DrVideo: Document Retrieval Based Long Video Understanding

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Abstract

Most of the existing methods for video understanding primarily focus on videos only lasting tens of seconds, with limited exploration of techniques for handling long videos. The increased number of frames in long videos poses two main challenges: difficulty in locating key information and performing long-range reasoning. Thus, we propose DrVideo, a document-retrieval-based system designed for long video understanding. Our key idea is to convert the long-video understanding problem into a long-document understanding task so as to effectively leverage the power of large language models. Specifically, DrVideo first transforms a long video into a coarse text-based long document to initially retrieve key frames and then updates the documents with the augmented key frame information. It then employs an agent-based iterative loop to continuously search for missing information and augment the document until sufficient question-related information is gathered for making the final predictions in a chain-of-thought manner. Extensive experiments on long video benchmarks confirm the effectiveness of our method. DrVideo significantly outperforms existing LLM-based state-of-the-art methods on EgoSchema benchmark (3 minutes), MovieChat-1K benchmark (10 minutes), and the long split of Video-MME benchmark (average of 44 minutes).

1. Introduction

Video understanding is a challenging task in computer vision, requiring the processing of spatio-temporal information and advanced reasoning abilities. Previous works have successfully processed short videos lasting around tens of seconds [8, 27, 32, 53, 68, 69]. However, how to deal with long video understanding remains unclear. Recent advancements in large language models (LLMs) [6, 10, 34, 41,

45, 48, 56] demonstrate strong abilities in language understanding and reasoning across long text sequences. These advancements have inspired the development of video-language models (Video-LMs) [26, 38, 67, 76] to address long video understanding issues.

Video-LMs typically encode a video as a sequence of visual tokens, which are then concatenated with language tokens into a long sequence and LLM is then used to understand this long sequence. Although Video-LMs improve video understanding, they have the following limitations. (i) They cannot process an entire video as input to a Video-LM (*e.g.,* the visual encoder OpenAI's CLIP-L-14 outputs 24×24 tokens for each image, while the max length of LLaVA-NeXT-Video [76] is only 8192). (ii) They typically perform uniform or random frame sampling at large strides to handle long videos without considering the content (*e.g.,* 16 for PLLaVA [67] and 6 for IG-VLM [26]), leading to potential key information loss. (iii) The simple concatenation of visual tokens increases the difficulty for the LLM to locate question-related (key) visual information within the long video sequence, complicating long-range reasoning across the vision token sequences.

Apart from the studies of encoding a video as a sequence of visual tokens, another line of research converts raw videos into captions and then utilities the long-range reasoning abilities of LLMs to predict the final answer. A pioneering work - LLoVi [73] uses a short-term video model [77] in conjunction with an LLM [40] to solve the long video understanding task. Given a long video, LLoVi first divides it into multiple short clips and converts them into short textual descriptions. Afterward, these short textual descriptions are summarized by the LLM, and the summary is finally used by LLoVi to answer the given question. Inspired by LLoVi, VideoAgent [61] designs an agent-based system to further leverage the reasoning abilities of LLMs and locate question-related video clips or images. Initially,
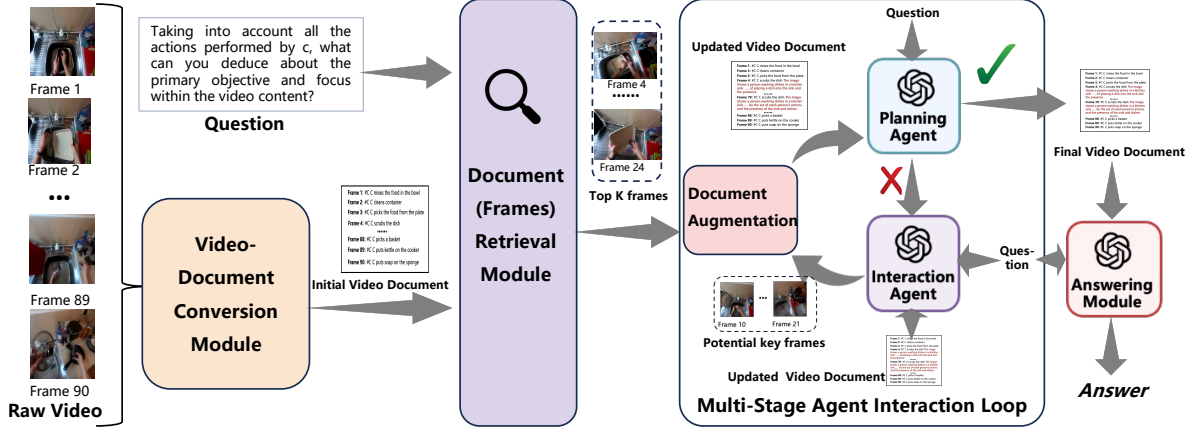
Figure 1. **Overview of our DrVideo framework.** It comprises five components: a video-document conversion module, a retrieval module, a document augmentation module, a multi-stage agent interaction loop and an answering module.

VideoAgent samples only a minimal number of frames from the video (*i.e.,* 5 frames), converting them into textual descriptions as input for the LLM. Then, through continuous feedback and interaction with the LLM [1], VLM [77], and CLIP [51], it gradually finds question-related frames in a coarse-to-fine manner via image-text similarity. Finally, VideoAgent answers the question based on these question-related frames. Despite these LLM-based methods overcoming the challenge of performing long-range reasoning and achieving promising results, they still suffer from the following problems.

- These methods struggle to accurately identify question-related frames. For instance, VideoAgent [61] leverages the LLM to infer missing question-related information based on prior knowledge and current key frame information, then uses CLIP's image-text similarity to select the most likely frames. However, such a coarse-to-fine method lacks a holistic grasp of video content and overly depends on the LLM's priors, often failing in locating question-relate frames, particularly in long videos.

- These methods convert videos into captions, addressing long-range reasoning but overlooking critical information loss. Specifically, even if question-related frames are identified, the generated captions cannot cover all the essential information in the key frames. For example, the caption *"a woman is looking in the mirror"* does not contribute to answering the question *"what is the woman wearing when standing in front of the mirror in the video"*. In this case, LLM can only make an aimless and biased surmise to answer the question.

To solve the above problem, we turn to how human understands a long video. In particular, a human needs to gain a general understanding of the video, identifying events across segments. Then, the human locates question-related segments, examines them in detail, and answers the question based on the extracted information. Inspired by this, in this paper, we propose DrVideo, a document retrieval-based system for long video understanding that progressively finds key frames and generates a question-related augmented document for LLMs to make confident predictions. Our key idea is to convert long video understanding into long document understanding and leverage the impressive capabilities of LLMs in key information location [46] and long-range reasoning [12] on various NLP tasks.

Specifically, DrVideo transforms raw long videos into long documents using a pretrained frame/clip-level visual captioner (*e.g.,* LLaVA-NeXT [33]) to make the LLM have a holistic grasp of video content. Different from VideoAgent [61], which identifies key frames via image-text similarity without information augmentation, DrVideo proposes a retrieval module and a multi-stage agent interaction loop that dynamically finds the potential missing information through sequential steps of reasoning and then interacts with a document augmentation module to request augmentation of the information within language space. Once sufficient question-related information is gathered, it feeds into the answering module to get the final prediction.

DrVideo achieves significant performance gains (3.8% on EgoSchema subset [36], 8.3% on MovieChat-1K global mode, 24.8% on MovieChat-1K breakpoint mode [49], and 6.3% on the long split of Video-MME [15]) over the existing LLM-based state-of-the-art methods [14, 37, 61, 73] across different long video benchmarks, from 3 minutes to 10 minutes and longer than 1 hour. Surprisingly, combining the subtitles on the long split of Video-MME benchmark, DrVideo obtains 71.7% accuracy, outperforming many heavily-engineered large-scale proprietary models (*e.g.,* Gemini 1.5 Flash [55], GPT-4o mini [44], and GPT-4V [42]). This highlights the great potential of DrVideo. Moreover, DrVideo is a training-free framework and is

researcher-friendly, as our results can be replicated on an RTX 4090 with a reasonable number of GPT accesses.

The contribution of this work can be summarized as:

- We propose DrVideo, the first document-retrieval-based system designed for the long video understanding task by converting it into a long-document retrieval and understanding task to effectively leverage the power of large language models.
- Different from previous works, we propose a retrieval module and a new multi-stage agent interaction loop that dynamically finds the potential missing information and augments these information within language space.
- DrVideo outperforms the existing LLM-based state-of-the-art methods across different long video benchmarks (*i.e.,* EgoSchema [36], MovieChat-1K [49], and the long split of Video-MME [15]) by a margin.

2. Related Work

Long Video Understanding. Modeling long videos, which are several minutes or more in length, generally requires advanced temporal modeling, resulting in complex model designs. LF-VILA [52] introduces a Temporal Window Attention (HTWA) mechanism to capture long-range dependencies in long videos. MeMViT [66] and MovieChat [49] employ a memory-based design to save question-related information from previous video segments. Some other approaches employ space-time graphs [22, 62] or relational space-time modules [70] to capture spatio-temporal dependencies from the raw long videos. Recently, S4ND [39], ViS4mer [23], and S5 [58] have used Structured State-Space Sequence (S4) [19] layers to capture long-range dependencies in videos. Different from these methods, our DrVideo does not design a complex module to perform long video understanding. Instead, we develop a document retrieval-based system with LLM for zero-shot long video understanding.

LLMs for Video Understanding. The recent rise of LLMs [72] and VideoChat [30] align the visual features extracted by pretrained visual models to LLMs and apply them to video understanding. Video ChatCaptioner [7] and ChatVideo [57] utilize LLMs to represent videos and engage users through dialogues, respectively. VidIL [64] applies the image-level models to video understanding tasks via few-shot learning. In addition to short-term video understanding, recent studies [4, 11, 32] have explored LLMs for long-range video modeling. For instance, GPT-4 is applied in various long-range video modeling tasks in [32], though quantitative evaluation is limited. Meanwhile, the research in [11] focuses on movie datasets with minimal visual analysis [36], relying largely on speech and subtitles. In contrast, DrVideo focuses on vision modality in multiple benchmarks.

LLM Agents. In parallel, the computer vision community has started exploring the use of LLMs as agents in various vision tasks such as GUI understanding and robot navigation [5, 13, 21, 53]. In the realm of long video comprehension, initial efforts have employed an agent-like approach, where LLMs interact with external tools or integrate additional functionalities [14, 17, 53, 61, 71]. In contrast to these approaches, our method, DrVideo, reconceptualizes long video understanding as a process of document retrieval, augmentation, and understanding, to leverage the strong capability of LLMs.

3. Methodology

In this section, we detail our proposed document retrieval-based system for long video understanding. As illustrated in Figure 1, given a long video and a question about the video, DrVideo first translates the long video into a long document, referred to as the initial video document. Then, the retrieval module identifies the top K key frames by calculating the similarity between the question and the initial video document. The document augmentation module enriches the information of these key frames and adds it to the initial video document, creating a new video document (named the updated video document), which is used as the starting point for the subsequent multi-stage agent interaction loop.

The loop contains two distinct agents: the planning agent and the interaction agent. The planning agent judges whether the updated video document is sufficient for answering the question. If not, the updated video document is fed into the interaction agent to dynamically find missing key frames. The interaction agent interacts with the document augmentation module to request the required information of these key frames. The output of the document augmentation module is added to the current document to obtain the latest updated video document. The new video document is then sent to the planning agent again to further judge whether the current information is sufficient. This searching and interaction loop continues until the planning agent considers the current information sufficient for answering the question or the maximum iteration is reached. After the loop ends, the final video document and the related question are given to the answering module to get the final prediction.

3.1. Video-Document Conversion Module

By translating each single video frame V_t (or a short video clip) into a short description S_{V_t}, we convert an input long video into the initial video document Doc_{init}:

$$Doc_{init} = \{\{1, S_{V_1}\}, \{2, S_{V_2}\}, \ldots, \{T, S_{V_T}\}\} \quad (1)$$

where T is the length of the video. Specifically, S_{V_t} is generated by a large vision-language captioning model ϕ_{vlm}

对T帧的视频请求VLM做简单描述不超过50words

(*e.g.,* LLaVA-NeXT [33]) , *i.e.,* $S_{V_t} = \phi_{vlm}(\mathcal{P}, V_t)$, where $\mathcal{P}$ is the prompt for requesting a short description about the image, *e.g., describe the picture in no more than 50 words.* The captioning model used in DrVideo can be replaced by other captioning models (*e.g.,* LaViLa [77], BLIP-2 [29]). The experimental results with different captioning models can be found in Table 6.

3.2. Document (Frames) Retrieval Module

After obtaining Doc_{init}, we introduce a document retrieval module to identify the top question-related frames by calculating the similarity between the question and the whole document. Specifically, we use the OpenAI embedding model ϕ_{emb} [43] to obtain the vector representation of the initial document, *i.e.,* $\mathcal{E}_{doc} = \phi_{emb}(Doc_{init})$. Given a specific retrieval text $\mathcal{RT}$, *i.e.,* the question Q, the retrieval module first computes the embedding $\mathcal{E}_{\mathcal{RT}} = \phi_{emb}(\mathcal{RT})$, and then retrieves the top K frames based on the cosine similarity between $\mathcal{E}_{\mathcal{RT}}$ and $\mathcal{E}_{doc}$:

$$topk\_doc = \arg\operatorname*{topK}_{t} \cos(\mathcal{E}_{\mathcal{RT}}, \mathcal{E}_{doc_t}) \qquad (2)$$

where $\mathcal{E}_{doc_t}$ is the embedding of the t-th description S_{V_t}.

3.3. Document Augmentation Module

For each $t' \in topk\_doc$, we use the LLaVA-NeXT model [33] with different prompts $\mathcal{AP}$ (augmented prompts) to generate a detailed description $L_{V_{t'}}$, *i.e.,* $L_{V_{t'}} = \phi_{vlm}(\mathcal{AP}_{t'}, V_{t'})$. The initial $\mathcal{AP}_{t'}$ is a general prompt: *If there are factual errors in the question, provide a precise description of the image; if not, proceed to answer the question:* $\{Q\}$. The updated video document $\mathcal{AD}$ becomes

$$\mathcal{AD} = \left\{ \begin{cases} \{t, S_{V_t}, L_{V_{t'}}\} & \text{if } t = t' \\ \{t, S_{V_t}\} & \text{otherwise} \end{cases} \middle| t = 1, \dots, T \right\}. \qquad (3)$$

Note that K is significantly smaller than the total number of frames (*e.g.,* $K = 5$ compared to $T = 90$), so the additional descriptions will not substantially increase the overall length of the document.

3.4. Multi-Stage Agent Interaction Loop

Apart from the retrieved key frames, we further introduce a multi-stage agent interaction loop to dynamically find other potential key frames and augment them with different types of information for the final answer. We employ two distinct agents: planning and interaction agents, each tailored for a specific task. Both agents utilize the same LLM, *i.e.,* GPT-3.5, but are given different prompts and reason varying types of information. The detail is shown in Fig. 2

Planning Agent. Given the question Q and the updated video document $\mathcal{AD}_i$ (where i denotes the iteration step), along with the analysis history $\mathcal{H}$ from all previous steps (initialized as empty $\{\}$), the planning agent first determines
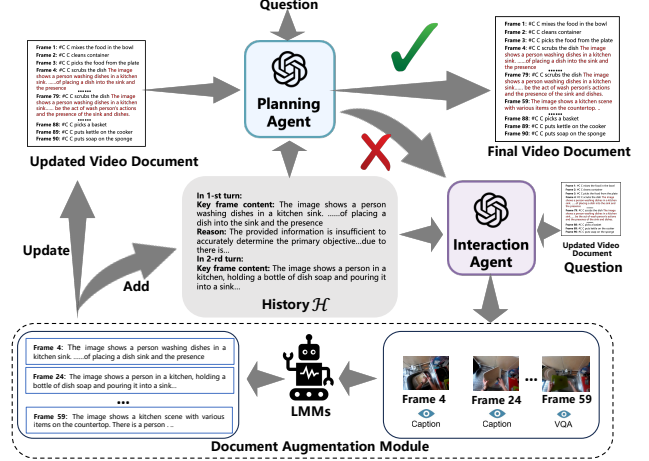

Figure 2. **Illustration of the multi-stage agent interaction loop and answering module.** There are two agents in the multi-stage agent interaction loop: a planning agent to plan the next step and an interaction agent to dynamically find missing information and interact with the document augmentation module.

whether the updated video document is sufficient to generate a confident answer. If the information is sufficient, the process moves to the answering module to get the final answer. If not, the agent provides an analysis of why the updated video document $\mathcal{AD}_i$ is inadequate. The agent then updates $\mathcal{H}_i$ with its analysis and passes the updated $\mathcal{H}_i$ to the interaction agent.

Interaction Agent. Given the current video document $\mathcal{AD}_i$ and the updated $\mathcal{H}_i$, the interaction agent finds N frames with missing details crucial for answering Q:

$$\forall n \in N, n \in T, n \notin topk\_doc, \text{ and } N < K. \qquad (4)$$

In addition to identifying the missing N key frames, the interaction agent also determines the augmented information type for each $n \in N$. To achieve it, we give a task-specific prompt to the interaction agent, *i.e., Your task is to determine which frame needs which type of information and can answer this question accurately, reasonably, and without contradiction. The two types of information are as follows: A: Given an image, get a detailed description of the image (image caption, just like what is shown in this image?) B: Given an image, get a response to the above question (visual question answering).* After obtaining N frames along with their required information type, the agent interacts with the document augmentation module to enrich the information of these frames to update the current video document for the next step.

3.5. Answering Module

Given the final video document $\mathcal{AD}_{final}$, we employ another agent to provide a prediction using a chain-of-thought

Method	(M)LLM	Subset	Fullset
MoReVQA [37]	PaLM-2	-	51.7
Vamos [60]	GPT-4	51.2	48.3
ProViQ [9]	GPT-3.5	57.1	-
LLoVi [73]	GPT-3.5	57.6	50.3
IG-VLM [26]	GPT-4V	59.8	-
VideoAgent [61]	GPT-4	60.2	54.1
MVU [47]	Mistral-13B	60.3	37.6
LLoVi [73]	GPT-4	61.2	-
VideoAgent [14]	GPT-4	<u>62.8</u>	<u>60.2</u>
DrVideo (ours)	GPT-3.5	**62.6**	-
DrVideo (ours)	GPT-4	**66.4**	**61.0**

Table 1. Results on EgoSchema compared to existing LLM-based state-of-the-art methods.

(CoT) approach [65]. The answering module outputs the corresponding answer, the confidence score, and the reasoning behind the answer. Besides improving prediction accuracy, the CoT approach allows us to trace inference steps, ensuring transparency and explainability in the decision-making process.

4. Experiments

In this section, we first introduce the datasets and implementation details and then present the results and ablations of our proposed DrVideo.

4.1. Datasets and Metrics

In our experiments, we evaluate our DrVideo using three well-established datasets, emphasizing its zero-shot long video understanding capabilities.

EgoSchema. EgoSchema dataset [36] consists of 5000 multiple-choice questions sourced from 5000 three-minute egocentric videos. This dataset only has a subset of 500 questions with publicly accessible labels, while the full set is evaluated on the leaderboard.

MovieChat-1K. MovieChat-1K [49] is a longer video understanding benchmark, which contains 1000 videos from movies and TV shows, each video lasting approximately 10 minutes. This dataset has two modes: global mode and breakpoint mode. The global mode refers to analyzing the entire video to understand its overall content and context, while the breakpoint mode focuses on analyzing specific frames or scenes.

Video-MME. Video-MME [15] is a recently proposed benchmark for comprehensive video analysis evaluation. We evaluate DrVideo on the "long-term videos" split of this dataset (long split), where video lengths vary from 30 to 60 minutes, with an average duration of 44 minutes.

Since EgoSchema and Video-MME are multi-choice tasks, we use accuracy as the evaluation metric for both

Method	Global		Breakpoint	
	Acc.	Score	Acc.	Score
Open-Source MLLM				
Video LLaMA [74]	51.7	2.72	39.1	2.11
Video Chat [30]	57.8	3.08	46.1	2.32
Video-ChatGPT [35]	47.6	2.89	48.0	2.43
MovieChat [49]	68.3	3.15	48.3	2.46
MovieChat+ [50]	71.2	<u>3.51</u>	<u>49.6</u>	<u>2.62</u>
Based on Open-source Captioners and Proprietary LLMs				
MM-VID [32]	58.6	2.86	10.4	0.56
LLoVi [73]	58.3	2.87	17.8	1.03
VideoAgent* [61]	65.4*	3.12*	31.6*	2.05*
Sullam Jeoung, et al [24]	<u>84.8</u>	-	-	-
DrVideo (ours)	**93.1**	**4.41**	**56.4**	**2.75**

Table 2. Performance comparison on the MoiveChat-1K [49] benchmark against state-of-the-art methods. * represents re-implemented results, implementation details refer to appendix.

datasets. The MovieChat-1K benchmark focuses on open-ended questions, We use GPT-assisted evaluation to assess both the accuracy (true/false) and quality (score 0-5) of the models. We select Gemini-Pro [54] as the evaluation assistant and use the same prompt [38] to conduct a fair comparison.

4.2. Implementation Details

For EgoSchema [36] dataset, we choose LaViLa [77] as the captioning model to convert videos into documents. Note that the training data of our LaViLa model does not include EgoSchema videos, which is the same as LLoVi [73]. For MovieChat-1K and Video-MME benchmarks, LLaVA-NeXT [33] is used as our captioning model to generate brief descriptions for each frame. We preprocess videos by simply sampling them at 0.5 FPS for EgoSchema [36] and MovieChat-1K [49] and 0.2 FPS for Video-MME [15]. LLaVA-NeXT [33] is chosen to augment key frames in both datasets via different prompts. In the comparison experiments, GPT-4 [1], *i.e.*, gpt-4-1106-preview, is used as the agent to evaluate the performance of our DrVideo on EgoSchema and MovieChat-1K. DeepSeek [20], *i.e.*, DeepSeek V2.5, is used as the agent to evaluate the performance on Video-MME. For the ablation study, we use GPT-3.5 [40], *i.e.*, gpt-3.5-turbo-1106, to evaluate the effectiveness of our DrVideo due to the API cost.

4.3. Main Results

Comparative results on EgoSchema. Table 1 compares our DrVideo with existing LLM-based state-of-the-art methods [9, 14, 26, 37, 47, 60, 61, 73] on EgoSchema benchmark [36]. Specifically, compared with LLoVi [73] and VideoAgent [61] that leverage the same visual captioner (LaViLa [77]) and LLM (GPT-4), DrVideo significantly

Method	Frames	w/o Subs	w Subs
Proprietary MLLM			
Claude 3.5 Sonnet [2]	20	51.2	54.7
GPT-4V [42]	10	53.5	56.9
GPT-4o mini [44]	250	58.6	63.4
Gemini 1.5 Flash [55]	0.5 FPS	61.1	68.8
GPT-4o [44]	384	65.3	72.1
Gemini 1.5 Pro [55]	0.5 FPS	**67.4**	**77.4**
Open-Source MLLM			
LongVA [75]	128	46.2	47.6
VITA-8x7B [16]	32	48.6	50.9
LLaVA-OneVision-72B [28]	32	60.0	62.4
Qwen2-VL-72B [3]	768	62.2	74.3
Based on Open-source Captioners and Proprietary LLMs			
VideoAgent* [61]	7.6	40.2*	44.4*
LLoVi* [73]	0.2 FPS	45.4*	67.7*
DrVideo (ours)	0.2 FPS	51.7	71.7
-only subs	0.2 FPS	-	68.5

Table 3. Video-MME long split results. *w/o subs* represents the model without any subtitles. *w subs* represents that the subtitles corresponding to the sampled frames are both fed into the LLM to evaluate the performance. Our DrVideo outperforms a strong proprietary MLLM (Claude 3.5 Sonnet) and some open-source MLLMs (*e.g.,* VITA-8x7B). * represents re-implemented results, implementation details refer to appendix.

RM	MSAIL	CoT	Acc.(%)
✓	✓	✓	**62.6**
✓	✓	✗	62.2
✓	✗	✓	60.6
✗	✓	✓	59.4
✗	✗	✓	57.4

Table 4. Ablation results on different combinations of the retrieval module (RM), the multi-stage agent interaction loop (MSAIL), and the CoT on EgoSchema.

outperforms these methods by 5.2% and 6.2% respectively. Compared with VideoAgent [14] which uses video-specific models (ViCLIP from InternVid [63] and Video-LLaVA [31]), DrVideo still performs better and achieves 3.6% higher accuracy on the subset evaluation. Moreover, DrVideo significantly outperforms IG-VLM [26] by 6.6%, which uses strong MLLM, *i.e.,* GPT-4V. These results confirm our idea of converting the long-video understanding task into a long-document understanding task is feasible and our DrVideo can find the question-related key frames more accurately.

Comparative results on longer video benchmarks. To further emphasize the advantage of our method on longer videos, we evaluate our DrVideo on the other two video benchmarks, *i.e.,* MoiveChat-1K (10 minutes) [49], and the long split of Video-MME (average 44 minutes) [15]. Table 2 presents the comparative results of our DrVideo and the current state-of-the-art methods [30, 38, 49, 73, 74] on the MovieChat-1K benchmark. Table 3 shows the comparative results of our DrVideo on the Video-MME benchmark, with comparisons against three types of methods: proprietary MLLMs [2, 42, 44, 55], open-source MLLMs [3, 16, 28, 75], and methods based on open-source captioners and proprietary LLMs [61, 73].

Compared to methods like LLoVi [73] and VideoAgent [61] that are based on open-source captioners (*e.g.,*

LLaVA-NeXT [33]) and proprietary LLMs (*e.g.,* GPT-4 [1]), DrVideo achieves a 8.3% improvement in global mode and a 24.8% improvement in breakpoint mode on the MovieChat-1K benchmark in Table 2. It also achieves at least 6.3% improvement under the w/o subtitle setting on the Video-MME benchmark in Table 3. This indicates that DrVideo can accurately identify question-related frames and avoid critical information loss through augmentation, highlighting the potential of document retrieval methods for processing longer videos. Compared to proprietary MLLMs and open-source MLLMs, DrVideo outperforms Claude 3.5 Sonnet [2] by 0.5% and some open-source MLLMs (*e.g.,* VITA-8x7B [16]) under the w/o subtitle setting on Video-MME benchmark. It also achieves a 21.9% improvement in global mode and a 6.8% improvement in breakpoint mode on MovieChat-1K benchmark. Moreover, combining the subtitle on the Video-MME benchmark, DrVideo achieves 71.7% accuracy and outperforms many heavily-engineered large-scale proprietary models (*e.g.,* Gemini 1.5 Flash [55], GPT-4o mini [44], and GPT-4V [42]). To better understand this significant improvement, we conduct an experiment where only the subtitle, question and options are input into the LLM (*i.e.,* DeepSeek [20]) to predict the answer and the accuracy is 68.5%. This suggests: (i) subtitles contain extensive question-related information, playing a crucial role in understanding long videos; (ii) compared with LLoVi and VideoAgent, DrVideo enhances visual information via document retrieval and augmentation, effectively integrating subtitles and resulting in a 3.2% improvement.

4.4. Ablation Studies

Unless otherwise specified, we use GPT-3.5 as the default setting in the below experiments on EgoSchema subset [36]. **Effects of different components of DrVideo.** We conduct experiments with different combinations of the individual components in DrVideo, including the retrieval module, the multi-stage agent interaction loop, and the CoT used in the answering module. The results are presented in Table 4. We can see that: (i) without the retrieval module and the agent loop, the performance of our DrVideo is similar to LLoVi [73]; (ii) By adding the retrieval module and then

VQA	Caption	Acc. (%)		Top-K	Acc. (%)
✓	✓	**62.6**		5	**62.6**
×	✓	60.4		10	61.4
✓	×	61.8		20	60.6

(a) Performance with different types of information   (b) Performance with different Top-K frames

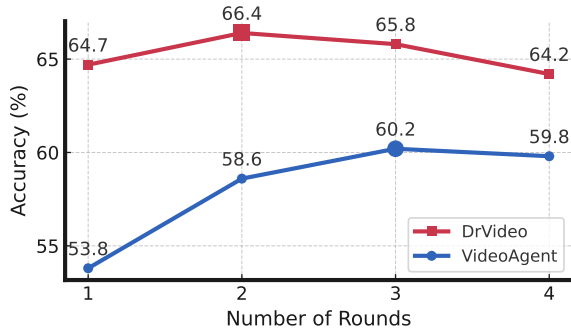Table 5. Ablation results with different settings on EgoSchema.

Figure 3. Performance of different rounds with DrVideo and VideoAgent [61] on EgoSchema. To align with VideoAgent, GPT-4, *i.e.,* gpt-4-turbo-1106-preview, is used as the LLM agents.

Captioning Model	Type	Acc.(%)
LaViLa [77]	Clip-based	**62.6**
LLaVA-NeXT [33]	Frame-based	61.2
BLIP-2 [29]	Frame-based	59.6

Table 6. Performance of different VLMs on EgoSchema.

LLMs	Type	Size	Acc.(%)
Mistral-8x7B [25]	Open-Source	8x7B	47.6
DeepSeek [20]	Proprietary	N/A	61.2
GPT-3.5 [40]	Proprietary	N/A	62.6
GPT-4 [1]	Proprietary	N/A	**66.4**

Table 7. Performance of different LLMs on EgoSchema.

the agent loop, the performance of DrVideo improves from 57.4% to 60.6% and then to 62.6%. This demonstrates that the retrieval module can identify key frames via measuring semantic similarity, while the agent loop can locate additional key frames through contextual inference; (iii) the additional CoT contributes to the accuracy improvement from 62.2% to 62.6%, demonstrating its effectiveness.

Effects of different types of augment information. To better enhance the required information for each potential key frame, we define two types of augment information, namely VQA (question-related information) and caption (general detailed information). Table 5a presents the performance of DrVideo with different types of information. We can see that when only one type of information (VQA or caption) is used for augmentation, the model's performance declines. This suggests the necessity of adaptively augmenting different types of information for each potential key frame.

Effects of different initial top K key frames. By default, the number of the initial key frames is set as $K = 5$. Intuitively, more frames should lead to better performance at the cost of increasing the complexity. However, our ablation in Table 5b shows an opposite trend, *i.e.*, more key frames resulting in worse performance. This suggests that enhancing more frames is not necessarily beneficial, as it can introduce a large amount of noisy and irrelevant information that interferes with the LLM's judgment.

Effects of iterative rounds. We also examined the impact of the iterative rounds I on model performance. Fig. 3 shows the performance of different iterative rounds with DrVideo and VideoAgent [61]. We have the following observations. (i) DrVideo consistently outperforms VideoAgent, reaching the peak performance at $I = 2$, while VideoAgent peaks at $I = 3$. This indicates that DrVideo can locate the information needed to answer questions in fewer interactions and with higher quality, underscoring the superiority of our document retrieval-based framework. (ii) When the number of interactions exceeds two, DrVideo's performance declines. This is likely due to more noisy and irrelevant information being introduced into the LLM with the increase of the iterations. This further confirms that excessive information is not necessarily beneficial.

Effects of different foundation models. DrVideo incorporates two types of foundational models — large language model (LLM), and visual language model (VLM), where VLM is used as the frame captioner while LLM is used as the planning agent, the interaction agent, and the answering agent. To assess the impact of the captions produced by different VLMs, we examine three state-of-the-art VLMs: frame-based BLIP-2 [29], LLaVA-NeXT [33], and clip-based LaViLa [77], as presented in Table 6. We observe that LaViLa achieves the best performance, while BLIP-2 is the worst. It indicates the superiority of the clip-based model which can capture motion information in videos and is more suited for video understanding.

To evaluate the effectiveness of DrVideo with different LLMs, Table 7 shows the results of DrVideo using open-source LLM (Mistral-8x7B [25]) or Proprietary LLM (DeepSeek [20], GPT-3.5 [40], or GPT-4 [1]) as the planning, interaction and answering agents. From the results, we can see that: (i) different LLMs in DrVideo exhibit significant performance gaps and the proprietary LLM significantly outperforms the open-source LLM, indicating DrVideo's dependency on the choice of LLM; (ii) as the LLM's capability increases, the performance of DrVideo

Question: By analyzing c's activities in this video, determine their overall focus or intention, and describe the progression of tasks leading to its fulfillment.
A. C's overall focus or intention in this video is to set up their work station and start working on their computer.
B. The central objective in this video, c's overall focus or intention, is to engage in conversation with the person.
C. C's overall focus or intention in this video is to eat the wrapper.
D. C's overall focus or primary intention in this specific video content is to effectively play the guitar
E. The primary objective and intention in this particular c's video is to demonstrate how to effectively clean the cloth.
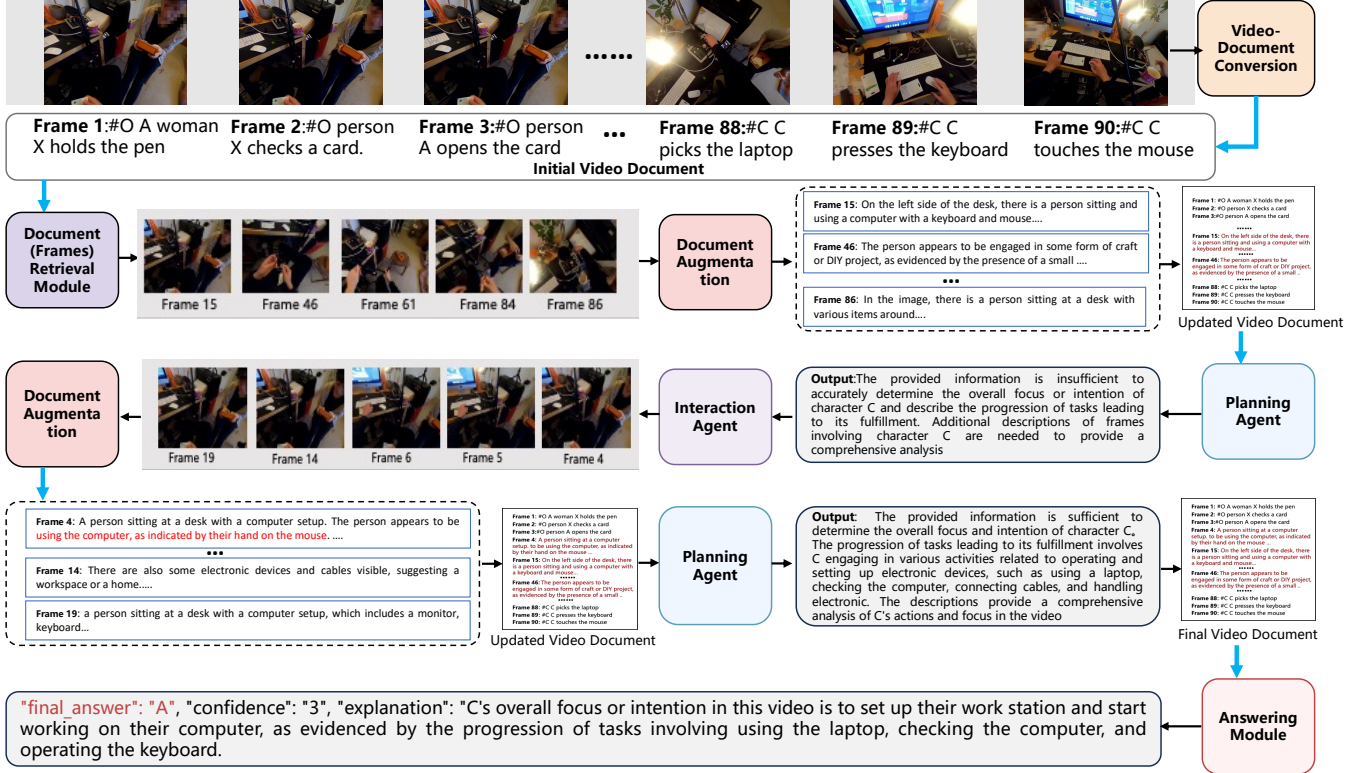
Figure 4. Case study on an instance from EgoSchema. DrVideo accurately identifies key frames and chooses the correct answer.

improves, demonstrating the great potential of DrVideo. It's worth noting that our main contribution is the introduction of a framework for translating the long video understanding into a document retrieval and understanding task to effectively leverage the power of large language models, rather than the employment of any specific models. Our DrVideo can be further improved by combining with better LLM and VLM models (*e.g.,* tarsier [59]).

Case study. Here we give a detailed example from EgoSchema [36] in Fig. 4 to qualitatively demonstrate the capability of our DrVideo. Specifically, the question is to determine the overall focus or intention and describe the progression of tasks leading to its fulfillment. DrVideo first converts the raw video into an initial video document, which is then processed by the frame retrieval module to obtain key frames (frames 15, 46, 61, 84, and 86) and is augmented with detailed key frame descriptions. The updated video document is then fed into the planning agent to assess if sufficient information is available for answering, *i.e.*,

the provided information is sufficient to infer character C's main focus or intent. This updated document, along with the rationale, is input to the interaction agent to identify the additional key frames (frames 4, 5, 6, 14, and 19 here). After further augmentation, the updated document is sent back to the planning agent, for which the agent confirms its sufficiency. Finally, the answering module takes in the final video document and predicts the correct answer.

5. Conclusion

We have proposed DrVideo, a document retrieval-based system for long video understanding. Different from previous LLM-based methods, DrVideo proposes to adapt long-video understanding to long-document understanding and searches for missing information via document retrieval and multi-stage agent loop. Extensive comparative experiments and ablation studies on the three challenging datasets, *i.e.,* EgoSchema, MovieChat-1K, and Video-MME, demonstrate the effectiveness of DrVideo. We believe our work

can serve as a strong baseline to stimulate further developments on the topic of long video understanding.

6. Limitation

Although Drvideo achieves impressive results on different long video benchmarks, it has several limitations. (i) The longest video DrVideo can handle depends on the maximum token length of the LLM, which is the bottleneck for much longer videos than the existing benchmarks, *e.g.,* 10 hours. (ii) It has space for further improvement on how to generate sufficient information while minimizing irrelevant information in the video document.

DrVideo: Document Retrieval Based Long Video Understanding

Supplementary Material

7. More Implementation Details

Experiments Compute Resources. All experiments are conducted on single NVIDIA RTX 4090 GPU. The minimal GPU memory requirement is 24GB. We set the temperature to 0 for all experiments using GPT-3.5 [40], GPT-4 [1], and DeepSeek [20].

Prompt Details. We provide detailed prompts for all agents (planning agent, interaction agent, and answering agent) in the EgoSchema benchmark [36]. Planing agent is to determine whether the video captions are sufficient for answering the question. Below is the planning agent prompt:

User
You are given some language descriptions of a first-person view video along with a question about the video.
1.The video is 3 minutes long, containing a total of 90 frames.
2. Each sentence in these language descriptions represents the text description for a single frame.
3. The format of each sentence is frame id, description. The frame id indicates the temporal position of the frame, ranging from 1 to 90.
Here are the original descriptions of this video: Documents
Here is the question: Question
Here is the memory: Memory
Your task is to determine whether these descriptions above can answer the question accurately, reasonably, and without contradiction.
If your answer is yes, please give me an reasonable explanation. the output will be as follows: **{"confidence": "1", "explanation": ["xxxx"]}**
If your answer is no, the confidence is 0, indicating the provided information is insufficient. Please give me a reasonable explanation for what frame is missing. For each frame identified as potentially relevant, provide a concise description focusing on essential visual elements(e.g., objects, humans, interactions, actions, and scenes) in the explanation. The output will be as follows: **{"confidence": "0", "explanation": ["xxxx"]}**
You must not provide any other response or explanation.

Assistant
"confidence": "0/1", "explanation": ["xxxx"]

Interaction agent is used to find potential missing key frames with different types of information. The interaction agent prompt in the EgoSchema benchmark is shown as below:

User
You are given some language descriptions of a first-person view video along with a question about the video.
1.The video is 3 minutes long, containing a total of 90 frames.
2. Each sentence in these language descriptions represents the text description for a single frame.
3. The format of each sentence is frame id, description. The frame id indicates the temporal position of the frame, ranging from 1 to 90.
Here are the original descriptions of this video: Documents
Here are the memory: Memory
To answer the following question: Question
Theses descriptions are insufficient and cannot answer this question accurately, reasonably, and without contradiction.
Your task is to determine which frame needs which type of information and can answer this question accurately, reasonably, and without contradiction.
The two types of information are as follows:
A: Given an image, get a detailed description of the image (image caption, just like what is shown in this image?)
B: Given an image, get a response to the above question (visual question answering)
Please note that frame selections range from 1 to 90. These frames (type_A) already have type A information and these frames (type_B) already have type B information, please note not to repeatedly select this type of information from these frames. Please note that the the key of frame only one number. The output must be as follows: **["frame": "1/2/3/.../90", "type": "A/B"]**

Assistant
["frame": "1/2/3/.../90", "type": "A/B"]

Finally, the answering agent is used to predict the answer once the video captions are sufficient. The answering agent is shown as below:

User

You are individual C, with others represented as O. Your task is to answer a question related to this video, choosing the correct option out of five possible answers. You are given some language descriptions of a first person view video along with a question about the video.

1.The video is 3 minutes long, containing a total of 90 frames.

2. Each sentence in these language descriptions represents the text description for a single frame.

3. The format of each sentence is frame id, description. The frame id indicates the temporal position of the frame, ranging from 1 to 90.

Here are the descriptions of this video: Documents
Please answer the following question: Question
Here are the choices. A: option1 B: option2 C: option3 D: option4 E: option5

The question has 5 choices, labeled as A, B, C, D, E. Please think step by step and write the best answer index. Note your final answer must be one of the letters (A, B, C, D, or E), the confidence must be one of the letters (1, 2, 3), please provide a concise one-sentence explanation for your chosen answer. the output must be the following format. You must not provide any other response or explanation.

{"final_answer": "xxx", "confidence": "xxx", "explaination": "xxx"}

Assistant

{"final_answer": "xxx", "confidence": "xxx", "explaination": "xxx"}

Details of LaViLa. For the experiments on EgoSchema [36], we utilize LaViLa [77] as the captioner, a CLIP-based captioning model. LaViLa processes input clips with a resolution of $4 \times 336 \times 336$ and is trained on the Ego4D dataset [18]. The original LaViLa training set contains 7,743 videos with 3.9 million video-text pairs, while the validation set includes 828 videos with 1.3 million video-text pairs. Since the EgoSchema dataset is cropped from Ego4D and designed for zero-shot evaluation, using the original LaViLa model could lead to overlap with EgoSchema videos, resulting in an unfair comparison. To address this, we use the retrained LaViLa model which same as LLoVi [73] that do not have any overlap with EgoSchema videos to avoid unfair comparison with other methods. The checkpoints are available at https://drive.google.com/file/d/1AZ5I4eTUAUBX31rL8jLB00vNrlFGWiv8/view.

Details of LLaVA-NeXT. For the experiments on MovieChat-1K [49] and Video-MME [15], we utilize LLaVA-NeXT [33] as the captioner, which is a frame-based captioning model. LLaVA-NeXT used in our framework has 7B parameters and the checkpoints are available at https://huggingface.co/llava-hf/llava-v1.6-mistral-7b-hf. We also use the same LLaVA-NeXT model to augment key frames with different prompts in both datasets.

VideoAgent Reproduce Details. To evaluate the performance of VideoAgent [61] on MovieChat-1K benchmark [49] and make a fair comparison, we select the LLaVA-NeXT model as the captioner and preprocess videos by simply sampling them at 0.5 FPS. GPT-4 [1], *i.e.,* gpt-4-1106-preview, is used as the agent to predict answer, self reflect, and find missing information. The prompt for each agent is same as the original paper. The max interaction rounds is set to 3 and the initial sampled frames for whole video is set to 5, which is the default setting in the original paper. The EVA-CLIP-8B-plus model [51], a state-of-the-art CLIP model that includes a vision encoder with 7.5 billion parameters and a text encoder with 0.7 billion parameters, is used for frame retrieval to align with the original paper [61]. The above setting is used to the global mode and breakpoint mode to ensure reproducibility. The checkpoints of LLaVA-NeXT model are available at https://huggingface.co/llava-hf/llava-v1.6-mistral-7b-hf. The website of GPT-4 API is available at https://openai.com/index/gpt-4-api-general-availability/. The checkpoints of EVA-CLIP-8B-plus model are available at https://huggingface.co/BAAI/EVA-CLIP-8B-448.

To evaluate the performance of VideoAgent [61] on Video-MME benchmark [15] and make a fair comparison, we preprocess videos by simply sampling them at 0.2 FPS and DeepSeek, *i.e.,* DeepSeek V2.5, is used as the agent to predict answer, self reflect, and find missing information. Except for those, the other settings are the same as the MovieChat-1K benchmark. The website of DeepSeek API is available at https://api-docs.deepseek.com/. Note that for the experiment with subtitles, we select the subtitles corresponding to the sampled frames to add to the LLM, rather than using all the subtitles. This is why the performance of VideoAgent is significantly lower than the other LLM-based methods under the *w subs* setting.

LLoVi Reproduce Details. To evaluate the performance of LLoVi [73] on Video-MME benchmark and make a fair comparison, we select the same LLaVA-NeXT model [33] as the captioner and preprocess videos by simply sampling them at 0.2 FPS. DeepSeek [20], *i.e.,* DeepSeek V2.5, is used as the agent to summary the sampled captions and predict the final answer. The summaries words are set to 500 and the prompt of each prompt is same as the original paper [73]. The website of DeepSeek API is available at https://api-docs.deepseek.com/. The checkpoints of LLaVA-NeXT model are available at https:

Sampling Rate	Accuracy (%)
1 FPS	61.6
0.5 FPS	**62.6**
0.25 FPS	58.8

Table 8. Performance of different sampling rate on EgoSchema.

//huggingface.co/llava-hf/llava-v1.6-mistral-7b-hf.

Only Subs Reproduce Details. In Section 4.3 of our paper, we conduct an experiment where only the subtitle, question and options are input into the LLM (*i.e.,* DeepSeek [20]) to predict the answer. Specifically, the subtitles used in the LLM are aligned with the sampled frames, while we preprocess videos by simply sampling them at 0.2 FPS. The prompt for the LLM is shown in below:

User
This video's subtitles are listed below:
subtitle_1
subtitle_2
...
subtitle_n
Select the best answer to the following multiple-choice question based on the subtitles and summary. Respond with only the letter (A, B, C, or D) of the correct option.
Question
OptionA
OptionB
OptionC
OptionD

Assistant
A/B/C/D

---

where n represents the number of subtitles under the 0.2 FPS sampling.

8. More Ablation Studies

In this paper, we choose LaViLa [77] as the captioning model to convert videos into documents. we preprocess videos by simply sampling them at 0.5 FPS for EgoSchema. To evaluate the impact of different sampling rates on the model's performance. We conduct the experiments with different sampling rates (1 FPS, 0.5 FPS, and 0.25 FPS) to convert videos into documents on EgoSchema subset. Besides, we use GPT-3.5 [40] as the planning agent, interaction agent, and answering agent for the below comparisons.

Algorithm 1: DrVideo

Input: V, Q
▶ **Video-Document Conversion Module**;
$\text{Doc}_{init} \leftarrow \text{getDoc}(V, \phi_{vlm}, \mathcal{P})$;
$\mathcal{E}_{\text{doc}} \leftarrow \text{getEmbedding}(\text{Doc}_{init}, \phi_{emb})$;
▶ **Document Retrieval Module**;
Initialize $\mathcal{RT}$ as Q;
$\mathcal{E}_{\mathcal{RT}} \leftarrow \text{getEmbedding}(\mathcal{RT}, \phi_{emb})$;
topk_doc $\leftarrow \text{Retrieval}(\mathcal{E}_{\mathcal{RT}}, \mathcal{E}_{\text{doc}}, K)$;
▶ **Document Augmentation Module**;
Initialize $\mathcal{AP}$;
$\mathcal{AD}_0 \leftarrow \text{Augment}(\text{topk\_doc}, \text{Doc}_{init}, \mathcal{AP})$;
$\mathcal{H} \leftarrow \text{addToMemory}(\text{topk\_doc})$;
▶ **Multi-Stage Agent Interaction**;
Initialize $i \leftarrow 0$;
while $i \leq I$ **do**
  Planning Agent:;
  $\mathcal{S}, R \leftarrow \text{checkSufficient}(\mathcal{AD}_i, \mathcal{H}_i, Q)$;
  if $\mathcal{S} == 1$ **then**
    | break;
  else
    $\mathcal{H} \leftarrow \text{addToMemory}(\mathcal{H}, R)$;
    Interaction Agent:;
    $\mathcal{M} \leftarrow \text{FindMissInfo}(\mathcal{AD}_i, \mathcal{H}, Q)$;
    $N, \mathcal{AP} \leftarrow \mathcal{M}$;
    $\mathcal{H} \leftarrow \text{addToMemory}(\mathcal{H}, N)$;
    $i \leftarrow i + 1$;
    $\mathcal{AD}_i \leftarrow \text{Augment}(N, \mathcal{AD}_i, \mathcal{AP})$;

▶ **Answering Module**;
$P \leftarrow \text{GetAnswer}(\mathcal{AD}_i)$;
return P;

Table 8 presents the results and we have the following observations: (i) When the sampling rate is set to 1 FPS, the performance is lower than the sampling rate is set to 0.5 FPS. It indicates that a higher sampling frequency is not always better, as higher frequencies introduce more redundant information. (ii) When the sampling rate is set to 0.25 FPS, the performance is also lower than the sampling rate is set to 0.5 FPS. This suggests that a low sampling frequency leads to the loss of significant information, which in turn causes a decline in performance. (iii) When the sampling rate is set to 0.5 FPS, DrVideo achieves the best performance. This highlights the importance of selecting an appropriate sampling rate to reduce redundant information while retaining critical details for DrVideo. It also leaves room for future improvements by adaptively sampling the video based on the question.

Question: How many colors of glaze are used in the video?

A. Five   **B.** Four   **C.** Three   **D.** Two

DrVideo	Find missing information after 1 round		{'final_answer': 'C', 'confidence': '2', 'explanation': 'The video mentions pink, green, and blue glazes, but does not mention any others.'} ✔
VideoAgent	Find missing information after 2 round		{'final_answer': 'D', 'confidence': '3'} ✘

Figure 5. Case study on an instance from Video-MME. Long Case of DrVideo. This video contains 33 minutes.

9. Detailed Algorithm

In Algorithm 1, we present the algorithm behind DrVideo to give the reader a clearer understanding. The definition of the symbols has already been provided in the main text.

10. More Case Studies

Fig. 5 shows how DrVideo can accurately solve hour-long videos from the long split of Video-MME benchmark. The question is about figuring out the colors of glaze used in the video, which not only requires the model to have a comprehensive understanding of the video but also a clear understanding of its local details. DrVideo accurately identifies the necessary information and predicts the answer correctly, outperforming state-of-the-art models like VideoAgent. This highlight the potential of our document retrieval method in handle longer videos.

Besides, we also provide a failure case to explore the limitations of our DrVideo as shown in Fig. 6. The question is determine the overarching theme of the video, considering the activities performed by both characters. DrVideo, after undergoing key frame retrieval enhancement and multi-stage interaction loop continuation retrieval enhancement, evaluates whether the information collected so far can accurately answer the question. However, due to the inability of the VLM to accurately describe the video content, DrVideo makes incorrect judgments, ultimately leading to a wrong answer. This indicates that DrVideo heavily relies on the capabilities of both LLMs and VLMs. We believe DrVideo will be improved with the development of better LLMs and VLMs in the future.

Question: What is the overarching theme of the video, considering the activities performed by both characters?
A. The overarching central theme presented in the video is that individuals can be both sociable and independent simultaneously. the visual content demonstrates that it is entirely possible to be both connected to others meaningfully and to savor solitary moments, emphasizing that it is crucial to find a harmonious balance between these two aspects.
B. The overarching theme of the video is that people can be both engaged in challenging activities and enjoying leisurely activities at the same time. the video shows that it is possible to be both productive and relaxed, and that it is important to find a balance between the two.
C. The primary, overarching theme presented in the video emphasizes that individuals can truly be both creative and practical simultaneously. the enlightening video demonstrates the realistic possibility of being both highly imaginative and remarkably efficient, while stressing the significance of discovering an equilibrium between these two essential aspects.
D. The overarching theme of the video is that people can be both ambitious and humble. the video shows that it is possible to be both driven and modest, and that it is important to find a balance between the two.
E. The primary overarching theme presented in the video is that individuals can simultaneously possess and exhibit both intelligence and emotional aspects. effectively, the video demonstrates that the coexistence of rational and intuitive qualities is feasible, emphasizing the significance of establishing equilibrium between these two crucial elements..
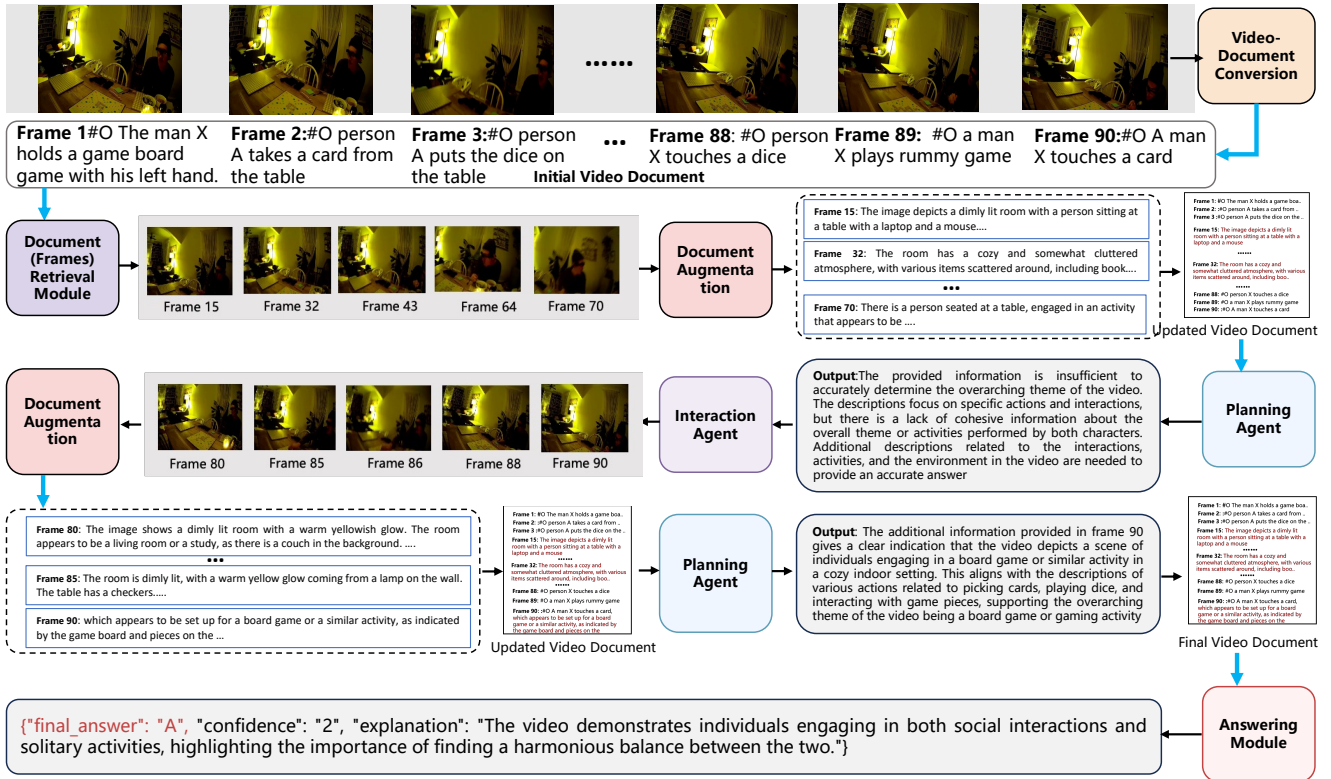

Figure 6. Case study on an instance from EgoSchema. Failure Case of DrVideo.

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