ADAPTIVE VIDEO UNDERSTANDING AGENT: ENHANCING EFFICIENCY WITH DYNAMIC FRAME SAMPLING AND FEEDBACK-DRIVEN REASONING

Anonymous authors
Paper under double-blind review

ABSTRACT

Understanding long-form video content presents significant challenges due to its temporal complexity and the substantial computational resources required. In this work, we propose an agent-based approach to enhance both the efficiency and effectiveness of long-form video understanding by utilizing large language models (LLMs) and their tool-harnessing ability. A key aspect of our method is query-adaptive frame sampling, which leverages the reasoning capabilities of LLMs to process only the most relevant frames in real-time, and addresses an important limitation of existing methods which typically involve sampling redundant or irrelevant frames. To enhance the reasoning abilities of our video-understanding agent, we leverage the self-reflective capabilities of LLMs to provide verbal reinforcement to the agent, which leads to improved performance while minimizing the number of frames accessed. We evaluate our method across several video understanding benchmarks and demonstrate that not only it enhances state-of-the-art performance but also improves efficiency by reducing the number of frames sampled.

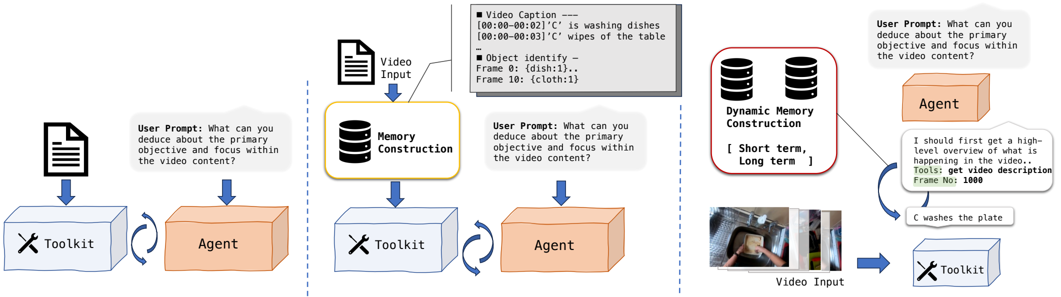
1 INTRODUCTION

Recent advancements in video understanding have been significantly driven by end-to-end pretrained large transformer models, particularly those built upon large language models (LLMs) Liu et al. (2023; 2024), known as multimodal LLMs. Despite these advancements, comprehending long form videos remains a considerable challenge due to prohibitive computational costs and suboptimal performance Dao et al. (2022). Various approaches have been proposed to extend the temporal context of video transformers, including techniques such as masking, attention approximations, and parametric memory modules (e.g. Wu et al. (2022), Piergiovanni et al. (2024)). However, these methods often add complexity by necessitating specialized architectures and training paradigms Song et al. (2024).

Efficient video processing requires strategic selection of relevant frames from the total video sequence Gao et al. (2023b); Li et al. (2024). Traditionally, methods in this domain mostly rely on uniform sampling Zhang et al. (2023a); Song et al. (2024) or selective retrieval from a subset of sampled frames Fan et al. (2024); Wang et al. (2023b). While these techniques improve processing efficiency by reducing the number of frames, they often lack adaptability, leading to potential redundancy.

To address the above shortcomings, here we propose a novel approach that leverages LLMs as adaptive agents for video understanding tasks. Our method utilizes the advanced reasoning, planning, and tool-use capabilities of LLMs (Pallagani et al. (2023); Zhao et al. (2024b); Schick et al. (2024)) to enhance sampling efficiency while maintaining robust performance in video understanding tasks. Specifically, our approach leverages a LLM-based agent that dynamically determines which frames to sample based on the specific context and query. This method ensures that frame selection is both relevant and efficient, effectively mitigating the limitations of static sampling methods.

Our approach draws inspiration from research indicating that humans strategically allocate attention and filter out irrelevant details based on the task at hand Lang et al. (2013); Heim & Keil (2012); Raymond et al. (1992). For example, when asked "*What is the main goal of the camera wearer in this video?*" versus "*What is the color of the bird that appears at the beginning?*", humans deploy distinct strategies: the former may necessitate a review of the entire video to understand its context, whereas the latter would involve focusing solely on the video's initial segment to identify the bird's color.


Toolkit
Agent
User Prompt: What can you deduce about the primary objective and focus within the video content?
Video Input
Memory Construction
■ Video Caption ---
[00:00-00:02]'C' is washing dishes
[00:00-00:03]'C' wipes of the table
…
■ Object identify –
Frame 0: {dish:1}..
Frame 10: {cloth:1}
Toolkit
Agent
User Prompt: What can you deduce about the primary objective and focus within the video content?
Dynamic Memory Construction
[Short term, Long term]
User Prompt: What can you deduce about the primary objective and focus within the video content?
Agent
I should first get a high-level overview of what is happening in the video..
Tools: get video description
Frame No: 1000
C washes the plate
Video Input
Toolkit

(a) Naïve Agent

(b) Agent with Pre-constructed Memory

(c)Agent with dynamic memory (Ours)

Figure 1: Comparison of methods: Our proposed method (c) is **query adaptive**, dynamically selecting frames based on query and video input to construct a responsive memory. In contrast, previous methods, including (a) Naïve agents and (b) Agents with pre-constructed memory, do not adapt to specific queries or utilize memory dynamically. We demonstrate that dynamically sampling frames have advantage over different set of benchmarks.

Our proposed framework adaptively samples and processes video frames in response to specific queries (see Figure 1 c). While previous approaches rely on static process which is independent of the query in extracting information such as captions Fan et al. (2024); Wang et al. (2023b), our approach attends to the given query and reasons strategically which frames to process during inference time without having to go through whole set of frames.

Our findings indicate that LLM agents, when used without guidance, exhibit suboptimal reasoning performance in terms of selecting the most informative frames. To enhance the reasoning ability of LLMs, we leverage the self-reflective capabilities of LLMs to provide insightful feedback Shinn et al. (2024); Pan et al. (2023a). Specifically, reflective statements serve as a form of verbal reinforcement, enabling the agents to develop an updated policy that facilitates more nuanced and sophisticated reasoning. Furthermore, our framework integrates long-term memory to store and utilize past experiences. The reasoning trajectories and the refinement is stored in the memory per instance. The key rationale behind adopting the memory is that retrieving past experiences that are relevant and semantically similar to a given query can significantly enhance the reasoning behavior of the LLM.

We validate the generalizability of our framework by evaluating it across a range of benchmarks, demonstrating its effectiveness and adaptability in various video understanding tasks. The results indicate that the proposed method outperforms existing approaches, achieving higher accuracy while maintaining a lowest number of frames accessed.

2 Related Work

2.1 Long Context Multimodal Agents

Several approaches have been developed to handle multimodal inputs through agent-based reasoning Gao et al. (2023a); Yang et al. (2024); Fan et al. (2024); Wang et al. (2023b). These methods leverage agents' reasoning abilities along with their tool-calling capabilities. For instance, Yang et al. (2024) employs Monte Carlo Tree Search for reasoning combined with tool-calling techniques, while Gao et al. (2023a) utilizes ReAct Yao et al. (2022) for flexible video input processing.

Recent advancements have also focused on long-context videos Fan et al. (2024); Wang et al. (2023b). For example, Fan et al. (2024) uses memory retrieval during inference to address specific queries, which can be effective for localizing detailed information but may become redundant depending on the query type. Similarly, Wang et al. (2023b) relies on predefined sampling methods, necessitating extensive frame access for caption generation. Wang et al. (2024a) aims to reduce frame access by using a predefined number of frames and dynamic sampling, but primarily addresses short-form videos and straightforward question-answering scenarios.

Existing methods for addressing long-context processing using agent based approach (see Fig 1, b) involves preprocessing and extracting relevant information from frames during a pre-processing stage, with the agent retrieving memory dynamically based on the question during runtime Fan et al. (2024); Wang et al. (2023b). Although this approach can be effective, it is resource-intensive in terms of memory and processing time. Additionally, it operates in a static manner, irrespective of the specific question, which can be redundant.

2.2 Frame Sampling Methods

Several methods have been proposed to enhance the efficiency of video frame handling by selectively subsampling relevant frames based on the content of the question or text, rather than using uniform sampling Gao et al. (2023b); Li et al. (2024); Yu et al. (2024); Pan et al. (2023a). For example, Romero & Solorio (2024) use CLIP model to retrieve pertinent frames through text prompts, while Han et al. (2023) propose a sampling technique that selects the most significant frames based on learned patterns. Although these approaches are effective, they often require pre-defined number of frames to sample or accessing to near all video frames to identify the relevant ones. These static ways of sampling frames may induce inefficiency as the video length becomes longer with exhaustive number of frames.

In contrast, our approach is inspired by human cognitive processes, which adaptively focus on information pertinent to the task at hand Lang et al. (2013); Heim & Keil (2012); Raymond et al. (1992); Heim & Keil (2017). We propose an agent that reasons about which frames to select based on the information from the question or previously extracted information, thereby improving the efficiency of information processing. While our method is similar to Wang et al. (2024b) in its query-adaptive nature, our method avoids the need for preprocessing (e.g., KNN clustering), thereby mitigating time-consuming operations.

Model	Long-Context	Query Adaptive Sampling	Long-term Memory	Reasoning
AssistGPT Gao et al. (2023a)	✗	✗	✗	ReAct
DoraemonGPT Yang et al. (2024)	✗	✗	✗	MCTS
VideoAgent Fan et al. (2024)	✓	✗	✗	ReAct
LifelongMemory Wang et al. (2023b)	✓	✗	✗	Prediction Ensemble
Ours	✓	✓	✓	Refinement + ReAct

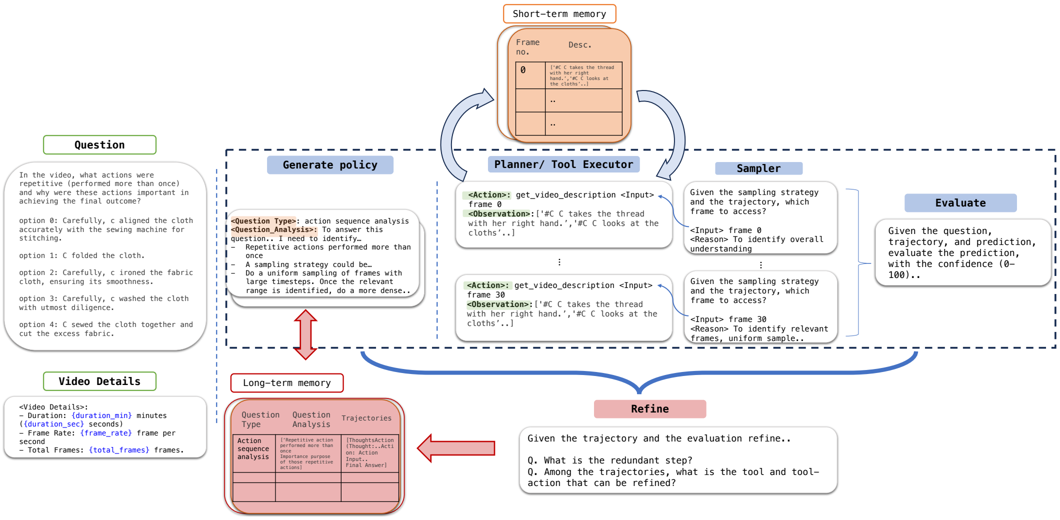
Table 1: Comparison of existing methods. Previous approaches attempted to handle long-form video agents, however, our approach focuses on addressing long-context videos, adopting query adaptive sampling and long-term memory.

3 Adaptive Video Understanding Agent

We propose **A**daptive **V**ideo **U**nderstanding **A**gent, which reasons about which frames to process based on the observations and interactions made between the tools. Inspired by recent advancements in self-reflective ability of LLMs Jang (2023); Pan et al. (2023b); Shinn et al. (2024), we utilize the error feedback of LLMs to enhance the reasoning of the agent. We formulate the task likewise: The dataset $\mathcal{D} = (Q, A, V)$ consists of question Q, answer A, and corresponding V. The agent $\mathcal{L}$ is equipped with available actions $\mathcal{A}$. The agent $\mathcal{L}$ has only access to the meta-data of the video V' (e.g. the total number of frames).

Generating Policy As illustrated in Figure 2, the initial step involves generating a policy π based on the question and the details of the video. This policy encompasses an analysis of the question type and a detailed question analysis, which includes a sampling strategy and identification of key elements that the agent should focus on during the reasoning process. The policy serves a dual purpose: it guides the agent in planning and reasoning, and it can be abstracted and utilized in long-term memory. The rationale behind this approach is that, while the specifics of the question may vary, the abstracted high-level question type can be retained and leveraged in a manner similar to how humans utilize their generalized experiences.

Planning/tool invoking At time step t, the agent $\mathcal{L}$ selects an action a_t and action input x_t based on policy π in solving problem $\mathcal{D}$. The actions $\mathcal{A}$ are the invokable tools, which are pre-defined and callable functions from the agent. The action input x_t is typically the frame number, indicating which frames the tools should access. The input often includes extra arguments, for example the question to query the tools (e.g. Frame index 0, what is happening in the frame?). Once the tools are invoked, it returns a observation $\mathcal{O}$ which is the extracted information of the selected frame. The agent $\mathcal{L}$ considers the previous observation-action trajectory $\tau_t = [a_1, o_1, \ldots, o_{t-1}]$: in choosing


Short-term memory
Frame no.
Desc.
0
['#C C takes the thread with her right hand.','#C C looks at the cloths'..]
..
..
Question
Generate policy
Planner/ Tool Executor
Sampler
Evaluate
Video Details
Long-term memory
Question Type
Question Analysis
Trajectories
Action sequence analysis
['Repetitive action performed more than once Importance purpose of those repetitive actions]
[ThoughtsAction (Thought:..Action: Action Input.. Final Answer]
Refine

In the video, what actions were repetitive (performed more than once) and why were these actions important in achieving the final outcome?

option 0: Carefully, c aligned the cloth accurately with the sewing machine for stitching.

option 1: C folded the cloth.

option 2: Carefully, c ironed the fabric cloth, ensuring its smoothness.

option 3: Carefully, c washed the cloth with utmost diligence.

option 4: C sewed the cloth together and cut the excess fabric.

```
<Video Details>:
- Duration: {duration_min} minutes ({duration_sec} seconds)
- Frame Rate: {frame_rate} frame per second
- Total Frames: {total_frames} frames.
```

```
<Question Type>: action sequence analysis
<Question_Analysis>: To answer this question.. I need to identify…
-   Repetitive actions performed more than once
-   A sampling strategy could be…
-   Do a uniform sampling of frames with large timesteps. Once the relevant range is identified, do a more dense..
```

```
<Action>: get_video_description <Input> frame 0
<Observation>:['#C C takes the thread with her right hand.','#C C looks at the cloths'..]
⋮
<Action>: get_video_description <Input> frame 30
<Observation>:['#C C takes the thread with her right hand.','#C C looks at the cloths'..]
```

```
Given the sampling strategy and the trajectory, which frame to access?

<Input> frame 0
<Reason> To identify overall understanding
⋮
Given the sampling strategy and the trajectory, which frame to access?

<Input> frame 30
<Reason> To identify relevant frames, uniform sample..
```

Given the question, trajectory, and prediction, evaluate the prediction, with the confidence (0–100)..

Given the trajectory and the evaluation refine..

Q. What is the redundant step?
Q. Among the trajectories, what is the tool and tool-action that can be refined?

Figure 2: **Overall Framework**. The video metadata and question are provided to the agent to **generate policy**, which includes analyzing the question type and determining the task-solving strategy, including the sampling strategy. **Planner/Tool Executor**, based on the ReAct-style reasoning, generates thought processes, actions, and action inputs, and receives observations from the tools. During this stage, the sampler may suggest improved frames. After formulating the final answer, the evaluator and refiner are applied. The final result is then stored in **long-term memory**.

which actions to call.

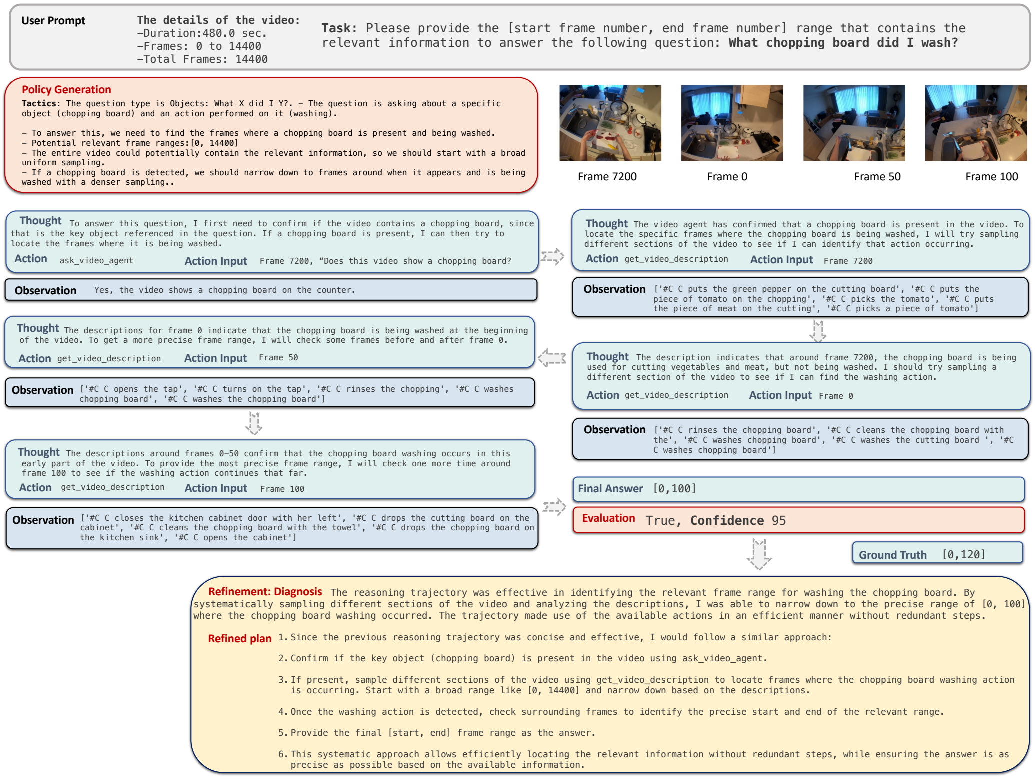
$$a_t = \mathcal{L}(\pi, \mathcal{D}, \tau_{t-1})$$

Specifically, the agent $\mathcal{L}$ navigates search space, $\mathcal{F} \times \mathcal{A}$, where $\mathcal{F}$ represents the set of frames within $\mathcal{V}(|V| = |F| = n)$. The main goal of the agent $\mathcal{L}$ is to effectively prune the search space (i.e., minimize the number of the frames access) while ensuring performance (i.e., maximizing the reward r). While making a decision of which action a_t to take along with the action inputs, the agent collaborates with the **Sampler**, another instantiated LLM, which is responsible for suggesting which frames to select. The sampler suggestions are based on the previous action-observation trajectory.

Evaluator We introduce an evaluator $\mathcal{E}$, which assesses the correctness of the prediction based on the question and the trajectory. It employs an error-feedback mechanism, iterating through trial-and-error to identify model errors. The evaluator $\mathcal{E}$ receives the question $\mathcal{Q}_i$, policy π_i and the trajectory $\mathcal{T}_i$ and makes an judgment whether the final answer made by the planner is valid or not. The evaluation is made in a binary style True or False with a confidence ranging from 0 to 100.

Refiner Once the evaluation is done, the refiner is given a question, policy, and the trajectory from the agent, and the evaluation to generate the refinement of the trajectory. Specifically, the refiner first generates diagnosis of the trajectory (e.g., if there is any redundant steps, or any actions or action input that can be refined). Then, it generates a refined plan. The refinement is generated regardless of the evaluation result. The reason behind this is that if the evaluation is correct, the refinement is stored along with the trajectory in the long-term memory to enhance the reasoning of future trials and if the evaluation if false, the refinement have direct purpose of refining the reasoning of the agent for the next trial.

Long/Short Memory We maintain the memory with Long-term memory $\mathcal{M}_{\text{long}}$ to store experiences, short-term memory $\mathcal{M}_{\text{short}}$ to store accessed frame information. This format allows us to utilize the long-term memory. When the The long-term memory $\mathcal{M}_{\text{long}}$ is present, it is indexed by the question type based on their semantic similarity, retrieving the semantically similar experiences (question type, and the trajectories). We append those memory in-context as a chat-history to let the agent be aware of previous experiences.



User Prompt

The details of the video:
–Duration:480.0 sec.
–Frames: 0 to 14400
–Total Frames: 14400

Task: Please provide the [start frame number, end frame number] range that contains the relevant information to answer the following question: **What chopping board did I wash?**

Policy Generation

Tactics: The question type is Objects: What X did I Y?. – The question is asking about a specific object (chopping board) and an action performed on it (washing).

- To answer this, we need to find the frames where a chopping board is present and being washed.
- Potential relevant frame ranges:[0, 14400]
- The entire video could potentially contain the relevant information, so we should start with a broad uniform sampling.
- If a chopping board is detected, we should narrow down to frames around when it appears and is being washed with a denser sampling..

Thought To answer this question, I first need to confirm if the video contains a chopping board, since that is the key object referenced in the question. If a chopping board is present, I can then try to locate the frames where it is being washed.
Action ask_video_agent **Action Input** Frame 7200, “Does this video show a chopping board?

Observation Yes, the video shows a chopping board on the counter.

Thought The video agent has confirmed that a chopping board is present in the video. To locate the specific frames where the chopping board is being washed, I will try sampling different sections of the video to see if I can identify that action occurring.
Action get_video_description **Action Input** Frame 7200

Observation ['#C C puts the green pepper on the cutting board', '#C C puts the piece of tomato on the chopping', '#C C picks the tomato', '#C C puts the piece of meat on the cutting', '#C C picks a piece of tomato']

Thought The description indicates that around frame 7200, the chopping board is being used for cutting vegetables and meat, but not being washed. I should try sampling a different section of the video to see if I can find the washing action.
Action get_video_description **Action Input** Frame 0

Observation ['#C C rinses the chopping board', '#C C cleans the chopping board with the', '#C C washes chopping board', '#C C washes the cutting board ', '#C C washes chopping board']

Thought The descriptions for frame 0 indicate that the chopping board is being washed at the beginning of the video. To get a more precise frame range, I will check some frames before and after frame 0.
Action get_video_description **Action Input** Frame 50

Observation ['#C C opens the tap', '#C C turns on the tap', '#C C rinses the chopping', '#C C washes chopping board', '#C C washes the chopping board']

Thought The descriptions around frames 0–50 confirm that the chopping board washing occurs in this early part of the video. To provide the most precise frame range, I will check one more time around frame 100 to see if the washing action continues that far.
Action get_video_description **Action Input** Frame 100

Observation ['#C C closes the kitchen cabinet door with her left', '#C C drops the cutting board on the cabinet', '#C C cleans the chopping board with the towel', '#C C drops the chopping board on the kitchen sink', '#C C opens the cabinet']

Final Answer [0,100]

Evaluation True, **Confidence** 95

Ground Truth [0,120]

Refinement: Diagnosis The reasoning trajectory was effective in identifying the relevant frame range for washing the chopping board. By systematically sampling different sections of the video and analyzing the descriptions, I was able to narrow down to the precise range of [0, 100] where the chopping board washing occurred. The trajectory made use of the available actions in an efficient manner without redundant steps.

Refined plan

1. Since the previous reasoning trajectory was concise and effective, I would follow a similar approach:
2. Confirm if the key object (chopping board) is present in the video using ask_video_agent.
3. If present, sample different sections of the video using get_video_description to locate frames where the chopping board washing action is occurring. Start with a broad range like [0, 14400] and narrow down based on the descriptions.
4. Once the washing action is detected, check surrounding frames to identify the precise start and end of the relevant range.
5. Provide the final [start, end] frame range as the answer.
6. This systematic approach allows efficiently locating the relevant information without redundant steps, while ensuring the answer is as precise as possible based on the available information.

Figure 3: **Example of Ego4d NLQ Instance**. The User Prompt includes the video's metadata and the question for the Agent to address. (1) Policy Generation: the agent generates an analysis of the question and a sampling strategy (2) Thoughts, Actions and Observation: The agent formulates a Thought based on current state, executes an Action $\mathcal{A}$, with Action Input, and uses tools to obtain an Observation $\mathcal{O}$. This process iterates until the agent comes up with the final answer. (3) Evaluation: the Final Answer is assessed. (4) Refinement: The trajectory $\mathcal{T}$ is refined, and the results are stored in Long-term Memory $\mathcal{M}_{\text{Long}}$.

Task	Source	Function
Video Caption Generation	LaViLa Zhao et al. (2023)	Detect actions, and objects
Video QA	Video-LlaVa Lin et al. (2023)	Extract Information
Image QA	Claude 3 Sonnet Anthropic (2024)	Image description
Object Tracking	RT-DETR Zhao et al. (2024a) ByteTrack Zhang et al. (2022)	Object detection
Text Caption	PaddleOCR PaddleOCR (2024)	Text caption Capture
Audio Transcription	Whisper Radford et al. (2023)	Audio capturing

Table 2: **List of Invokable Tools**. This includes multi-modal tools, video-based tools (e.g., LaViLa, Video-LLaVa), image-based tools (e.g., Claude-3-Sonnet, PaddleOCR), and audio-based tools (e.g., Whisper)

4 Experiments

4.1 Tools

In the experiments, the LLM used for reasoning and tool invocation is `Claude-3-Sonnet` Anthropic (2024). The tools used in the framework are detailed in Table 2. The tools are chosen to support multi-modalities, such as video, image, or audio. The **Video Caption Generation** model, LaViLa Zhao et al. (2023), generates descriptions for selected frames. To accommodate the model's requirement for frame sequences, we sample 3 additional frames (for a total of 4) for information extraction. Similarly, the **VideoQA** model, Video-LlaVa Lin et al. (2023), samples 3 additional frames (totaling 4) for video frame analysis. The **Object Tracking** model, RT-DETR Zhao et al. (2024a), identifies objects with a confidence level above 0.6. The text caption tool PaddleOCR (2024) outputs text only if it is present in the frame.

4.2 Evaluation Datasets

Dataset	Task	Example	Avg duration	# Instances
Egoschema	Action and scene understanding, abstract reasoning	***Q: What is the overarching behavior of C and the man in the video?*** *Option 0: C teaches the man game rules but the man seems distracted and is not paying attention* . . . . *Option 5: The man shows C a new card game while C takes notes for future references* ***A: Option 3***	3mins	0.5k
Ego4d NLQ	Temporal Localization	***Q: "What did I pick up before leaving the party?"*** ***A: [3410,4000]***	8.7mins	3.9k
MovieChat	Long-term video understanding	***Q: "When does the things in the video happens, ancient age, modern age or future?"*** ***A: "modern age"***	9.4mins	0.5k
NextQA	Causal and temporal action Reasoning	***Q:"Why was the toddler in red crying at the end of the video?"*** ***A: Fell backwards***	44secs	8.5k

Table 3: Overview of the evaluation Datasets.These benchmarks evaluate video understanding through a video question answering format, focusing on specific focus (denoted as Task).The average video duration varies from short form (<1min) to long form (<10min).

EgoSchema Mangalam et al. (2024) comprises broad spectrum videos of daily human activities, three-minute egocentric video segments. Each question is associated with five possible answers, in multiple choice question answering format. To correctly answer the question, it requires long-term temporal understanding. In this paper, we use a subset of the Egoschema dataset, consisting of 500 question and answer pairs.

Ego4D NLQ Grauman et al. (2022) consists of egocentric videos capturing a diverse range of daily activities from individuals wearing cameras. The primary task involves temporal localizing relevant frames within these extensive video contexts (e.g. Where did I put X?). The task can be formalized, given a video $\mathcal{V}$ and a natural language question $\mathcal{Q}$, the goal is to identify a relevant frame window A, such that the answer to $\mathcal{Q}$ can be deduced from A. We utilize the validation set for evaluation. The average length of the video is around 8.7 minutes and the expected prediction time window is around 9.3 seconds.

MovieChat Song et al. (2024) encompasses a range of categories , including documentary and detective films. The benchmark involves questions such as identifying common objects, temporal elements (e.g., day, night), and various scenes through open-ended questions and answers. The average duration of the videos is 9.4 minutes. For our evaluation, we utilize the test set (Global mode) of this benchmark. As it involves open-ended questions, we utilized *Cluade-3.5-sonnet* as an evaluator to evaluate whether the prediction matches with the ground truth answer. To be rigorous, we made the evaluator to generate the confidence of its judgment, counting only the instances with confidence over 80 (out of 100) as correct.

NextQA Xiao et al. (2021) is a benchmark designed to assess various aspects of video understanding, including causal action reasoning, temporal action reasoning, and common scene comprehension. Compared to other evaluation benchmarks used in this study, NextQA focuses on relatively short video clips, with an average duration of 44 seconds. While it does not align with the long form video question-answer evaluation criteria, we include this benchmark to demonstrate the generalizability of our framework across short-from videos. Also, NextQA benchmark consists of questions with ‘textual cues’, for example, *Why was the toddler in red crying at the **end** of the video?*, it allows us to investigate the adaptive behavior of the agents when presented with questions with textual cues and without textual cues.

Model	# Frames	Accuracy
MultiModalLLM		
FrozenBiLM	90	26.9
InternVid	90	32.1
ViT		
ShortViViT	32	49.6
LongViViT	256	56.8
Agent		
LLoVi	180	57.6
VideoAgent	180	60.2
LifelongMemory	180	62.4
Ours	14.27	66.98
Total Avg Frames	5400 (30 fps)	

Table 4: **Egoschema** Results. The number of frames accessed and Accuracy.

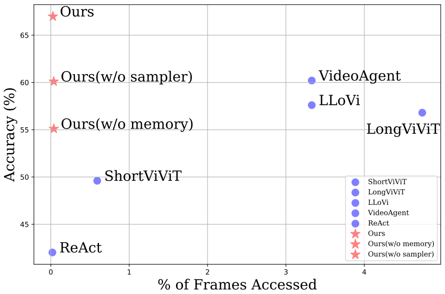


Figure 4: **Frames Accessed Ratio vs. Accuracy(%)** Our method demonstrate reduced % of frames accessed while maintaining high accuracy.

4.3 Baselines

We experiments with several strong baselines which are comprised of multiModal LLMs incorporating the visual components along with the textual querys as inputs. FrozenBiLM Yang et al. (2022) learns cross modalities by training image projection layer. Similarly, InternVid Wang et al. (2023a) uses a image captioning model along with transformer based text embeddings to align the image and the text. These methods work on fixed and limited number of frames. Vision transformer (ViT) based methods are based on vision transformer utilizing joint space time attention. ShortViViT and LongViViT Papalampidi et al. (2024) harness input masking strategy, supporting prefixed number of frames 32 frames and 256 number of frames respectively.

We also experiment with agent-based methods, which utilize language models as agents harnessing external tools to solve video question and answering task. LLoVi Zhang et al. (2023a) extracts captions and LLM tackles the QA task based on the extracted captions. Analogously, LifelongMemory Wang et al. (2023b) process extracted captions and adopts voting by confidence strategy to conclude answers. VideoAgent Fan et al. (2024) harness multiple tools to process video. These methods typically sample frames with predefined fps rate (e.g. 1fps).

5 Results

5.1 Performance Analysis

Egoschema Results Table 4 shows the results of evaluation on Egoschema benchmark. Our proposed method achieves accuracy of 66.98% which is more than 4% improvement over the best performing basline method, LifelongMemory (62.4%). For the baselines, we also observe a trade-off between the number of frames accessed and accuracy. For instance, Multimodal LLMs Yang et al. (2022) and Wang et al. (2023a) use a fixed sampling of 90 frames, but achieve relatively low accuracy (30%), whereas agent-based methods achieve significantly higher accuracy but sample twice as many frames. In contrast, our approach, which dynamically accesses relevant frames based on reasoning, reduces the number of frames accessed by approximately 93% while maintaining significant accuracy improvements. Existing methods typically use a uniform sampling strategy (1 frame per second), leading to a static number of frames. Our method avoids preprocessing all sub-sampled frames, thereby enhancing both accuracy and efficiency (Fig 4).

Ego4d NLQ Results We evaluate the intersection over union (IoU) at top-1 recall. (Table 5). Our method surpasses the baselines by 2% for IoU=0.3(%). Specifically, our method shows large improvement in IoU=0.5(%), which is around 10 % larger than the agent approach, and 11 % larger than the supervised approach. This may be attributed to the adaptive sampling strategy, which dynamically samples the frames, allowing both fine grained and coarse sampling. The frames are accessed on average 80% less than the agent method.

		IoU=0.3(%) r@1	IoU=0.5(%) r@1	#Frames
Supervised	2D-TAN	5.04	3.12	1024
	VSLNet	5.45	6.63	1461
Agent	VideoAgent	17.38	7.47	avg 487(1fps)
	LifelongMemory	15.99	-	avg 487(1fps)
	Ours	19.5	**17.1**	avg 98 (0.002%)

Table 5: Ego4d NLQ Results.

	Accuracy	#Frames
VideoChat	57.8	32
VideoLlaMA	51.7	32
VideoChatGPT	47.6	100
MovieChat	62.3	2048
Ours	84.8	13.59 (0.1%)

Table 6: **MovieChat** Results.

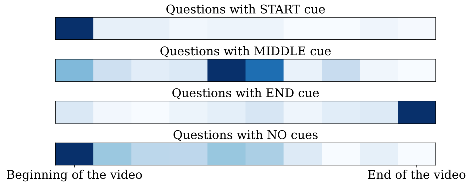


Figure 5: Frame accessed ratio based on textual cues from NextQA benchmark. Darker color corresponds to the higher ratio of access.

MovieChat Results Our method shows more than 22% increase in accuracy, while accessing only 0.1% of frames (Table 6), compared to the baseline models. This indicates that our method is more effective at processing long-form videos compared to both multimodal LLM–based (MovieChat Song et al. (2024)) and agent–based (VideoChatGPT, VideoLlama,VideoChat Maaz et al. (2023); Zhang et al. (2023b); Li et al. (2023)) baselines.

		Temporal	Causal	Descriptive	Average	# Frames (%)
Supervised	InternVid	43.4	48	65.1	49.1	19.92 (1.8%)
	SeViLA	61.3	61.5	75.6	63.6	39.85 (3.5%)
	MVU	55.4	48.1	64.1	55.2	39.85 (3.5%)
Agent	LLoVi	61	69.5	75.6	67.7	39.85 (3.5%)
	VideoAgent	64.5	72.7	81.1	71.3	39.85 (3.5%)
	Ours	**71.42**	69.1	77.77	**72.7**	12.37(1.1%)

Table 7: **NextQA results** The NextQA results are categorized by question types: temporal or causal reasoning and descriptive QA. Our method achieves a +1.4% higher accuracy compared to baseline methods, while accessing 2.4% fewer frames.

NextQA Results Our method shows a 1.4% improvement in overall average accuracy (Table 7). When analyzed by question type—temporal, causal, and descriptive—our method particularly excels in temporal reasoning tasks, providing around 6.9% absolute improvement over the next best method.

5.2 Ablation Analysis

Agents Without Guidance are Suboptimal Reasoners LLM agents using the default ReAct reasoning, without any intervention, exhibit suboptimal performance (Table 8, 9 ReAct). This approach results in both low accuracy and a reduced percentage of frames accessed. Although LLMs have the potential to examine all avaiable frames and provide accurate answers, they often produce suboptimal results with fewer frames access. This is similar to observations where LLMs given one-shot questions demonstrate less rigorous reasoning compared to those using chain-of-thought or step-by-step interventions Wei et al. (2022); Yao et al. (2024). Our framework, akin to the chain-of-though method, enhances reasoning by incorporating internal interventions, leading to more accurate answers even if it requires accessing more frames.

Questions including textual vs. non textual cues Our proposed framework suggests that agents are query-adaptive, meaning they sample more efficiently when textual cues are present, as these cues guide their focus. For instance, a question like 'Why was the toddler crying at the end of the video?' will direct the agent to focus on the end of the video. The NextQA benchmark provides a natural testbed for evaluating whether agents leverage textual cues, as it includes both types of questions. Results indicate that the questions with textual cues result in an average of 10.56 frames accessed (.008%), compared to 12.26 (.01%) for questions without cues. Figure 8 presents a detailed analysis, showing that the ratio of frame accessed correlates with the presence of textual cues in the query. (e.g., a higher ratio of frames accessed at the beginning when 'Start' cues are included).

Ablation of a component results in accuracy drop A clear trend demonstrated across benchmarks (Table 8, 9) is that ablating any component consistently reduces accuracy. For Egoschema, the largest accuracy drop occurs when the evaluator is removed, while for Ego4D, the sampler's removal has the greatest impact. Although accuracy trends are clear, the effect on the number of frames accessed is less consistent. For example, ablating the sampler or refiner generally increases frame access, whereas in Ego4D, it decreases. This indicates that the role of components like the sampler and refiner may vary with benchmark characteristics. Ego4D benefits from extensive frame search, while Egoschema needs a holistic video understanding. Thus, these components help balance frame access and accuracy depending on the benchmark's requirements.

	Egoschema		Ego4d		
Model	# Frames(%)	Accuracy	# Frames (%)	IoU=0.3(%) r@1	IoU=0.5(%) r@1
ReAct	12.87 (.0024)	42.02	23.987(.00)	3.71	3.7
Ours	14.27 (.0026)	**66.98**	98 (.002)	**19.51**	**17.07**
-w/o memory	20.57 (.0038)	55.1	90.04 (.0022)	9.09	9.09
-w/o evaluator	15.69 (.003)	50.1	40.0 (.001)	5.41	4.69
-w/o sampler	19.77 (.0037)	60.1	55.67(.002)	5.01	5
-w/o refiner	20.46(0.003)	53.2	65.33(.001)	5.1	3.5

Table 8: **Ablation results on Frames Accessed and Accuracy**. The ReAct model, with no interventions, exhibits the lowest accuracy and frame access ratio. Ablations of different components reveal varying performance trends. The ablation results of Moviechat and NextQA can be found in Table 9

6 Conclusion

In this paper, we introduced a novel framework for video understanding that addresses the limitations of current methods by leveraging the daynamic reasoning capabilities of LLMs. While traditional approaches often rely on static or uniform frame sampling, which can be inefficient and redundant, our method enhances sampling efficiency by enabling the LLM based agent to adaptively select relevant frames based on specific queries. The results from extensive benchmarking validate the effectiveness and adaptability of our framework, showcasing its ability to handle diverse video understanding tasks more efficiently than traditional methods.

7 Limitations

While our method demonstrated effectiveness across several benchmark tasks, it is important to acknowledge its limitations. First, the performance of our approach is dependent on the capabilities of the tools it utilizes. Variations in tool performance can directly impact the overall effectiveness of the framework. Additionally, reliance on API calls introduces potential latency issues. This dependency on external APIs may affect the consistency and speed of the processing.

8 Broader impact

The proposed framework for video understanding presents several broader impacts with potential implications across various domains. By leveraging dynamic LLM-based agents for adaptive frame sampling, our approach offers a more efficient and effective solution to the challenges of long-form video comprehension. This advancement could significantly enhance applications in fields such as automated video content analysis, surveillance, and multimedia indexing, where processing large volumes of video data is essential.

References

Anthropic. The claude 3 model family: Opus, sonnet, haiku, 2024. URL https://www-cdn.anthropic.com/de8ba9b01c9ab7cbabf5c33b80b7bbc618857627/Model_Card_Claude_3.pdf.

Tri Dao, Dan Fu, Stefano Ermon, Atri Rudra, and Christopher Ré. Flashattention: Fast and memory-efficient exact attention with io-awareness. *Advances in Neural Information Processing Systems*, 35:16344–16359, 2022.

Yue Fan, Xiaojian Ma, Rujie Wu, Yuntao Du, Jiaqi Li, Zhi Gao, and Qing Li. Videoagent: A memory-augmented multimodal agent for video understanding. *arXiv preprint arXiv:2403.11481*, 2024.

Difei Gao, Lei Ji, Luowei Zhou, Kevin Qinghong Lin, Joya Chen, Zihan Fan, and Mike Zheng Shou. Assistgpt: A general multi-modal assistant that can plan, execute, inspect, and learn. *arXiv preprint arXiv:2306.08640*, 2023a.

Difei Gao, Luowei Zhou, Lei Ji, Linchao Zhu, Yi Yang, and Mike Zheng Shou. Mist: Multi-modal iterative spatial-temporal transformer for long-form video question answering. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pp. 14773–14783, 2023b.

Kristen Grauman, Andrew Westbury, Eugene Byrne, Zachary Chavis, Antonino Furnari, Rohit Girdhar, Jackson Hamburger, Hao Jiang, Miao Liu, Xingyu Liu, et al. Ego4d: Around the world in 3,000 hours of egocentric video. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 18995–19012, 2022.

Wei Han, Hui Chen, Min-Yen Kan, and Soujanya Poria. Sas video-qa: Self-adaptive sampling for efficient video question-answering. *arXiv preprint arXiv:2307.04192*, 2023.

Sabine Heim and Andreas Keil. Developmental trajectories of regulating attentional selection over time. *Frontiers in Psychology*, 3:277, 2012.

Sabine Heim and Andreas Keil. Too much information, too little time: How the brain separates important from unimportant things in our fast-paced media world. *Frontiers for Young Minds*, 5(1), 2017.

Eric Jang. Can llms critique and iterate on their own outputs? evjang. com. *URL https://evjang. com/2023/03/26/self-reflection. html*, 2023.

Peter J Lang, Margaret M Bradley, and Bruce N Cuthbert. Motivated attention: Affect, activation, and action. In *Attention and orienting*, pp. 97–135. Psychology Press, 2013.

KunChang Li, Yinan He, Yi Wang, Yizhuo Li, Wenhai Wang, Ping Luo, Yali Wang, Limin Wang, and Yu Qiao. Videochat: Chat-centric video understanding. *arXiv preprint arXiv:2305.06355*, 2023.

Yunxin Li, Xinyu Chen, Baotain Hu, and Min Zhang. Llms meet long video: Advancing long video comprehension with an interactive visual adapter in llms. *arXiv preprint arXiv:2402.13546*, 2024.

Bin Lin, Bin Zhu, Yang Ye, Munan Ning, Peng Jin, and Li Yuan. Video-llava: Learning united visual representation by alignment before projection. *arXiv preprint arXiv:2311.10122*, 2023.

Haotian Liu, Chunyuan Li, Qingyang Wu, and Yong Jae Lee. Visual instruction tuning. *Advances in neural information processing systems*, 36, 2024.

Shilong Liu, Hao Cheng, Haotian Liu, Hao Zhang, Feng Li, Tianhe Ren, Xueyan Zou, Jianwei Yang, Hang Su, Jun Zhu, et al. Llava-plus: Learning to use tools for creating multimodal agents. *arXiv preprint arXiv:2311.05437*, 2023.

Muhammad Maaz, Hanoona Rasheed, Salman Khan, and Fahad Shahbaz Khan. Video-chatgpt: Towards detailed video understanding via large vision and language models. *arXiv preprint arXiv:2306.05424*, 2023.

Karttikeya Mangalam, Raiymbek Akshulakov, and Jitendra Malik. Egoschema: A diagnostic benchmark for very long-form video language understanding. *Advances in Neural Information Processing Systems*, 36, 2024.

PaddleOCR. Paddleocr, 2024. URL https://github.com/PaddlePaddle/PaddleOCR.

Vishal Pallagani, Bharath Muppasani, Keerthiram Murugesan, Francesca Rossi, Biplav Srivastava, Lior Horesh, Francesco Fabiano, and Andrea Loreggia. Understanding the capabilities of large language models for automated planning. *arXiv preprint arXiv:2305.16151*, 2023.

Junting Pan, Ziyi Lin, Yuying Ge, Xiatian Zhu, Renrui Zhang, Yi Wang, Yu Qiao, and Hongsheng Li. Retrieving-to-answer: Zero-shot video question answering with frozen large language models. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pp. 272–283, 2023a.

Liangming Pan, Michael Saxon, Wenda Xu, Deepak Nathani, Xinyi Wang, and William Yang Wang. Automatically correcting large language models: Surveying the landscape of diverse self-correction strategies. *arXiv preprint arXiv:2308.03188*, 2023b.

Pinelopi Papalampidi, Skanda Koppula, Shreya Pathak, Justin Chiu, Joe Heyward, Viorica Patraucean, Jiajun Shen, Antoine Miech, Andrew Zisserman, and Aida Nematzdeh. A simple recipe for contrastively pre-training video-first encoders beyond 16 frames. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 14386–14397, 2024.

AJ Piergiovanni, Isaac Noble, Dahun Kim, Michael S Ryoo, Victor Gomes, and Anelia Angelova. Mirasol3b: A multimodal autoregressive model for time-aligned and contextual modalities. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 26804–26814, 2024.

Alec Radford, Jong Wook Kim, Tao Xu, Greg Brockman, Christine McLeavey, and Ilya Sutskever. Robust speech recognition via large-scale weak supervision. In *International conference on machine learning*, pp. 28492–28518. PMLR, 2023.

Jane E Raymond, Kimron L Shapiro, and Karen M Arnell. Temporary suppression of visual processing in an rsvp task: An attentional blink? *Journal of experimental psychology: Human perception and performance*, 18(3):849, 1992.

David Romero and Thamar Solorio. Question-instructed visual descriptions for zero-shot video question answering. *arXiv preprint arXiv:2402.10698*, 2024.

Timo Schick, Jane Dwivedi-Yu, Roberto Dessì, Roberta Raileanu, Maria Lomeli, Eric Hambro, Luke Zettlemoyer, Nicola Cancedda, and Thomas Scialom. Toolformer: Language models can teach themselves to use tools. *Advances in Neural Information Processing Systems*, 36, 2024.

Noah Shinn, Federico Cassano, Ashwin Gopinath, Karthik Narasimhan, and Shunyu Yao. Reflexion: Language agents with verbal reinforcement learning. *Advances in Neural Information Processing Systems*, 36, 2024.

Enxin Song, Wenhao Chai, Guanhong Wang, Yucheng Zhang, Haoyang Zhou, Feiyang Wu, Haozhe Chi, Xun Guo, Tian Ye, Yanting Zhang, et al. Moviechat: From dense token to sparse memory for long video understanding. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 18221–18232, 2024.

Xiaohan Wang, Yuhui Zhang, Orr Zohar, and Serena Yeung-Levy. Videoagent: Long-form video understanding with large language model as agent. *arXiv preprint arXiv:2403.10517*, 2024a.

Yi Wang, Yinan He, Yizhuo Li, Kunchang Li, Jiashuo Yu, Xin Ma, Xinhao Li, Guo Chen, Xinyuan Chen, Yaohui Wang, et al. Internvid: A large-scale video-text dataset for multimodal understanding and generation. *arXiv preprint arXiv:2307.06942*, 2023a.

Ying Wang, Yanlai Yang, and Mengye Ren. Lifelongmemory: Leveraging llms for answering queries in egocentric videos. *arXiv preprint arXiv:2312.05269*, 2023b.

Ziyang Wang, Shoubin Yu, Elias Stengel-Eskin, Jaehong Yoon, Feng Cheng, Gedas Bertasius, and Mohit Bansal. Videotree: Adaptive tree-based video representation for llm reasoning on long videos. *arXiv preprint arXiv:2405.19209*, 2024b.

Jason Wei, Xuezhi Wang, Dale Schuurmans, Maarten Bosma, Fei Xia, Ed Chi, Quoc V Le, Denny Zhou, et al. Chain-of-thought prompting elicits reasoning in large language models. *Advances in neural information processing systems*, 35:24824–24837, 2022.

Chao-Yuan Wu, Yanghao Li, Karttikeya Mangalam, Haoqi Fan, Bo Xiong, Jitendra Malik, and Christoph Feichtenhofer. Memvit: Memory-augmented multiscale vision transformer for efficient long-term video recognition. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 13587–13597, 2022.

Junbin Xiao, Xindi Shang, Angela Yao, and Tat-Seng Chua. Next-qa: Next phase of question-answering to explaining temporal actions. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pp. 9777–9786, 2021.

Antoine Yang, Antoine Miech, Josef Sivic, Ivan Laptev, and Cordelia Schmid. Zero-shot video question answering via frozen bidirectional language models. *Advances in Neural Information Processing Systems*, 35:124–141, 2022.

Zongxin Yang, Guikun Chen, Xiaodi Li, Wenguan Wang, and Yi Yang. Doraemongpt: Toward understanding dynamic scenes with large language models. *arXiv preprint arXiv:2401.08392*, 2024.

Shunyu Yao, Jeffrey Zhao, Dian Yu, Nan Du, Izhak Shafran, Karthik Narasimhan, and Yuan Cao. React: Synergizing reasoning and acting in language models. *arXiv preprint arXiv:2210.03629*, 2022.

Shunyu Yao, Dian Yu, Jeffrey Zhao, Izhak Shafran, Tom Griffiths, Yuan Cao, and Karthik Narasimhan. Tree of thoughts: Deliberate problem solving with large language models. *Advances in Neural Information Processing Systems*, 36, 2024.

Shoubin Yu, Jaemin Cho, Prateek Yadav, and Mohit Bansal. Self-chained image-language model for video localization and question answering. *Advances in Neural Information Processing Systems*, 36, 2024.

Ce Zhang, Taixi Lu, Md Mohaiminul Islam, Ziyang Wang, Shoubin Yu, Mohit Bansal, and Gedas Bertasius. A simple llm framework for long-range video question-answering. *arXiv preprint arXiv:2312.17235*, 2023a.

Hang Zhang, Xin Li, and Lidong Bing. Video-llama: An instruction-tuned audio-visual language model for video understanding. *arXiv preprint arXiv:2306.02858*, 2023b.

Yifu Zhang, Peize Sun, Yi Jiang, Dongdong Yu, Fucheng Weng, Zehuan Yuan, Ping Luo, Wenyu Liu, and Xinggang Wang. Bytetrack: Multi-object tracking by associating every detection box. In *European conference on computer vision*, pp. 1–21. Springer, 2022.

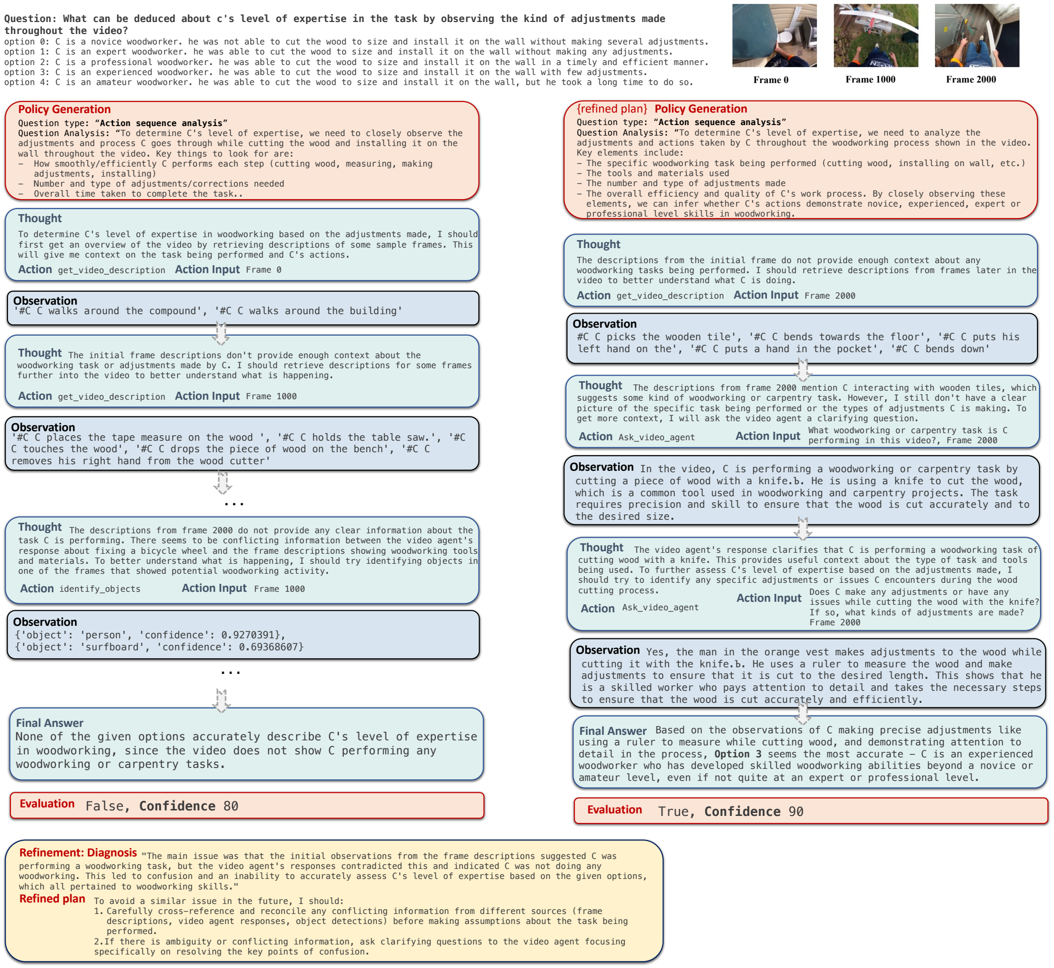
Yian Zhao, Wenyu Lv, Shangliang Xu, Jinman Wei, Guanzhong Wang, Qingqing Dang, Yi Liu, and Jie Chen. Detrs beat yolos on real-time object detection. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 16965–16974, 2024a.

Yue Zhao, Ishan Misra, Philipp Krähenbühl, and Rohit Girdhar. Learning video representations from large language models. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 6586–6597, 2023.

Zirui Zhao, Wee Sun Lee, and David Hsu. Large language models as commonsense knowledge for large-scale task planning. *Advances in Neural Information Processing Systems*, 36, 2024b.

APPENDIX

A.CASE STUDY



Question: What can be deduced about c's level of expertise in the task by observing the kind of adjustments made throughout the video?

```
option 0: C is a novice woodworker. he was not able to cut the wood to size and install it on the wall without making several adjustments.
option 1: C is an expert woodworker. he was able to cut the wood to size and install it on the wall without making any adjustments.
option 2: C is a professional woodworker. he was able to cut the wood to size and install it on the wall in a timely and efficient manner.
option 3: C is an experienced woodworker. he was able to cut the wood to size and install it on the wall with few adjustments.
option 4: C is an amateur woodworker. he was able to cut the wood to size and install it on the wall, but he took a long time to do so.
```

Policy Generation
Question type: "**Action sequence analysis**"
Question Analysis: "To determine C's level of expertise, we need to closely observe the adjustments and process C goes through while cutting the wood and installing it on the wall throughout the video. Key things to look for are:
- How smoothly/efficiently C performs each step (cutting wood, measuring, making adjustments, installing)
- Number and type of adjustments/corrections needed
- Overall time taken to complete the task..

Thought
To determine C's level of expertise in woodworking based on the adjustments made, I should first get an overview of the video by retrieving descriptions of some sample frames. This will give me context on the task being performed and C's actions.
Action get_video_description **Action Input** Frame 0

Observation
'#C C walks around the compound', '#C C walks around the building'

Thought The initial frame descriptions don't provide enough context about the woodworking task or adjustments made by C. I should retrieve descriptions for some frames further into the video to better understand what is happening.
Action get_video_description **Action Input** Frame 1000

Observation
'#C C places the tape measure on the wood ', '#C C holds the table saw.', '#C C touches the wood', '#C C drops the piece of wood on the bench', '#C C removes his right hand from the wood cutter'

...

Thought The descriptions from frame 2000 do not provide any clear information about the task C is performing. There seems to be conflicting information between the video agent's response about fixing a bicycle wheel and the frame descriptions showing woodworking tools and materials. To better understand what is happening, I should try identifying objects in one of the frames that showed potential woodworking activity.
Action identify_objects **Action Input** Frame 1000

Observation
{'object': 'person', 'confidence': 0.9270391},
{'object': 'surfboard', 'confidence': 0.69368607}

...

Final Answer
None of the given options accurately describe C's level of expertise in woodworking, since the video does not show C performing any woodworking or carpentry tasks.

Evaluation False, **Confidence** 80

Refinement: Diagnosis "The main issue was that the initial observations from the frame descriptions suggested C was performing a woodworking task, but the video agent's responses contradicted this and indicated C was not doing any woodworking. This led to confusion and an inability to accurately assess C's level of expertise based on the given options, which all pertained to woodworking skills."
Refined plan To avoid a similar issue in the future, I should:
1. Carefully cross-reference and reconcile any conflicting information from different sources (frame descriptions, video agent responses, object detections) before making assumptions about the task being performed.
2. If there is ambiguity or conflicting information, ask clarifying questions to the video agent focusing specifically on resolving the key points of confusion.

{refined plan} **Policy Generation**
Question type: "**Action sequence analysis**"
Question Analysis: "To determine C's level of expertise, we need to analyze the adjustments and actions taken by C throughout the woodworking process shown in the video. Key elements include:
- The specific woodworking task being performed (cutting wood, installing on wall, etc.)
- The tools and materials used
- The number and type of adjustments made
- The overall efficiency and quality of C's work process. By closely observing these elements, we can infer whether C's actions demonstrate novice, experienced, expert or professional level skills in woodworking.

Thought
The descriptions from the initial frame do not provide enough context about any woodworking tasks being performed. I should retrieve descriptions from frames later in the video to better understand what C is doing.
Action get_video_description **Action Input** Frame 2000

Observation
#C C picks the wooden tile', '#C C bends towards the floor', '#C C puts his left hand on the', '#C C puts a hand in the pocket', '#C C bends down'

Thought The descriptions from frame 2000 mention C interacting with wooden tiles, which suggests some kind of woodworking or carpentry task. However, I still don't have a clear picture of the specific task being performed or the types of adjustments C is making. To get more context, I will ask the video agent a clarifying question.
Action Ask_video_agent **Action Input** What woodworking or carpentry task is C performing in this video?, Frame 2000

Observation In the video, C is performing a woodworking or carpentry task by cutting a piece of wood with a knife.ъ. He is using a knife to cut the wood, which is a common tool used in woodworking and carpentry projects. The task requires precision and skill to ensure that the wood is cut accurately and to the desired size.

Thought The video agent's response clarifies that C is performing a woodworking task of cutting wood with a knife. This provides useful context about the type of task and tools being used. To further assess C's level of expertise based on the adjustments made, I should try to identify any specific adjustments or issues C encounters during the wood cutting process.
Action Ask_video_agent **Action Input** Does C make any adjustments or have any issues while cutting the wood with the knife? If so, what kinds of adjustments are made? Frame 2000

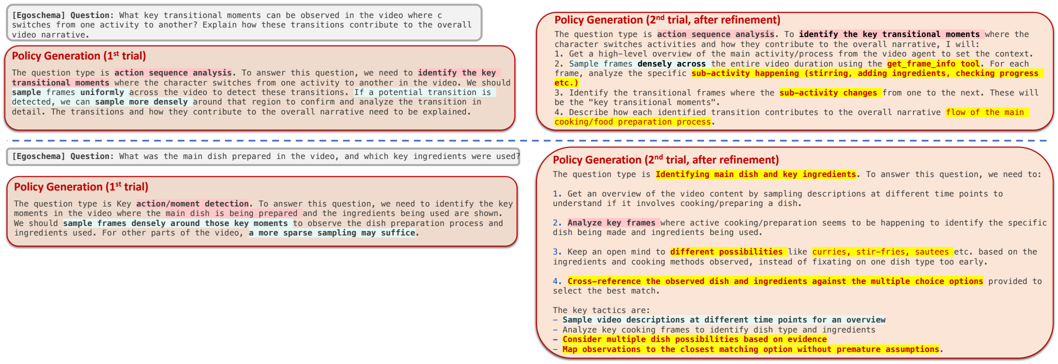
Observation Yes, the man in the orange vest makes adjustments to the wood while cutting it with the knife.ъ. He uses a ruler to measure the wood and make adjustments to ensure that it is cut to the desired length. This shows that he is a skilled worker who pays attention to detail and takes the necessary steps to ensure that the wood is cut accurately and efficiently.

Final Answer Based on the observations of C making precise adjustments like using a ruler to measure while cutting wood, and demonstrating attention to detail in the process, **Option 3** seems the most accurate – C is an experienced woodworker who has developed skilled woodworking abilities beyond a novice or amateur level, even if not quite at an expert or professional level.

Evaluation True, **Confidence** 90

Figure 6: **Example of Egoschema Refinement**. Given the refinement based on the first trial (left), it attempts a second trial, with a refined policy π^*, which leads to the correct evaluation.

Refined policy is more detailed and specific What distinguishes the refined policy π^* from the initial generated policy? Figure 7 illustrates examples of refined policies, where the initial trial produced an incorrect prediction, while the second trial yielded a correct one. Compared to the original policy, the refined policy is notably more detailed. Specifically, it includes: 1) updates in question analysis, and 2) a more nuanced approach to sampling strategies. Although the sampling strategies in both trials were largely similar, the refined policy offers a more granular description. For instance, while the initial policy merely referenced dense and sparse sampling, the updated policy provides a comprehensive overview of when to transition between different sampling strategies.



[Egoschema] Question: What key transitional moments can be observed in the video where c switches from one activity to another? Explain how these transitions contribute to the overall video narrative.

Policy Generation (1st trial)

The question type is **action sequence analysis.** To answer this question, we need to **identify the key transitional moments** where the character switches from one activity to another in the video. We should **sample** frames **uniformly** across the video to detect these transitions. If a potential transition is detected, we can **sample more densely** around that region to confirm and analyze the transition in detail. The transitions and how they contribute to the overall narrative need to be explained.

Policy Generation (2nd trial, after refinement)

The question type is **action sequence analysis**. To **identify the key transitional moments** where the character switches activities and how they contribute to the overall narrative, I will:
1. Get a high-level overview of the main activity/process from the video agent to set the context.
2. Sample frames **densely across** the entire video duration using the **get_frame_info tool**. For each frame, analyze the specific **sub-activity happening (stirring, adding ingredients, checking progress etc.)**
3. Identify the transitional frames where the **sub-activity changes** from one to the next. These will be the "key transitional moments".
4. Describe how each identified transition contributes to the overall narrative flow of the main cooking/food preparation process.

[Egoschema] Question: What was the main dish prepared in the video, and which key ingredients were used?

Policy Generation (1st trial)

The question type is Key **action/moment detection.** To answer this question, we need to identify the key moments in the video where the main dish is being prepared and the ingredients being used are shown. We should **sample frames densely around those key moments** to observe the dish preparation process and ingredients used. For other parts of the video, **a more sparse sampling may suffice**.

Policy Generation (2nd trial, after refinement)

The question type is **Identifying main dish and key ingredients**. To answer this question, we need to:

1. Get an overview of the video content by sampling descriptions at different time points to understand if it involves cooking/preparing a dish.

2. **Analyze key frames** where active cooking/preparation seems to be happening to identify the specific dish being made and ingredients being used.

3. Keep an open mind to **different possibilities** like curries, stir-fries, sautees etc. based on the ingredients and cooking methods observed, instead of fixating on one dish type too early.

4. **Cross-reference the observed dish and ingredients against the multiple choice options** provided to select the best match.

The key tactics are:
- **Sample video descriptions at different time points for an overview**
- Analyze key cooking frames to identify dish type and ingredients
- **Consider multiple dish possibilities based on evidence**
- **Map observations to the closest matching option without premature assumptions**.

Figure 7: **Example of Refined Policy** Compared to the original policy, the refined policy is notably more detailed. Texts highlighted in yellow shows the added instruction.

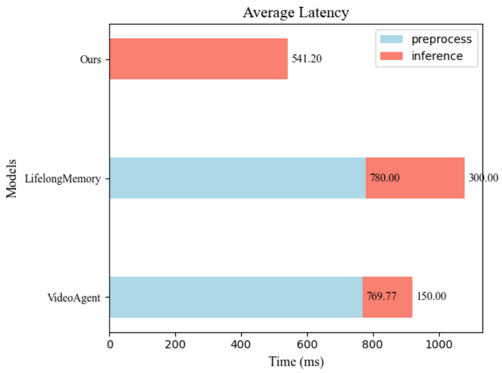


Figure 8: Latency Comparison with Other Agent Approaches: Our method reduces latency by processing videos only at runtime, compared to LifelongMemory Wang et al. (2023b) and Videoagent Fan et al. (2024), which require preprocessing.

B. Latency Analysis

C. Prompts Configuration

Policy Generation Prompt

```
 You are an advanced AI agent tasked with efficiently and accurately
processing video question and answering tasks.

You will be given a question related to a video, and you are responsibile
for coming up with a set of tactics and plans based on the characteristics
of each question.  The questions you will encounter will vary greatly,
ranging from inquires about the overall plot to specific details within
the video.

To effectively handle these tasks, you must first generate a set of tactics
and plans based on the characteristics of each question. You will be given
a question, please analyze the question.

- Determine the type of question (e.g. purpose/goal identification, tools
and materials usage, key action/moment detection, character interaction,
action sequence analysis..etc)

- How should the frames be sampled to solve the question? (e.g. Uniform
sampling with timestep 30.  If relevant frame is detected, more uniform
sample with timestep 2.)

{Question}
{Video details}
```

Agent Prompt

You are an advanced AI specialized in video question-answering tasks. Your capabilities include executing necessary tools and interpreting their outputs. Your objective is to select which frames to process and strategize which tools to deploy and use their outputs to provide accurate answers to questions related to a video.
<Video Details>:
- Duration: {duration_min} minutes ({duration_sec} seconds)
- Frame Rate: {frame_rate} frame per second
- Total Frames: {total_frames} frames.
- Frames with scene change: {scene_list}

Among the total {total_frames}, you will first choose sample frames to understand the context. Please use the tool ‘get_frame_info’ to get the general information of the frame. You can use the tools listed below. You can reason what’s happening between frames, and what’s described in the frame itself.
Use these tools to help: {tools}
Use the following format:
Thought: Consider what to do next.
Action: The action to take, using one of [{tool_names}].
Action Input: The input for the action.
You will receive the result of the action as Observation: The result of the action. Please repeat the Thought/Action/Action Input/Observation cycle as needed.
The final answer should be provided under ’Final Answer:’ You must choose one of the options among Option 0, Option 1, Option 2, Option 3, Option 4.
Please start with Thought:
Begin!

Refiner Prompt

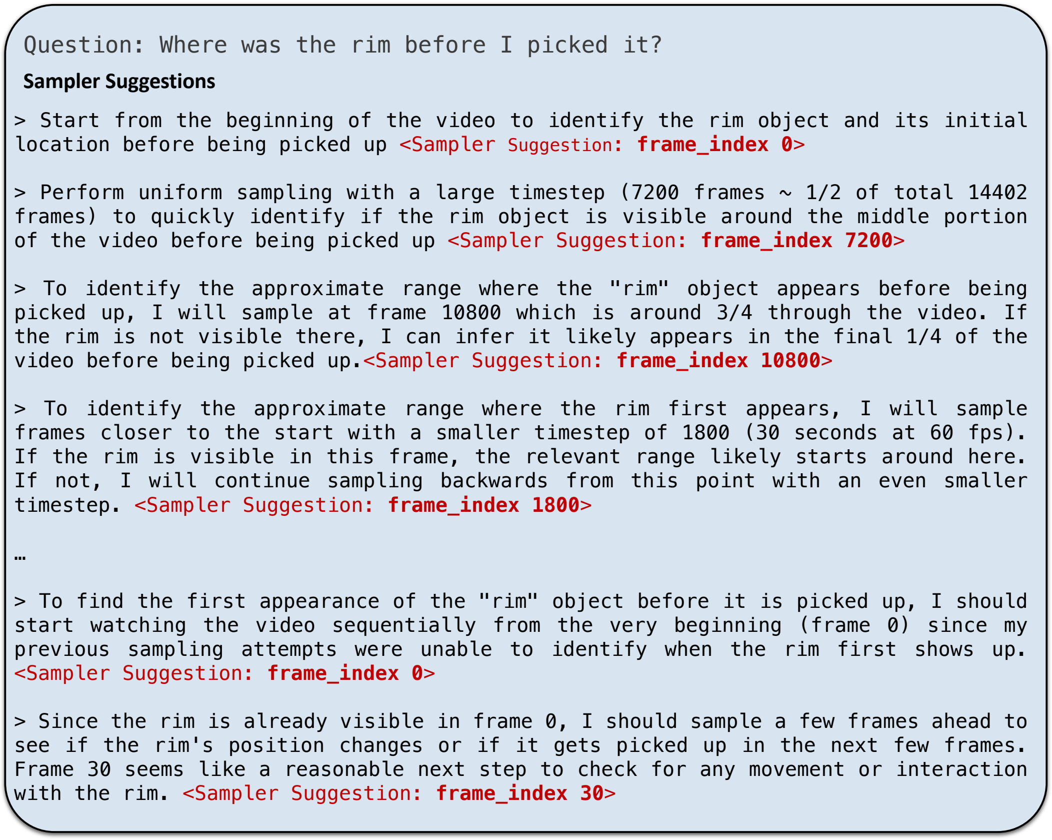
You are an advanced reasoning agent that can improve based on self refection. Your goal is to come up with a diagnoses and a refinement plan that is effective in making a correct prediction. You will be given a previous reasoning trial in which you were given access to execute tools to solve and an evaluation to the trial.
If the evaluation is False, you were unsuccessful in answering the question either because you guessed the wrong answer with Final Answer, or you used up your set number of reasoning steps. The optimal goal is to have concise reasoning path without having redundant actions. Even if the evaluation is True, you can improve the reasoning path by removing the redundant steps or by refining the repetitive actions. In a few sentences, Diagnose a possible reason for failure and devise a new, concise, reasoning paths that aims to mitigate the same failure. Be detailed as possible and use complete sentences.

Evaluator Prompt

You are an advanced agent that evaluates whether the predicted answer is correct or not. You will be given a question, reasoning trajectories, and the final answer predicted by an agent. Please evaluate whether the prediction is valid or not. You can give your confidence in percentage (0-100). Remember that the reasoning and predictions are not always correct.
For example, Evaluation: True, Confidence: 90

Table 9: Ablation result of Moviechat and NextQA. The results are consistent in exhibiting a drop in accuracy when ablating any component. However, the trends of the number of frames accessed are not consistent, varying across the benchmark, and the components

	MovieChat		NextQA	
Model	# Frames	Accuracy	# Frames	Accuracy
ReAct	10.62	69.4	9.87	47.27
Ours	13.59	**84.8**	12.37	**71.6**
-w/o memory	15.84	70.3	11.79	63.11
-w/o evaluator	15.31	72.43	13.59	58.97
-w/o sampler	15.51	80.2	13.87	60.2
-w/o refiner	15.51	70.2	11.8	65.42



Question: Where was the rim before I picked it?

Sampler Suggestions

> Start from the beginning of the video to identify the rim object and its initial location before being picked up <Sampler Suggestion: **frame_index 0**>

> Perform uniform sampling with a large timestep (7200 frames ~ 1/2 of total 14402 frames) to quickly identify if the rim object is visible around the middle portion of the video before being picked up <Sampler Suggestion: **frame_index 7200**>

> To identify the approximate range where the "rim" object appears before being picked up, I will sample at frame 10800 which is around 3/4 through the video. If the rim is not visible there, I can infer it likely appears in the final 1/4 of the video before being picked up.<Sampler Suggestion: **frame_index 10800**>

> To identify the approximate range where the rim first appears, I will sample frames closer to the start with a smaller timestep of 1800 (30 seconds at 60 fps). If the rim is visible in this frame, the relevant range likely starts around here. If not, I will continue sampling backwards from this point with an even smaller timestep. <Sampler Suggestion: **frame_index 1800**>

…

> To find the first appearance of the "rim" object before it is picked up, I should start watching the video sequentially from the very beginning (frame 0) since my previous sampling attempts were unable to identify when the rim first shows up. <Sampler Suggestion: **frame_index 0**>

> Since the rim is already visible in frame 0, I should sample a few frames ahead to see if the rim's position changes or if it gets picked up in the next few frames. Frame 30 seems like a reasonable next step to check for any movement or interaction with the rim. <Sampler Suggestion: **frame_index 30**>

Figure 9: **Sampler Example** The Sampler examples demonstrates that it is able to 1) calculate the frames in terms of sparse sampling 2) Dynamically switch sampling fps, based on previous observation 3) Densly sample relevant frames