string of 'yes' or 'no' and value of 'score' is in INTEGER, not STRING."
        "DO NOT PROVIDE ANY OTHER OUTPUT TEXT OR EXPLANATION. Only provide the Python dictionary string. "
        "For example, your response should look like this: {'pred': 'yes', 'score': 4.8}."
    }
  ]
)

```

Figure C1. Prompt for ChatGPT in LLM-Assisted Evaluation for the short video question-answering task.

taining 32 tokens. When the short-term memory reaches its capacity, it is directed to the memory consolidation module to be merged into 2 representative frames. The 2 frames are simultaneously input into the long-term memory with a total length of 256 and used to reinitialize the short-term memory.

E. LLM-Assisted Evaluation for short video generative performance.

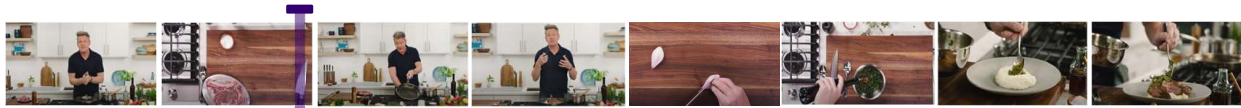
We use LLM-Assisted Evaluation proposed by [43] for short video generative performance in Section 5.1. The evaluation pipeline assesses various capabilities of the model and assigns a relative score (1 to 5) to the generated predictions, in the following five aspects: *Correctness of Information*, *Detail Orientation*, *Contextual Understanding*,

Temporal Understanding and *Consistency*. We follow the corresponding prompts provided in <https://github.com/mbzuai-oryx/Video-ChatGPT> and report the baseline results of short video generative performance from it.

F. Ablation study on large language models.

Most previous video understanding methods [37, 43, 82, 83] primarily employed LLama [64] and its variants [20] as text decoders. With the average results of GPT-3.5 [46], Claude [3] and human blind rating, Tab. F4 and Tab. F5 illustrate how the performance of MovieChat changes when using LLama [64] and LLama2 [65] as the large language model respectively.

Contrary to our hypothesis, under every evaluation



Q#1 at 4250

Question

Which step took the longest to complete this dish?

MovieChat-LLama

The longest step to complete this dish would be the **preparation of the food on the cutting board**. It requires chopping the meat and adding other ingredients like broccoli and carrots, and mixing them together before putting them in the pan. The chef had to carefully chop and arrange the ingredients before cooking the dish.

MovieChat-LLama2

The step that took the longest to complete this dish was the **cooking the meat on the stovetop**. It took around 30 minutes to complete this step, followed by 20 minutes to prepare the ingredients and cook the pasta, and 10 minutes to cook the meat and vegetables.

Figure F2. Question and answer about clips from *YouTube*, which is a tutorial on how to cook steak. When asked “Which step took the longest to complete this dish?” in global mode, MovieChat powered by different large language models provided divergent answers.

Method	Global Mode		Breakpoint Mode	
	Accuracy	Score	Accuracy	Score
LLama [64]	67.8	3.81	50.4	2.96
LLama2 [65]	64.2	3.79	48.1	2.98

Table F4. Ablation Study on how LLM affects the long video question answering. The best result is highlighted in bold.

Method	Global Mode					Breakpoint Mode				
	CI	DO	CU	TU	CO	CI	DO	CU	TU	CO
LLama [64]	3.32	3.28	3.40	2.97	3.48	2.97	3.24	3.31	2.70	3.45
LLama2 [65]	3.27	3.28	3.41	2.95	3.45	2.96	3.12	3.38	2.68	3.34

Table F5. Ablation Study on how the large language model affects the long video generative performance. MM stands for memory mechanism, CI stands for correctness of information, DO stands for detail orientation, CU stands for contextual understanding, TU stands for temporal understanding, and CO stands for consistency. The best result is highlighted in bold.

conditions, the performance metrics of MovieChat with LLama2 [65] hardly surpassed those of MovieChat with LLama [64]. We further investigate a specific example to analyze this phenomenon. As shown in Fig. F2, the bold segments represent direct responses to the questions from two versions of MovieChat. MovieChat with LLama [64] provided answers that are more aligned with the video content. Surprisingly, MovieChat with LLama2 [65] of-

fer an approximation of the time required for each step (indicated by underlines Fig. F2). While its time estimates do not precisely match the actual durations, the proportion of time provided was realistic. Even though LLama2 [65] cannot obtain specific time information when processing feature-rich video frames, MovieChat’s memory buffer design allows for dense sampling of video frames, enabling LLama2 [65] to estimate the proportion of time for each scene based on adjacent similar frames. Therefore, we propose that the lower evaluation metric results of MovieChat with LLama2 [65] compared to MovieChat with LLama [64] may be attributed to the question-answer pairs provided by the dataset.

G. Manual filtering strategy for LLM-Assisted Evaluation.

For each test data, [43] utilized GPT-3.5 [46] to provide an evaluation result in terms of a ‘yes/no’ response and a corresponding score, as demonstrated in Fig. C1. The score is an integer value ranging from 0 to 5, where a score of 5 indicates the highest degree of meaningful correspondence. However, we observe instances where GPT-3.5 [46] offered judgments and scores that do not align, such as providing a ‘yes’ response with a score of 0 or a ‘no’ response with a score of 5. This discrepancy has the potential to impact the accuracy of results and introduce fluctuations. We adapt the prompts used for GPT-3.5 [46] with the aim of addressing this concern and did not yield the desired mitigation. Hence,

Method	Total		Multi-choice		Open-ended	
	Accuracy	Score	Accuracy	Score	Accuracy	Score
Video Chat [37]	<u>61.0</u>	<u>3.34</u>	74.8	<u>3.83</u>	<u>56.4</u>	<u>3.02</u>
Video LLaMA [82]	51.4	3.10	<u>78.3</u>	3.58	38.8	2.67
Video-ChatGPT [43]	44.2	2.71	52.5	3.16	37.7	2.54
MovieChat (<i>ours</i>)	67.8	3.81	80.9	4.02	57.5	3.74

Table H6. Quantitative evaluation for long video different types question answering in global mode. The best result is highlighted in bold, and the second best is underlined.

Method	Total		Multi-choice		Open-ended	
	Accuracy	Score	Accuracy	Score	Accuracy	Score
Video Chat [37]	48.3	2.43	62.4	<u>3.46</u>	44.5	2.19
Video LLaMA [82]	38.2	2.33	57.3	2.39	33.1	2.31
Video-ChatGPT [43]	<u>49.8</u>	<u>2.71</u>	<u>58.3</u>	3.05	<u>47.5</u>	<u>2.37</u>
MovieChat (<i>ours</i>)	50.2	2.96	62.4	3.65	46.7	2.70

Table H7. Quantitative evaluation for long video different types question answering in breakpoint mode. The best result is highlighted in bold, and the second best is underlined.

we introduce an artificial filtering strategy. For each evaluation result generated by GPT-3.5 [46], we conduct manual screening. We retain only those outcomes that exhibited consistency between the ‘yes/no’ judgments and the associated scores, thus enhancing the reliability of the evaluations. Similarly, we applied the same filtering strategy to the evaluation results generated by Claude [3].

H. Quantitative evaluation for long video different types question answering.

As shown in Fig. 3, MovieChat-1K contains question-answer pairs of varies types. To better assess the performance of MovieChat, we conduct evaluations on the long video question answering task using various types of questions. We roughly categorize the question types into multiple-choice questions and open-ended questions. With the average results of GPT-3.5 [46], Claude [3] and human blind rating, Tab. H6 and Tab. H7 respectively present the accuracy and scores of MovieChat and the baseline across different question categories in both global mode and breakpoint mode. In various research conditions, our approach consistently outperforms the baseline, thus substantiating the robustness of MovieChat.

I. Quantitative evaluation for long video generative performance in breakpoint mode

Similar to Tab. 4, with the average results of GPT-3.5 [46], Claude [3] and human blind rating, Tab. 18 demonstrates that our method outperforms the baseline in long video generative performance in breakpoint mode.

Method	CI	DO	CU	TU	CO
Video Chat [37]	2.42	2.51	2.81	2.10	2.78
Video LLaMA [82]	2.04	2.29	2.63	2.00	2.87
Video-ChatGPT [43]	<u>2.62</u>	2.65	<u>2.86</u>	<u>2.32</u>	<u>2.96</u>
MovieChat (<i>Ours</i>)	2.64	<u>2.60</u>	2.87	2.49	3.08

Table I8. Quantitative evaluation for long video generation performance in breakpoint mode with the average of GPT-3.5 [46], Claude [3] and human blind rating. CI stands for correctness of information, DO stands for detail orientation, CU stands for contextual understanding, TU stands for temporal understanding, and CO stands for consistency. The best result is highlighted in bold, and the second best is underlined.

J. Pearson correlation coefficient of different score methods.

Evaluation Method	Pearson Correlation Coefficient
GPT3.5 VS. Claude	0.927
GPT3.5 VS. Human Blind Rating	0.955
Claude VS. Human Blind Rating	0.978

Table J9. Pearson correlation coefficient of GPT-3.5 [46], Claude [3], and human blind rating on score. We calculate the mean score across each score dimensions for MovieChat and previous methods [37, 43, 82, 83], and then computes the Pearson correlation between these means for each pair of evaluation methods. The Pearson correlation coefficient, which ranges from -1 to +1, indicates a stronger positive linear relationship between the two sets of data when the coefficient is higher (closer to +1).

The Pearson correlation coefficient is represented by the formula:

$$r_{xy} = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^n (x_i - \bar{x})^2} \sqrt{\sum_{i=1}^n (y_i - \bar{y})^2}}$$

where r_{xy} is the Pearson correlation coefficient between two variables x and y , x_i and y_i are the individual sample points for variables x and y , \bar{x} and \bar{y} are the averages of the x and y samples respectively, and n is the number of sample points. The formula essentially assesses the extent of linear correlation between two variables by evaluating the product of their deviations from their respective means. The numerator represents the covariance between the two variables, and the denominator normalizes this value, ensuring that the coefficient remains between -1 and +1. The Pearson correlation coefficient quantifies the extent to which two variables co-vary in comparison to their individual variations.

As shown in Tab. J9 and Fig. J3, we conduct pearson correlation analysis between GPT-3.5 [46], Claude [3], and human blind rating. The result indicates a substantial agree-

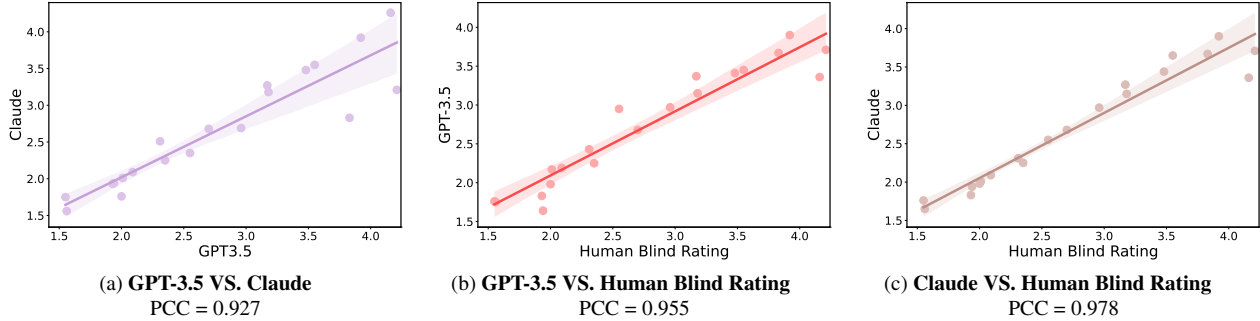


Figure J3. Results of the Pearson correlation analysis between three evaluation methods, including GPT-3.5 [46], Claude [3], and human blind rating. PCC stands for Pearson Correlation Coefficient.

Method	# Frames	Global Mode		Breakpoint Mode	
		Accuracy	Score	Accuracy	Score
Video Chat [37]	32	<u>61.0</u>	<u>3.34</u>	48.3	2.43
Video LLaMA [82]	32	51.4	3.10	38.2	2.31
Video-ChatGPT [43]	100	44.2	2.71	<u>49.8</u>	<u>2.71</u>
MovieChat (<i>ours</i>)	2048	67.8	3.81	50.4	2.96

Table K10. Quantitative evaluation for long video question answering on MovieChat-1K test set with GPT-3.5 [46]. The best result is highlighted in bold, and the second best is underlined.

ment among these evaluation methods. The alignment of scores across different score methods strengthens the reliability of our assessment. Crucially, our proposed method, MovieChat outperforms previous methods [37, 43, 82, 83] in long video understanding tasks. The superior performance of MovieChat is evident across a broad spectrum of categories, suggesting that our model not only has a deeper understanding of long videos and respective questions but also exhibits a more accurate and consistent ability to generate relevant responses.

K. Evaluation results with GPT, Claude and human blind rating.

As shown in K10–K18, we provide detailed scoring results for GPT-3.5 [46], Claude [3], and human blind rating across various experiments.

L. Analysis on hyperparameter ablations.

As the lengths of the short-term and long-term memory buffers increase, the information acquired by MovieChat from the video expands, as illustrated in Fig. 5. However, more video compression leads to the loss of more detailed information, while the length of the merged tokens remains constant. Therefore, as the lengths of two memory buffers increase, the performance of MovieChat exhibits a trend of initially rising and then declining.

Method	# Frames	Global Mode		Breakpoint Mode	
		Accuracy	Score	Accuracy	Score
Video Chat [37]	32	<u>52.1</u>	<u>2.59</u>	<u>43.8</u>	2.12
Video LLaMA [82]	32	47.3	2.19	33.2	1.69
Video-ChatGPT [43]	100	39.8	2.04	46.4	<u>2.21</u>
MovieChat (<i>ours</i>)	2048	55.3	2.73	46.4	2.28

Table K11. Quantitative evaluation for long video question answering on MovieChat-1K test set with Claude [3]. The best result is highlighted in bold, and the second best is underlined.

Method	# Frames	Global Mode		Breakpoint Mode	
		Accuracy	Score	Accuracy	Score
Video Chat [37]	32	<u>60.2</u>	<u>3.08</u>	46.3	2.32
Video LLaMA [82]	32	56.3	2.72	45.8	2.11
Video-ChatGPT [43]	100	58.7	2.89	<u>47.8</u>	<u>2.43</u>
MovieChat (<i>ours</i>)	2048	63.7	3.15	48.1	2.46

Table K12. Quantitative evaluation for long video question answering on MovieChat-1K test set with human blind rating. The best result is highlighted in bold, and the second best is underlined.

Method	CI	DO	CU	TU	CO
Video Chat [37]	3.26	<u>3.20</u>	<u>3.38</u>	2.97	<u>3.47</u>
Video LLaMA [82]	<u>3.30</u>	2.53	3.28	2.77	3.42
Video-ChatGPT [43]	2.48	2.78	3.03	2.48	2.99
MovieChat (<i>Ours</i>)	3.32	3.28	3.44	3.06	3.48

Table K13. Quantitative evaluation for long video generation performance in global mode with GPT-3.5 [46]. CI stands for correctness of information, DO stands for detail orientation, CU stands for contextual understanding, TU stands for temporal understanding, and CO stands for consistency. The best result is highlighted in bold, and the second best is underlined.

Fig. 5 demonstrates how memory consolidation influences the performance. Since the LLM-based evaluation shows a positive correlation between accuracy and score,

Method	CI	DO	CU	TU	CO
Video Chat [37]	<u>2.83</u>	<u>2.43</u>	<u>3.02</u>	<u>2.87</u>	<u>2.93</u>
Video LLaMA [82]	2.04	1.66	2.46	2.07	2.36
Video-ChatGPT [43]	1.81	1.65	2.05	2.07	2.07
MovieChat (<i>Ours</i>)	2.88	2.82	3.11	3.04	2.96

Table K14. Quantitative evaluation for long video generation performance in global mode with Claude [3]. CI stands for correctness of information, DO stands for detail orientation, CU stands for contextual understanding, TU stands for temporal understanding, and CO stands for consistency. The best result is highlighted in bold, and the second best is underlined.

Method	CI	DO	CU	TU	CO
Video Chat [37]	3.03	2.61	2.87	3.15	3.23
Video LLaMA [82]	2.91	2.54	2.74	3.01	3.12
Video-ChatGPT [43]	2.83	2.47	2.66	2.92	3.01
MovieChat (<i>Ours</i>)	3.12	2.68	3.17	3.41	3.31

Table K15. Quantitative evaluation for long video generation performance in global mode with human blind rating. CI stands for correctness of information, DO stands for detail orientation, CU stands for contextual understanding, TU stands for temporal understanding, and CO stands for consistency. The best result is highlighted in bold, and the second best is underlined.

Method	CI	DO	CU	TU	CO
Video Chat [37]	2.96	3.09	3.24	2.46	3.22
Video LLaMA [82]	2.42	2.85	2.87	2.00	2.87
Video-ChatGPT [43]	3.11	3.32	<u>3.29</u>	<u>2.62</u>	<u>3.29</u>
MovieChat (<i>Ours</i>)	<u>3.07</u>	<u>3.24</u>	3.31	2.70	3.45

Table K16. Quantitative evaluation for long video generation performance in breakpoint mode with GPT-3.5 [46]. CI stands for correctness of information, DO stands for detail orientation, CU stands for contextual understanding, TU stands for temporal understanding, and CO stands for consistency. The best result is highlighted in bold, and the second best is underlined.

Method	CI	DO	CU	TU	CO
Video Chat [37]	2.12	2.20	2.30	1.97	2.37
Video LLaMA [82]	1.62	1.85	2.20	1.34	2.02
Video-ChatGPT [43]	<u>2.36</u>	2.26	<u>2.34</u>	<u>2.23</u>	2.70
MovieChat (<i>Ours</i>)	2.38	<u>2.16</u>	2.35	2.43	<u>2.68</u>

Table K17. Quantitative evaluation for long video generation performance in breakpoint mode with Claude [3]. CI stands for correctness of information, DO stands for detail orientation, CU stands for contextual understanding, TU stands for temporal understanding, and CO stands for consistency. The best result is highlighted in bold, and the second best is underlined.

Method	CI	DO	CU	TU	CO
Video Chat [37]	2.17	2.24	2.89	1.87	2.75
Video LLaMA [82]	2.09	2.18	2.82	1.74	2.68
Video-ChatGPT [43]	<u>2.39</u>	<u>2.36</u>	2.96	<u>2.10</u>	<u>2.89</u>
MovieChat (<i>Ours</i>)	2.48	2.41	<u>2.94</u>	2.33	3.12

Table K18. Quantitative evaluation for long video generation performance in breakpoint mode with human blind rating. CI stands for correctness of information, DO stands for detail orientation, CU stands for contextual understanding, TU stands for temporal understanding, and CO stands for consistency. The best result is highlighted in bold, and the second best is underlined.

we use accuracy to gauge performance. When memory buffer parameters remain constant, shorter merged tokens indicate increased frame information compression, potentially resulting in information loss when excessive. Conversely, longer merged tokens, despite retaining a greater extent of short-term memory in the face of compression, correspondingly result in less overall information acquisition. Moreover, when the length of the memory buffer changes, as exemplified by long-term memory, the corresponding peak performance of MovieChat shifts in response to the altered length of merged tokens. This demonstrates the need to strike a balance between dense information extraction and information compression in long video understanding tasks.

We also conduct experiments to compare various methods for initializing the short-term memory, including selecting the last few tokens, uniform sampling, and using merged tokens. The results indicate that the use of merged tokens produces the best performance. When initializing the next short-term memory with the last few tokens from the previous short-term memory, it is unable to adequately represent the information from the previous time step. Consequently, this leads to the final merged tokens being either repetitive or lacking coherence with the previous time step. Uniform sampling faces similar issues, but it manages to capture information with representative frames from the previous time step. Consequently, its performance surpasses that of initializing with the last few tokens, yet it remains inferior to using merged tokens for initialization.

M. Examples for scene understanding and temporal understanding of MovieChat.

We perform an extensive case study of MovieChat on a variety of open-ended long video (such as cartoon movie in and TV series) for long video question-answering and captioning task, including the ■ global mode and the ■ breakpoint mode. The evaluation tasks include scene understanding and temporal understanding as shown in Fig. M4, Fig. M5, Fig. M6 and Fig. M7. For Q#1 and

Q#2, we remarks timestamps in frames. For long videos over 10K frames, MovieChat is still capable of providing excellent responses to questions regarding both the current moment and the entire video content.



Q#1 at 3930

Q#2 at 11130

Question #1 What is Chief Bogo doing?

Answer #1 In the video, the character Chief Bogo is seen talking to someone on a laptop while sitting at a table in a dark room. Chief Bogo is a cartoon character wearing a brown outfit.

Question #2 Who is this rabbit named Judy talking to?

Answer #2 In the video, the rabbit police named Judy is talking to the person in a movie theater, who is a fox.

Question #3 Can you describe this video?

Answer #3 The video shows various scenes of an animation with different animals in a restaurant or office environment. At the beginning, we see an animated cartoon rabbit and a deer talking to each other in a restaurant. Next, there is a cartoon bunny talking to a cat at a desk, followed by a scene of a cartoon deer and a mouse talking to each other. The video then continues with the animated cartoon dog and cat sitting at a table in a restaurant, and another scene where a man and a dog are in a room with a computer on a table. There are more scenes of the same characters later on, including one with a bunny and a fox sitting at a desk, and another with a bunny and a dog talking to each other in the background. Finally, there are several more scenes with different animals, including a fox, a mouse, and a cat, all of which are in a different environment.

Figure M4. Question and answer about clips from *Zootopia*, a cartoon, which tells the story of a determined police officer rabbit named Judy who pairs up with a cunning fox to uncover a conspiracy about missing animals and develop an unexpected friendship.



Q#1 at 10290

Q#2 at 14250

Question #1 What is she doing?

Answer #1 In the given video, we see a young woman walking down a street in the city, and a young man also walks down the street behind her. The woman is wearing a red and black outfit.

Question #2 Where is this couple?

Answer #2 This couple is standing in the middle of a city street with a black hat on the man's. The scene is shot in a park, and there are a few trees and bushes visible.

Question #3 Can you tell me what happened in this movie?

Answer #3 Certainly! In the video, you can see a group of people standing in a park with a green hill in the background. There are also people walking on the street and in a courtyard with trees. Some of the people are holding red umbrellas, and there is a woman wearing a red coat. She is then seen walking down a street at night with a man following her. Next, we see a couple standing on a balcony overlooking a street in the evening with a man walking by and then walking down the street. Towards the end of the video, a group of people are seen walking through a snowy town.

Figure M5. Question and answer about clips from *Goblin*, which tells the story of Kim Shin, an immortal "goblin" who needs to find a human bride to end his endless life but instead meets Ji Eun-tak, a girl fated to die who claims to be the "goblin's bride," leading to a romantic tale unfolding between them.



Q#1 at 8250

Q#2 at 14400

Question #1

In which scene does the movie mainly focus on what happened? Are there other scenarios?

Answer #1

In the video, the main focus is on the scene where people are standing in front of a group of buildings, followed by another scene where people are standing at a table with a man standing behind them.

Question #2

Do they let the soldiers go first or negotiate with the general first?

Answer #2

In this video, the soldiers are being let go of by the general first, then the general negotiates with the soldiers.

Question #3

What plot does this movie clip include?

Answer #3

The movie clip starts with a black background and text written in white on it. Next, we see a man in a black robe with a shining light and a large white flag on the background. There are also people standing and sitting in front of a large building on a black background with text. Then, we see a man with a beard and a man in a dress, standing on the ground. We also see a man with a shirt on and a man in a blue shirt standing on the ground. Finally, we see a black background with a large black bear and a large bird on it.

Figure M6. Question and answer about clips from *Game of Thrones*, which tells the epic fantasy tale of power struggles and political intrigue among the Seven Kingdoms, entwined with intricate family relationships, all set against the backdrop of an ancient, mystical threat.



Q#1 at 4500

Q#2 at 10000

Question #1

What is this clip talking about now?

Answer #1

It shows a young man standing in a dugout on a black background. He is then seen kneeling on the field during a football game, followed by two young men in a dugout. Next, we see a young man standing on the field. And finally, we see a group of young men standing on the field and watching the game. The video also features football players and fans, as well as a football field, field, and dugout.

Question #2

Has there been a black speaker in the video so far?

Answer #2

Yes, there is a man in a red shirt standing on a street with a dark blue sky in the background, and a man with a tie standing on a street with a red car in the background. There is also a man in a black suit and another man in a white jacket standing in front of a building with a street light.

Question #3

Which movie sequence lasts the longest?

Answer #3

The video shows the scene of a dark night with a football field and a group of people playing football.

Figure M7. Question and answer about clips from *YouTube*, which contains a compilation of some inspirational movies scenes. This video clip comprises several segments from *The Death Crawl*, *Coach Carter*, *Rocky Balboa*, and *We Are Marshall*, which vary in duration.