


When Thinking Drifts: Evidential Grounding for Robust Video Reasoning

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Abstract

Video reasoning, the task of enabling machines to infer from dynamic visual content through multi-step logic, is crucial for advanced AI. While the Chain-of-Thought (CoT) mechanism has enhanced reasoning in text-based tasks, its application to video understanding remains underexplored. This paper presents a systematic analysis revealing that CoT often degrades performance in video reasoning, generating verbose but misleading internal monologues, and leading to hallucinated visual details and overridden correct intuitions—a phenomenon we term "visual thinking drift." We explain this drift through a Bayesian lens, positing that CoT traces often diverge from actual visual evidence, instead amplifying internal biases or language priors, causing models to storytell rather than engage in grounded reasoning. To counteract this, we introduce Visual Evidence Reward (VER), a novel reinforcement learning framework that explicitly rewards the generation of reasoning traces that are verifiably grounded in visual evidence. Comprehensive evaluation across 10 diverse video understanding benchmarks demonstrates that our Video-VER consistently achieves top performance. Our work sheds light on the distinct challenges of video-centric reasoning and encourages the development of AI that robustly grounds its inferences in visual evidence—for large multimodal models that not only "think before answering", but also "see while thinking".

1 Introduction

Imagine watching a cooking tutorial video: As the chef chops vegetables, combines ingredients, and adjusts the heat, we are not just passively observing isolated actions. Our minds actively connect these steps, anticipating the next move, understanding the purpose behind each technique, and envisioning the delicious outcome. This act of deriving understanding from a sequence of visual events, inferring intent, and predicting results through a series of logical thoughts, mirrors the core challenge addressed by *video reasoning*: empowering machines to draw inferences and conclusions from dynamic content of video through multi-step logical reasoning [16, 41, 43, 17, 54, 42].

As researchers strive to imbue systems with this capability, their efforts have largely branched into two complementary strategies. One prominent path is the agentic workflow, also referred to as modular reasoning [42], which deconstructs video understanding into focused sub-problems—such as event parsing, object tracking, and temporal grounding addressed by specialized models [65, 15, 54, 37, 42]. Alongside this modular approach, a parallel evolution in Multimodal Large Language Models (MLLMs) has ushered in a more holistic reasoning paradigm, where a model executes end-to-end inference by harnessing both vision and text [5, 29, 72, 66, 69, 10, 34, 31, 9]. Within this architecture, the vision encoder typically assumes the role of a perceptual engine, tasked with extracting high-fidelity visual representations, whereas the language model component takes the helm of the reasoning process itself, generating textual rationales and constructing logical chains.

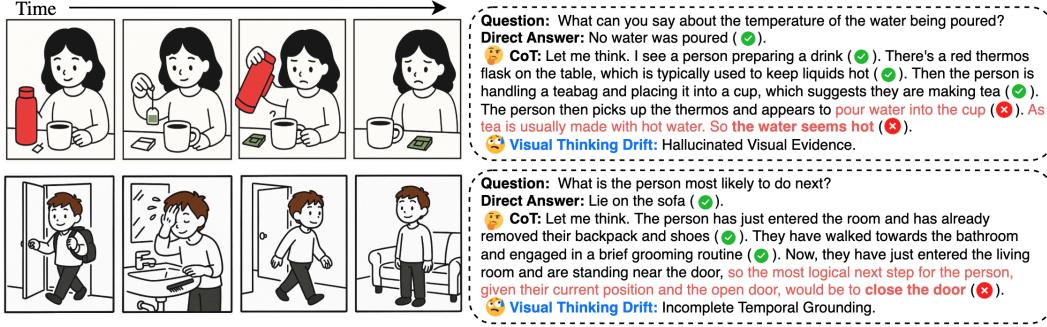


Figure 1: Two examples of *Visual Thinking Drift* phenomenon, where the reasoning chain, as it grows longer, increasingly relies on hallucinated facts or incomplete temporal context—drawing conclusions from language patterns rather than grounding in the actual video content.

Building upon this foundational capability, a significant body of recent work explores chain-of-thought (CoT) reasoning for MLLMs, both through high-quality reasoning datasets with spatio-temporal annotations [47, 39, 22] as well as reinforcement learning (RL) post-training approaches inspired by influential image- and text-based reasoners [21, 23, 63, 50, 57] that refine the MLLM’s reasoning pathways [17, 71, 33] with rule-based rewards. Early results suggest that simply encouraging “thinking before answering” can often pay off. However, despite these promising advancements, the unique challenges encountered when transposing *text*-based chain-of-thought reasoning to the distinct demands of *video*-centric tasks warrant deeper exploration.

In this paper, we aim to both expose the gaps in CoT-based video reasoning, and propose a solution. First we present a systematic study covering 10 video benchmarks, multiple MLLMs, and 20 video QA subtasks, revealing that CoT reasoning often backfires for video understanding, especially with open-sourced models. We identify a recurring failure mode we term “*Visual Thinking Drift*” where an MLLM introduces hallucinated facts or bias to outdated frames for temporal reasoning. Rather than enhance reasoning, the CoT prompts frequently induce models to produce verbose but misleading internal monologues—hallucinating visual details, overriding correct instincts, and ultimately reducing accuracy. See Figure 1. For instance, in next-action prediction tasks, the model may base its logic on earlier events while ignoring more recent cues—despite being able to answer correctly when prompted directly, without CoT. This drift reveals a critical flaw: CoT reasoning in video models often becomes performative rather than grounded—fluent, plausible, but ultimately wrong. To understand this phenomenon, we adopt a Bayesian lens, showing that CoT traces often diverge from actual visual evidence and instead amplify internal biases or language priors.

Next, to counter the visual thinking drift problem, we introduce Visual Evidence Reward (VER), a novel reward mechanism for reinforcement learning-based MLLM post-training framework. Our VER explicitly encourages reasoning traces grounded in visual evidence. The key insight is that genuine video reasoning emerges when the internal thought process itself is actively and granularly tethered to perceived content, compelling models to truly “see while thinking”, not just “think before answering”. In the proposed model, an auxiliary LLM acts as a judge, evaluating the factual alignment between intermediate thoughts and visual inputs. This automatically encourages not just coherent but correct reasoning, stabilizing inference, and boosting overall accuracy.

We evaluate our Video-VER model across 10 diverse video understanding benchmarks. Compared to strong base models and existing reasoning techniques, Video-VER consistently ranks first or second. Furthermore, our model achieves consistently strong margins compared to its respective base MLLM (trained without the Visual Evidence Reward)—as much as +9.0% absolute accuracy gains, and an average of +4.0% across all 10 benchmarks. Our results suggest that in video reasoning, grounding—not verbosity—is essential to true video intelligence.

2 Related Work

Eliciting Reasoning Ability from Large Language Models Large language models (LLMs) have shown strong performance on complex reasoning tasks such as mathematics and programming [7, 11, 49, 2, 46]. These capabilities are often elicited through few-shot [57, 8, 61, 75] and zero-shot prompting [62, 27], or through instruction tuning with large-scale chain-of-thought (CoT)

datasets [12, 44, 51]. Recent advances show that even simple rule-based incentive mechanisms and lightweight reinforcement learning can induce robust reasoning without explicit supervision [21]. However, studies also highlight that LLM-generated reasoning traces may be unreliable or unfaithful to the model’s internal processes [45, 52]. Motivated by these insights, we investigate how to elicit reasoning abilities from multimodal LLMs for video understanding—a domain that introduces unique challenges due to the dynamic temporal nature of video data.

Video Reasoning Video reasoning entails drawing conclusions from video content through multi-step logical inference [16]. As overviewed above, research in this area follows two directions: modular reasoning [42] that decomposes tasks into addressable subcomponents [65, 15, 54, 37, 42] and MLLMs that perform end-to-end inference by jointly leveraging visual and textual information [5, 29, 72, 66, 69, 10, 34, 31, 9].

Building on this, some recent work explores enhanced chain-of-thought (CoT) reasoning for MLLMs. One line focuses on constructing high-quality reasoning datasets, grounded temporally or spatially, to guide more structured logic generation [47, 39, 22]. Another emerging direction, inspired by DeepSeek-R1 [21], Open Reasoner Zero [23], Skywork R1V [63] and Kimi k1.5 [50], applies reinforcement learning (RL) [48, 40] to refine the reasoning process through lightweight, targeted reward mechanisms [17, 71, 33]. Despite these promising developments, systematic analyses of challenges of text-based chain-of-thought reasoning in video tasks remain limited. We contribute to this space by offering both empirical insights and a simple yet effective reward strategy designed to improve the faithfulness to visual content for reasoning chains.

Hallucination in MLLMs We identify a novel phenomenon termed "*Visual Thinking Drift*", a specific manifestation of hallucination in MLLMs. While hallucination—producing descriptions, or conclusions misaligned with visual input—has long been a persistent challenge for MLLMs [6], visual thinking drift is distinguished by its emergence within chain-of-thought reasoning: errors introduced at earlier reasoning steps, once hallucinated, can propagate through subsequent steps, ultimately leading to conclusions that significantly diverge from the visual evidence. In the image domain, prior research has primarily focused on object hallucination, where models misidentify object categories, attributes, or relationships [6]. In the video domain, hallucinations involve misinterpretations of dynamic actions, events, and narrative sequences [56, 67]. To mitigate such issues, existing work explores test-time interventions [36, 53, 25, 30] and preference modeling during training to reduce vision-language misalignment [59, 70]. In contrast, we propose a lightweight and data-efficient alternative: reinforcement fine-tuning to mitigate hallucination within the reasoning process itself. Rather than focusing solely on perception-level correction, our approach targets the integrity of logical progression, aiming to curb the cascading effects of visual thinking drift.

3 Dilemma of Chain-of-Thought Reasoning in Video Understanding

The standard approach to evaluating Video LLMs (a.k.a., MLLMs) for Video Question Answering (VQA) [32, 18] focuses on their ability to provide direct answers—such as returning an integer for a question like “How many objects enter the scene?” Recent advances in LLM reasoning, particularly Chain-of-Thought (CoT) prompting [57], have encouraged models to reason step by step. This approach offers benefits in decomposing complex questions and improving the explainability of responses. In this study, we aim to systematically evaluate the two core prompting strategies: *Direct Response Generation* and *Reasoning-Driven Generation (Chain-of-Thought)*.

Direct Response Generation Under this scheme, the video LLM produces the output answer a by directly leveraging the input question q and the accompanying video context v . The generation task can be formally expressed as:

$$p(a | q, v).$$

In this approach, the model is expected to yield the final answer immediately, without constructing any intermediate reasoning path or justification.

Reasoning-Driven Generation (Chain-of-Thought) Conversely, this method decomposes the output generation into two sequential phases. Initially, the model infers a rationale sequence $c_{1:T}$ based on the input query q and the contextual video data v . Subsequently, it conditions the final prediction a on both the generated rationale and the original inputs. This approach is captured by the

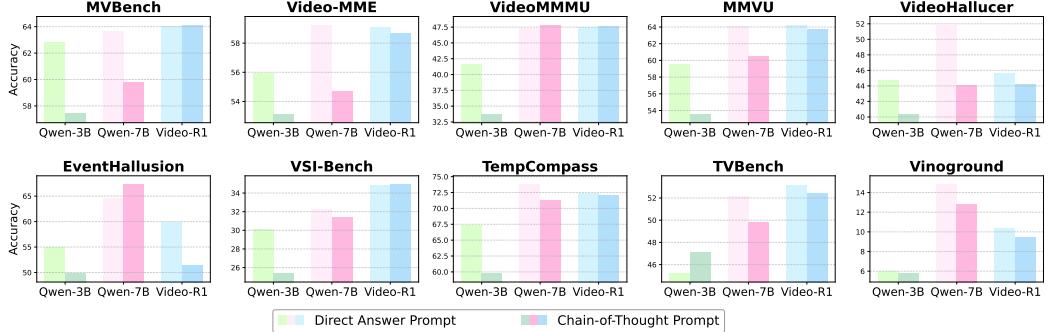


Figure 2: Compared to directly prompting the model for an answer, instructing the model to "think before answering" leads to a noticeable performance drop in open-source MLLMs such as Qwen2.5-VL [5] and Video-R1 [17] across multiple benchmarks (10 are shown here).

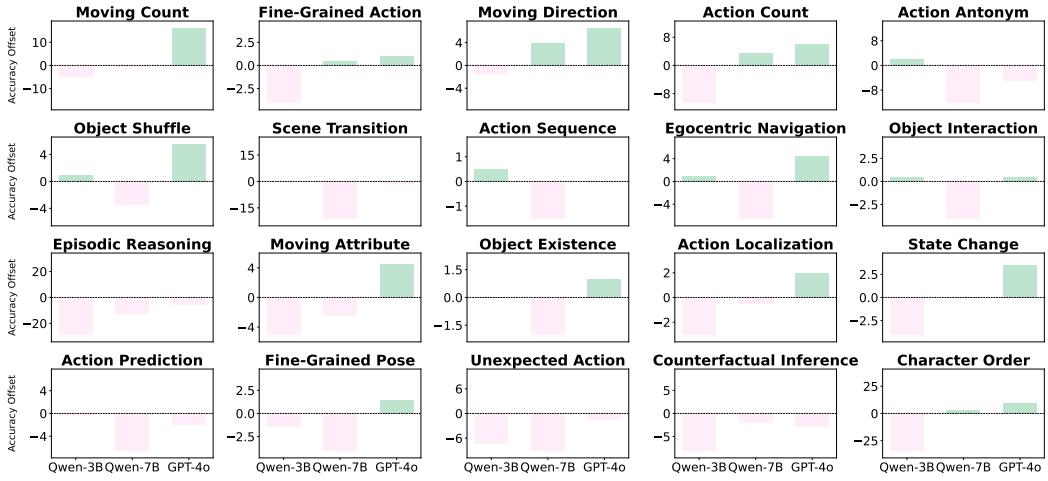


Figure 3: Gains (green) and losses (pink) with CoT prompt, showing that reasoning-driven generation is valuable for multi-hop, causal, or interpretability-driven tasks like object counting, but weakens both large and small models on lightweight perceptual questions such as scene transition detection.

following formulation:

$$p(c_{1:T} | q, \mathbf{v}) \cdot p(a | c_{1:T}, q, \mathbf{v}).$$

3.1 How Does CoT Make Models Weaker on Simple Video Perception Tasks?

To assess the impact of reasoning-driven generation on video understanding, we conduct a systematic study comparing it to direct response generation. Our key question: Does prompting models to "think step-by-step" improve performance in state-of-the-art Video LLMs?

As illustrated in Figure 2, we evaluate both generation strategies across three leading open-sourced MLLMs—Qwen2.5-VL-3B [5], Qwen2.5-VL-7B [5], and Video-R1-7B [17]—on 10 diverse video benchmarks, spanning general video understanding [18] to complex temporal [68] and spatial reasoning tasks [60].¹ Surprisingly, reasoning-driven (CoT) prompting often leads to lower accuracy, particularly on benchmarks demanding rapid visual perception, like Video-MME [18].

To further dissect the impact of CoT prompting, we analyze 20 subtasks from MVBench (Figure 3), leveraging its structured task taxonomy. The results show that forcing models to "think out loud" reduces accuracy on tasks that rely on quick visual yes/no or single-label judgments, such as scene transition detection. The additional tokens invite over-rationalization, hallucinated details, and context-length dilution—turning what should be a fast lookup into an opportunity to override the correct first impression. In contrast, CoT improves accuracy on more cognitively demanding tasks,

¹We also experimented with LLaVa-OneVision-7B [29], but it failed to follow the instruction to generate a thought trace, likely due to its use of a weaker underlying language model.

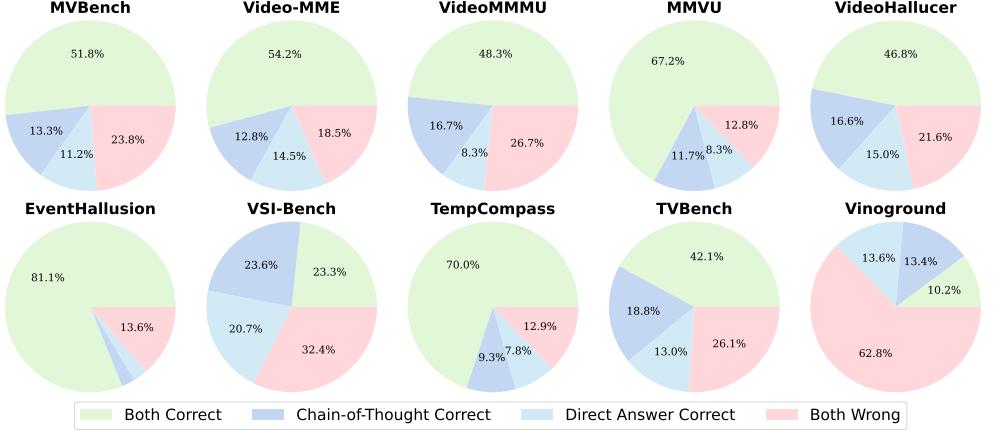


Figure 4: Even with GPT-4o (a strong reasoning model), a considerable portion of questions (light blue areas) are better answered directly than with CoT reasoning, implying significant room for improvement in CoT reasoning. For VSI-Bench and MMVU, results are based on MCQ subset.

like counting object movements or actions. As shown in Figure 4, even with the much larger proprietary model GPT-4o—a strong model with advanced reasoning capabilities—a significant portion of questions are better answered directly than with CoT.

In summary, while reasoning-driven generation is promising for complex tasks requiring explicit decomposition, it can hinder performance on simpler perceptual tasks by introducing unnecessary reasoning steps, leading to errors or hallucinations.

3.2 Visual Thinking Drift: When Reasoning Ignores the Video

Reasoning implicitly unfolds in two stages: first, identifying the relevant rules and facts needed to reach a conclusion, and second, applying them effectively to arrive at that conclusion [28]. Simply encoding knowledge is not enough—robust reasoning under uncertainty is essential. However, the verbose nature of CoT traces introduces stochasticity into the reasoning process. Drawing inspiration from self-consistency [55], we found that majority voting over 20 responses generated with CoT prompt significantly improves accuracy (see supplementary material for details). Yet, this improved stability comes at the cost of considerable computational overhead.

To investigate the source of this instability, we analyzed multiple erroneous chains of thought. Paradoxically, we found that many flawed thinking traces in video analysis are logically flawless. The culprit? A phenomenon we call “**Visual Thinking Drift**”, illustrated in Figure 1. The model’s reasoning is sound, but it is unmoored from the video’s true content—building its logic on hallucinated visual details or isolated temporal fragments, which inevitably steer the inference off track.

To better understand the Visual Thinking Drift phenomenon, we adopt a Bayesian lens, which helps disentangle why CoT can damage a video LLM’s answer even when the direct answer alone is correct. Consider a video LLM that, given a question q and video features \mathbf{v} , generates a chain of reasoning tokens $c_{1:T}$ followed by a final answer a . Its implicit generative story is

$$p(c_{1:T}, a | q, \mathbf{v}) = p(a | c_{1:T}, q, \mathbf{v}) \prod_{t=1}^T p(c_t | c_{<t}, q, \mathbf{v}).$$

Because the chain tokens are never supervised, each inference step samples a high-variance *latent* state. Early in the generation process, visual evidence does influence the softmax

$$p(c_t | c_{<t}, q, \mathbf{v}) \propto \exp(\underbrace{\mathbf{h}_{c_{<t}}^\top W_{\text{lang}}}_{\text{language prior}} + \underbrace{\mathbf{h}_\mathbf{v}^\top W_{\text{vis}}}_{\text{visual likelihood}}),$$

yet in practice $\|W_{\text{lang}}\| \gg \|W_{\text{vis}}\|$. As t grows, self-attention focuses ever more on the already-generated tokens, so the visual likelihood is *diluted*. A linguistically plausible but ungrounded narrative emerges, and a single hallucinated detail can dominate all subsequent probabilities.

If each individual step is correct with probability $p_s = 1 - \varepsilon$, the probability that an entire chain of length T is error-free is $(1 - \varepsilon)^T \approx 1 - T\varepsilon$ for small ε ; thus the failure rate grows *linearly* with chain

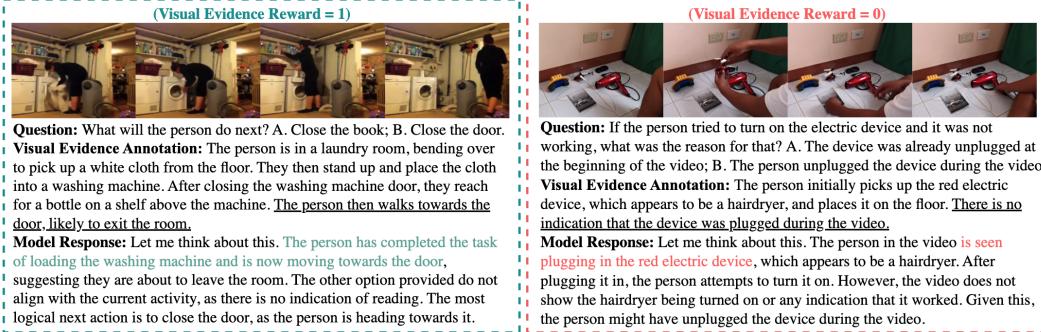


Figure 5: Visualization of visual facts generated from the training data. Chain-of-thought responses that actively reference visual evidence are rewarded, while those that do not receive zero reward.

length. Once an early token commits to a nonexistent visual fact (e.g. “the man holds a red ball”), all later tokens and the answer are conditioned on this fiction. Because autoregressive decoding has no backward message-passing to re-verify the video, the posterior mass collapses around the hallucination and recovery becomes nearly impossible.

Crucially, the model’s high-probability *logical scaffolds*—“if–then” structures, counting loops, temporal ordering—stay intact, while the low-entropy visual details are weakly weighted. The result is a chain of thought that *looks* logically sound but is built on visually hallucinated content: the essence of *visual thinking drift*.

We show two concept examples of visual thinking drift made by CoT prompting in Figure 1, where CoT brings hallucinations or mismatches with visual evidence. When inconsistencies arise, MLLMs faithfully trust textual data over visual data, leading to wrong reasoning paths.

4 Visual Evidence Reward (VER) for MLLM Video Reasoning

Continuing this Bayesian perspective, a key insight into the visual thinking drift dilemma is that CoT tokens are never explicitly supervised during training. Without clear guidance, reasoning can easily drift away from the visual evidence it is meant to be grounded in. To tackle this, we enhance the lightweight rule-based reinforcement learning algorithm, Group Relative Policy Optimization (GRPO) [46, 21], by introducing a novel reward mechanism: Visual Evidence Reward (VER). VER directly supervises the model’s reasoning process by rewarding it when its chain-of-thought includes accurate and relevant visual details—effectively anchoring abstract reasoning in concrete visual facts.

For each question q , we have a policy model π_θ to generate a group of responses $\{o_i\}_{i=1}^G$, where G is the group size. A large language model (LLM)-based judge evaluates each response o_i for its reference to the visual evidence v , assigning a binary score $e_i \in \{0, 1\}$, where 1 indicates a proper reference. We define the evidence reward coefficient as $r_e = \alpha$ if $e_i = 1$, and $r_e = 0$ otherwise, where α is a tunable reward weight. Note that using an auxiliary LLM to generate similarity scores for reward calculation is a common practice in recent work [74, 20, 58] in the language domain.

The evidence-augmented reward is computed as $r_i^{\text{evid}} = r_i + r_e$ if both o_i is correct and $e_i = 1$; otherwise, $r_i^{\text{evid}} = r_i$. For each question, we compute the group reward $\mathbf{r} = \{r_i^{\text{evid}}\}_i^G$, and use it to normalize the rewards: $A_i = \frac{r_i^{\text{evid}} - \text{mean}(\mathbf{r})}{\text{std}(\mathbf{r})}$.

With this, the policy is optimized via the clipped GRPO objective:

$$\begin{aligned} \mathcal{J}_{\text{evid-GRPO}}(\theta) = & \mathbb{E}_{q, \{o_i\}_{i=1}^G \sim \pi_{\theta_{\text{old}}}(O|q)} \left[\frac{1}{G} \sum_{i=1}^G \left(\min \left(\frac{\pi_\theta(o_i | q)}{\pi_{\theta_{\text{old}}}(o_i | q)} A_i, \right. \right. \right. \\ & \left. \left. \left. \text{clip} \left(\frac{\pi_\theta(o_i | q)}{\pi_{\theta_{\text{old}}}(o_i | q)}, 1 - \epsilon, 1 + \epsilon \right) A_i \right) - \beta \mathbb{D}_{\text{KL}}(\pi_\theta \| \pi_{\text{ref}}) \right) \right] \end{aligned}$$

where ϵ and β are hyperparameters for clipping and KL regularization, respectively. π_θ denotes the current policy, $\pi_{\theta_{\text{old}}}$ is the prior policy used for importance sampling, and $\pi_{\theta_{\text{ref}}}$ is the reference model set to the initial checkpoint for regularization.

By incorporating an evidence-based reward signal, Visual Evidence Reward explicitly encourages models to ground their reasoning in visual context, leading to more contextually relevant responses.

Visual Evidence Generation What exactly qualifies as visual evidence? A straightforward approach might be to use general video captions [1]—but this quickly runs into the issue of granularity. Captions often miss the specific visual cues needed to answer particular questions. To resolve this, we define visual evidence in a question-dependent manner: it consists of the visual details necessary to answer a given question, which can vary significantly across tasks.

To generate such evidence, we leverage a strong MLLM, Qwen2.5-VL-72B [5], prompting it with both the video and the question. The model is asked to produce not only an answer but also a list of visual observations that support that answer. This way, the reasoning process remains tightly grounded in relevant visual input. Full prompt details are provided in the supplementary materials. Qualitative examples of the generated visual evidence used for GRPO training are shown in Figure 5.

The external VLM is only used to generate training data in the form of question-specific visual evidence. Our policy model (Video-VER), trained on this evidence, performs inference independently and does not rely on the external VLM at test time. We recognize that VLM-generated outputs may include speculative or hallucinated content. To mitigate this, we filter and structure the visual evidence via carefully designed prompts (see supplementary materials), ensuring that the extracted visual details are question-relevant and textually explicit. Empirically, this approach results in higher alignment between reasoning chains and observable video content, as demonstrated in Figure 6.

5 Experiments

Training Strategy Our model is a post-trained Qwen2.5-VL-7B [4], employing a two-stage pipeline that combines supervised fine-tuning (SFT) and reinforcement learning (RL). The process begins with SFT, where we train the model on Video-R1-COT-165k dataset [17], a dataset providing chain-of-thought (CoT) annotations, helping bootstrap the model’s reasoning abilities during the cold-start phase. Following this, the model undergoes reinforcement learning using GRPO with our Visual Evidence Reward (VER). This phase uses a dataset mixture comprising Reversed-in-Time [14] and Video-R1-260k [17] samples. The RL stage is designed to move the model beyond the constraints of supervised learning, allowing it to develop more robust and adaptable reasoning patterns through exploration and self-guided optimization. We call our final post-trained model Video-VER.

Benchmarks We extensively evaluate our model across a broad spectrum of 10 public video understanding benchmarks, covering a wide range of reasoning skills. These include comprehensive, all-around benchmarks such as MV-Bench [32] and Video-MME [18]; temporal reasoning benchmarks like TVBench [13], Vinoground [68], and TempCompass [38]; spatial reasoning benchmarks such as VSI-Bench [60]; and knowledge-intensive datasets including Video-MMMU [24] and MMVU [73]. We also assess robustness to hallucination using dedicated benchmarks such as EventHallusion [67] and VideoHallucer [56]. Most benchmarks consist of multiple-choice questions (MCQs), with the exception of Video-MMMU and VSI-Bench, which include questions requiring numerical answers. For MMVU, we follow the protocol from [17] and use its MCQ subset to ensure robust and consistent evaluation. Subtitles are excluded in the Video-MME evaluation setting.

Implementation Details During training, the maximum number of video frames is set as 16, and increased to 32 at inference time for both our model and all baselines, unless otherwise specified. For GRPO training, we incorporate four reward components: an accuracy reward, our visual evidence reward (with weight $\alpha = 0.3$), a format reward to encourage consistent answer structure, and a length reward to promote moderately long, informative responses. We train our model with 8 NVIDIA H200 GPUs. GRPO group size G is set as 8. The number of RL iterations is set to 2,000. Further implementation details can be found in the supplementary material.

Baselines We compare our model against both proprietary and open-source video LLMs. For the proprietary model, we evaluate GPT-4o [26]. For open-source baselines, we evaluate against LongVA [69], Video-UTR [64], LLaVA-OneVision [29], Kangaroo [35], and Qwen2.5-VL [5]. Additionally, to assess reasoning capabilities, we include two recently released video reasoning models: TinyLLaVA-Video-R1 [71] and Video-R1 [17], both of which are explicitly designed for text-based multi-step video reasoning tasks. Together, these baselines span the full spectrum

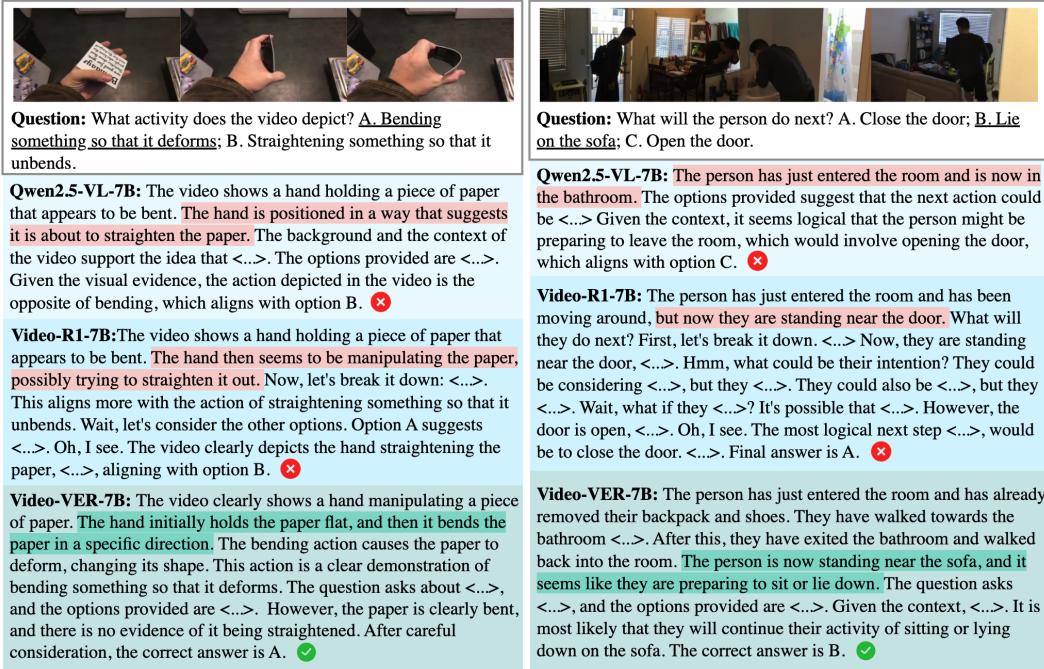


Figure 6: Comparison of reasoning traces from baselines and our Video-VER model. Notice how baseline models often include speculative or hallucinated details not grounded in the video, whereas Video-VER maintains alignment between intermediate reasoning steps and observable evidence.

of contemporary video-language systems—from large, commercially deployed models to lean, community-driven releases—ensuring that our evaluation is both representative of the strongest available competitors and informative for researchers and practitioners who rely on open tools.

5.1 Evidence-Grounded Chains Lead to Better Video Understanding

Table 1 demonstrates that Video-VER consistently surpasses existing open-source video MLLMs across a comprehensive suite of benchmarks, ranking first in 9 out of 10 evaluations, except for the VSI-Bench where Video-R1 [17] achieves the strongest performance. Video-VER shows superior results in temporally nuanced data like TempCompass (74.0%) and TVBench (52.8%), underscoring its ability to interpret sequential information and dynamic visual content with precision. These results validate the strength of our proposed method and its generalization across diverse video-language tasks, all while utilizing a 7B parameter model with an innovative RL training strategy.

Figure 6 presents qualitative examples of the thinking chains generated by our model and baseline methods. Some raw text has been omitted for brevity. The results illustrate that the reasoning of baseline models is often distracted by speculative or hallucinated details, which are not grounded in the actual actions or the full temporal context of the video. In contrast, Video-VER better maintains alignment between intermediate reasoning steps and observable evidence, leading to the correct answer. We discuss common **failure cases** and **limitations** of our Video-VER in the appendix.

5.2 Ablation Study

Types of Visual Evidence As shown in Table 2, we experiment with two approaches to generating visual evidence to train our Video-VER model: question-dependent visual evidence (QD-VE), obtained by prompting a MLLM with both the question and the video, and a generic video caption (VC), generated by asking the MLLM to produce a detailed caption of the video alone. The Group score is reported for the Vinoground benchmark. Our ablation shows that QD-VE outperforms VC on 9 out of 10 benchmarks, and falls behind only on EventHallusion. These results highlight the effectiveness of aligning visual evidence with the specific question, confirming that question-tailored context is more beneficial than a general-purpose description.

Table 1: Comparison of Video-VER with baselines across 10 video benchmarks. Our model consistently ranks **first** or **second** overall, demonstrating the effectiveness of evidence-grounded chain-of-thought (CoT) reasoning. Notably, across most base models (e.g., Qwen2.5-VL), CoT prompting often leads to lower accuracy compared to direct answering (DA), highlighting the risk of ungrounded reasoning. In contrast, Video-VER maintains or improves performance with CoT by explicitly grounding reasoning in question-relevant visual evidence. To emphasize this, we annotate the accuracy margins (\uparrow) between Video-VER and its base model Qwen2.5-VL-7B—both with CoT—in **small offset font**, drawing attention to the consistent gains enabled by our visual grounding reward.

Model	Size	Prompt	MVBench	Video-MME	VideoMMMU	MMVU	VideoHallucer	EventHallusion
GPT-4o [3]	-	DA	62.9	68.7	56.7	75.5	61.8	83.9
GPT-4o [3]	-	COT	65.1	67.0	65.0	78.9	63.4	83.6
LongVA [69]	7B	DA	-	52.6	23.9	-	-	-
Video-UTR [64]	7B	DA	58.8	52.6	-	-	-	-
LLaVA-OneVision [29]	7B	DA	57.1	57.7	33.8	49.2	34.7	61.1
Kangeroo [35]	8B	DA	61.1	56.0	-	-	-	-
TinyLLaVA-Video-RL [71]	3B	COT	49.5	46.6	-	46.9	-	-
Video-R1 [17]	7B	COT	63.9	59.3	52.3	63.8	44.2	51.4
Qwen2.5-VL [5]	3B	DA	62.8	55.9	41.7	59.5	44.8	54.9
Qwen2.5-VL [5]	3B	COT	57.4	53.2	33.8	53.6	40.4	49.9
Qwen2.5-VL [5]	7B	DA	63.6	59.2	47.3	64.2	51.8	64.5
Qwen2.5-VL [5]	7B	COT	59.8	54.7	47.8	60.5	44.1	67.3
Video-VER (Ours)	7B	COT	64.1 (+4.3)	59.3 (+4.6)	52.7 (+4.9)	65.1 (+4.6)	53.1 (+9.0)	70.0 (+2.7)
Model	Size	Prompt	VSI-Bench	TempCompass	TVBench	Vinoground		
GPT-4o [3]	-	DA	27.8	77.8	55.1	57.6	34.4	23.8
GPT-4o [3]	-	COT	45.3	79.3	60.9	62.2	38.0	23.6
LongVA [69]	7B	DA	-	56.9	-	-	-	-
Video-UTR [64]	7B	DA	-	59.7	-	-	-	-
LLaVA-OneVision [29]	7B	DA	32.9	67.8	47.2	42.0	28.4	12.8
Kangeroo [35]	8B	DA	-	62.5	-	-	-	-
Video-R1 [17]	7B	COT	35.8	73.2	52.4	34.6	24.8	9.4
Qwen2.5-VL [5]	3B	DA	30.1	67.3	45.2	30.2	21.2	6.0
Qwen2.5-VL [5]	3B	COT	25.4	59.8	47.2	30.8	22.6	5.8
Qwen2.5-VL [5]	7B	DA	32.3	73.7	52.2	42.2	29.2	14.8
Qwen2.5-VL [5]	7B	COT	31.4	71.3	49.9	40.6	28.0	12.8
Video-VER (Ours)	7B	COT	34.6 (+3.2)	74.0 (+2.7)	52.8 (+2.9)	42.8 (+2.2)	28.2 (+0.2)	14.4 (+1.6)

Table 2: Ablation on types of visual evidence, showing that question-dependent visual evidence (QD-VE) is generally preferred over general video captions (VC) for visual evidence generation.

Model	#Type	MVBench	Video-MME	VideoMMMU	MMVU	VideoHal.	EventHal.	VSI-Bench	TempC.	TVBench	Vinog.
Video-VER	QD-VE	64.1	59.3	52.7	65.1	53.1	70.0	34.6	74.0	52.8	14.4
Video-VER	VC	63.9	58.7	52.2	64.8	52.5	70.3	34.4	73.6	52.4	13.6

Table 3: Ablation study on the scalability of Video-VER across varying temporal context lengths.

Model	#Frames	MVBench	Video-MME	VideoMMMU	MMVU	VideoHal.	EventHal.	VSI-Bench	TempC.	TVBench	Vinog.
Video-VER	32	64.1	59.3	52.7	65.1	53.1	70.0	34.6	74.0	52.8	14.4
Video-VER	16	63.2	56.0	50.0	64.8	51.4	69.8	35.2	72.8	51.0	10.6
Video-VER	8	60.5	53.3	45.4	63.2	50.4	70.5	32.6	69.6	48.3	11.0

Scalability with Frames Table 3 presents an ablation study assessing the scalability of Video-VER with varying numbers of input frames. The Group score is reported for the Vinoground benchmark. The results reveal a consistent trend: performance improves as more frames are provided, with the 32-frame setting achieving the best results on 8 out of 10 benchmarks. This demonstrates that our method effectively leverages more frames with longer temporal context, confirming its ability to scale and generalize well across different video lengths.

6 Conclusions and Future Work

Bridging the gap between the linear, symbolic structure of chains-of-thought and the inherently fuzzy, non-linear, and temporally distributed nature of video remains a central challenge. This paper has highlighted a critical failure mode in this pursuit: “*Visual Thinking Drift*”, where reasoning processes, despite appearing coherent, become unmoored from actual video content. We then introduced Visual Evidence Reward (VER), a novel reinforcement learning reward mechanism specifically designed to counteract this drift. Our VER excels in closed-ended tasks like multiple-choice question answering where rule-based reward computation is effective. Extending this framework to open-ended tasks, such as free-form QA, and thereby ensuring that verbosity is replaced by genuinely grounded video intelligence, presents an exciting and crucial avenue for future work.

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A Self-consistency Decoding for Video Reasoning

Motivated by the decoding strategy self-consistency proposed in [55], which samples a diverse set of reasoning paths instead of relying solely on greedy decoding, and then selects the most consistent answer by marginalizing over the sampled paths, we explore its implications for video reasoning tasks. The intuition behind self-consistency is that complex reasoning problems often allow for multiple valid reasoning trajectories that converge on a unique correct answer.

However, our focus is on video reasoning tasks, which generally exhibit lower reasoning complexity than language-only tasks such as mathematical problem solving or code generation. Moreover, the diversity of reasoning paths in video-based tasks tends to be more constrained due to the fixed visual context and limited temporal narrative. For example, while a math problem might allow several logical formulations or decompositions, a video clip typically presents a specific sequence of events that restricts interpretive variation.

Despite this, we observe that simple majority voting over 20 responses generated using Chain-of-Thought (CoT) prompting (with the same model) significantly boosts accuracy across all models in most scenarios. See Figure 7. In particular, this indicates that the reasoning traces for video tasks are often unstable, and greedy decoding is more prone to getting trapped by the *visual thinking drift*—the phenomenon discussed in Section 3.2, where subtle ambiguities or misinterpretations in the visual context derail the reasoning process. By aggregating multiple responses, self-consistency helps to smooth out these drifts and converge on more robust answers.

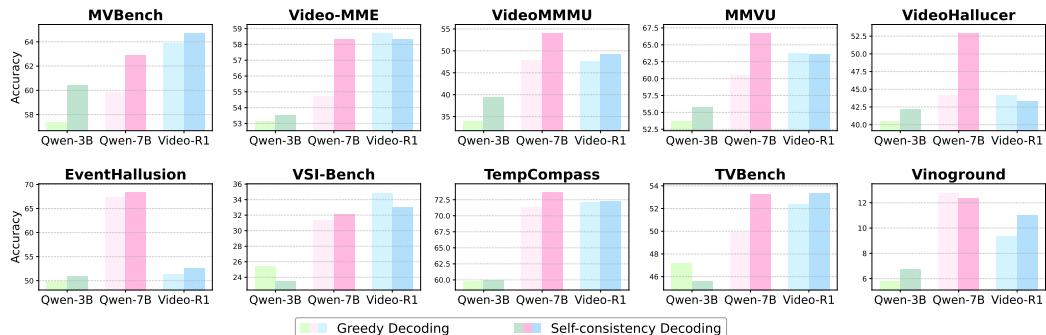


Figure 7: Sampling multiple independent CoT responses per question and aggregating them via majority voting yields a clear accuracy improvement—indicating that reasoning traces are often stochastic rather than dependable. Each chart is a different popular video benchmark.

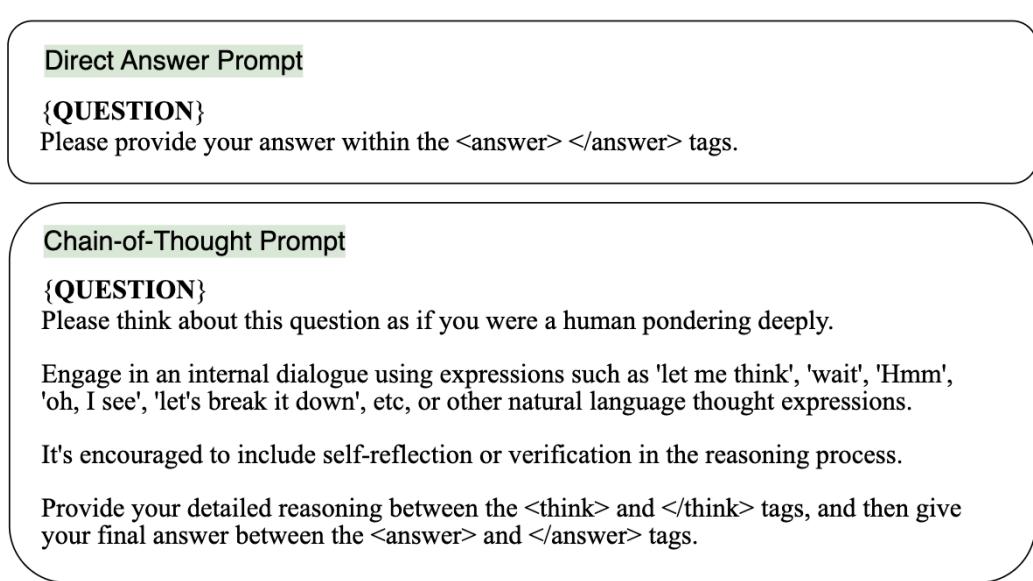


Figure 8: Prompts used for direct response generation and reasoning-driven generation (chain-of-thought). The CoT prompt is borrowed from Video-R1 [17].

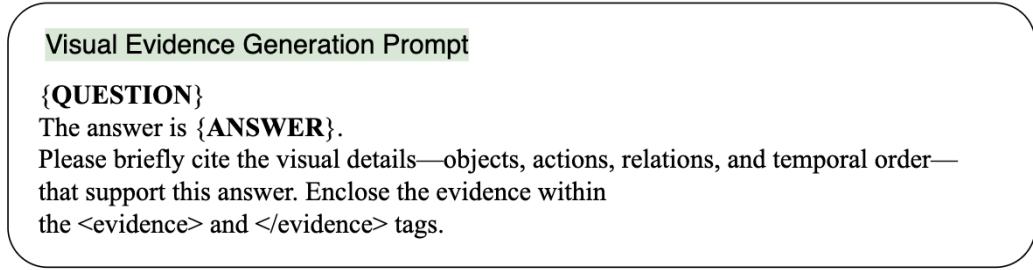


Figure 9: Inverted Prompting used for generating visual evidence annotations.

B Implementation Details

Training and Testing Configurations For evaluation, we set the temperature to 0.01 for all baseline models as well as our model. During training, the maximum video token budget is set to $128 \times 28 \times 28$ pixels. During testing, this is increased to $256 \times 28 \times 28$ pixels. The sampling rate is set to 2.0 FPS across all benchmarks, except for Vinoground, which uses 4 FPS. To manage API costs, the maximum number of frames used by GPT-4o is limited to 16 frames per video, except for TempCompass, where only 8 frames are used.

The results for VSI-Bench reported in Table 1 represent the average accuracy across both multiple-choice and regression-based tasks. For the baseline model Video-R1, we adopt the reported results of MVBench, Video-MME, VideoMMMU, MMVU, VSI-Bench, and TempCompass under the 32-frame setting as specified in their respective papers. For the remaining four benchmarks—VideoHallucer, EventHallusion, TVBench, and Vinoground—we conduct our own evaluations due to the absence of publicly available results. In Figure 2 and Figure 7, to ensure a fair and consistent comparison across all prompting and decoding strategies, we re-evaluate Video-R1 on all benchmarks in our experimental setting, including those with reported numbers, wherever applicable.

Length Reward To encourage deeper reasoning without excessive verbosity, we apply a length reward targeting response lengths in the range of 320 to 512 tokens.

LLM Judge We utilize Llama-3.1-70B-Instruct [19] as our LLM-based judge. It is prompted to produce a binary label—1 for successfully referencing the visual evidence, and 0 for failing to do so.

Prompt Details All prompts used in our training and evaluation are illustrated in Figures 8 and 9.

Prompt for LLM-Judge

You are an expert in evaluating whether the reasoning trace of a video reasoning model is grounded in the visual evidence. You will be provided with a reasoning trace and a description of the visual evidence. Determine whether the reasoning process uses facts from the visual evidence to arrive at the final answer.

Visual Evidence: {**VISUAL EVIDENCE**}

Thinking Trace: {**THINKING TRACE**}

Output only a single numeric value: **1** if the reasoning uses the visual evidence, **0** if it does not.

Figure 10: The prompt used for LLM Judge, producing reward value 0 or 1.

C LLM-Based Judge for Visual Evidence Grounding

Evaluating whether a model’s reasoning references the correct visual evidence is inherently a semantic task that goes beyond exact string or token overlap. It requires assessing whether the generated rationale mentions visual facts that are relevant, specific, and consistent with what is shown in the video. To enable this, we adopt an auxiliary LLM-based judge to compute a binary reward—assigning 1 if the rationale includes grounded, question-relevant visual details, and 0 otherwise.

This design aligns with common practice in recent reinforcement learning and reward modeling studies, where LLMs are used to produce reward signals for complex, fuzzy objectives such as factuality, helpfulness, or alignment [74, 20, 58]. Unlike token-level metrics, the LLM judge offers flexible, high-level reasoning about textual similarity and visual grounding. While this introduces some approximation and risk of bias, it is essential for enabling scalable supervision at training time where human annotation is impractical. To reduce their influence we use temperature-0 decoding for more deterministic decoding and use the carefully designed prompt shown in Figure 10. In Figure 11, we present qualitative examples where the LLM-assigned rewards reflect accurate judgments of visual grounding, demonstrating the judge’s effectiveness in identifying whether reasoning is properly anchored in the video content.

D Visual Evidence Generation: Bootstrapping Grounded Reasoning

Generating high-quality, question-specific visual evidence is crucial for anchoring Chain-of-Thought (CoT) reasoning in video understanding. This task demands identifying precise visual cues—objects, actions, and temporal events—that directly justify a given answer. Given the current limitations of most video-language models (MLLMs) in reliably producing such granular evidence without explicit supervision, we employ a strong external MLLM, Qwen2.5-VL-72B, as an **offline generator** during training. Our goal is to bootstrap a lightweight, yet effective, reward signal that explicitly encourages reasoning traces to be grounded in observable visual content, thereby circumventing the need for expensive human annotation.

Potential Concerns Introducing an external “teacher” MLLM for evidence generation naturally raises valid concerns regarding noise, potential circularity in the training process, and the risk of hallucinated details. We’ve implemented several strategies to rigorously mitigate these issues.

First, and crucially, the external MLLM is utilized *solely offline* to create question-specific visual evidence for training. Our policy model, Video-VER, learns from these generated outputs but operates *entirely independently at inference time*. This ensures there’s no direct feedback loop or reliance on the teacher’s rationale during deployment, preserving the integrity of our trained model.

Second, the reward signal derived from the generated visual evidence is intentionally *binary*. We don’t demand exhaustive or perfectly nuanced evidence; instead, the judge model merely verifies if the generated reasoning trace cites *any* verifiable visual fact relevant to the answer. This design choice significantly attenuates the impact of occasional hallucinations or minor inaccuracies from the teacher model: incorrect or missing evidence simply results in a zero reward, rather than actively

pushing the policy towards an erroneous trace. This robustness ensures that the reward signal guides the model toward *grounded reasoning*, rather than penalizing minor deviations.

Third, a core innovation in our visual evidence generation strategy lies in our *inverted prompting approach*. Unlike conventional CoT, where the model simultaneously explores reasoning steps and the final answer, we feed the external MLLM the (*question, ground-truth answer*) pair and instruct it to generate visual evidence that *supports* this already-known answer. This inversion offers two benefits. By fixing the answer upfront, the model’s task is narrowed considerably. It no longer has to navigate the full reasoning space; its sole objective is to retrieve the *minimal, verifiable visual facts* that logically lead to the given answer (e.g., “a red ball enters the basket”). Furthermore, in typical CoT, models can sometimes drift into generic narratives before settling on an answer. Our inverted prompt structure forces each generated evidence snippet to directly explain the already-known answer to the specific question asked. This creates an intrinsic alignment pressure: any statement irrelevant to the question or unsupported by the video becomes effectively useless, and thus discouraged by our binary evidence reward. The model is incentivized to produce *highly relevant and visually verifiable facts*, directly addressing the “Visual Thinking Drift” problem by ensuring reasoning is tethered to pertinent visual cues. A potential concern is that providing the question text might allow the MLLM to generate evidence based on linguistic cues, bypassing direct pixel analysis. However, our empirical results in Table 2 address this: generating visual evidence conditioned on the question text significantly outperforms using generic video captions. This suggests that the question text’s primary contribution is not an increase in hallucination; rather, it provides crucial, task-specific context that guides the MLLM towards more relevant visual features, thereby enhancing overall performance.

Put differently, a standard CoT prompt induces the distribution $p(c_{1:T}, a \mid q, v)$, where both the reasoning chain and the answer are uncertain. Our evidence prompt, by contrast, conditions on the correct answer and samples from $p(e_{1:K} \mid q, a, v)$. This constitutes a far lower-entropy target that inherently prioritizes *visual grounding over linguistic priors*. This fundamental structural difference in how the evidence is generated explains why our teacher model can reliably produce visual evidence *without* itself needing the very reinforcement signal we are about to learn.

Figure 11 provides further samples of our generated visual evidence, demonstrating how our *inverted prompting* approach yields highly relevant and specific visual cues that directly support the answers, effectively anchoring the reasoning process.

E More Qualitative Examples

As shown in Figure 12 and 13, we present additional qualitative examples of reasoning chains produced by our model alongside the baseline models Qwen2.5-VL-7B and Video-R1-7B. These examples further demonstrate that baseline models frequently rely on speculative or hallucinated details, often misaligned with the actual actions or broader temporal context of the video. In contrast, Video-VER consistently grounds its intermediate reasoning steps in observable evidence, resulting in more accurate answers.

(Visual Evidence Reward = 1)

Question: What does the person rely on for support while descending the cliffside?

Options:

- A. A ladder
- B. A harness
- C. A rope
- D. A bridge

Visual Evidence: The person is using a rope for support while descending the cliffside. This is evident from the visible rope attached to the individual, which is likely part of a climbing or rappelling setup. The person is also wearing a harness, which is a safety device used in climbing to secure the rope and prevent falls. The presence of the rope and harness, along with the individual's posture and the context of the activity, strongly supports the answer that the person relies on a rope for support.

Model Response: Let me think about this. The climber is clearly using a rope for support while descending the cliffside. The rope is visible in the video, and it is being used to control the descent, ensuring safety and stability. The climber's posture and the way they are holding onto the rope indicate that they are relying on it for support. There is no mention or indication of a ladder, a harness, or a bridge in the video. The rope is the only tool that can be seen and used for this purpose.

Question: Which object would the person take next?

Options:

- A. The shoe.
- B. The book.
- C. The towel.
- D. The phone/camera.

Visual Evidence: The video shows the person removing both shoes, and the next step would be to put them away or put on the other shoe. The shoe is located on the floor near the person, making it easily accessible for the next action.

Model Response: Let me think about this. The person has already taken the shoe and placed it on the floor. They are now standing up and appear to be looking around the room. Given the options, the most logical next step would be to pick up an object that is commonly used in a room like this. The book seems like a plausible choice as it is often found on nightstands or dressers. The towel and phone/camera are less likely to be the next item of interest.

(Visual Evidence Reward = 0)

Question: Which object would the person take next?

Options:

- A. The shoe.
- B. The book.
- C. The towel.
- D. The phone/camera.

Visual Evidence: The video shows the person removing both shoes, and the next step would be to put them away or put on the other shoe. The shoe is located on the floor near the person, making it easily accessible for the next action.

Model Response: Let me think about this. The person has already taken the shoe and placed it on the floor. They are now standing up and appear to be looking around the room. Given the options, the most logical next step would be to pick up an object that is commonly used in a room like this. The book seems like a plausible choice as it is often found on nightstands or dressers. The towel and phone/camera are less likely to be the next item of interest.

Question: The person interacts with an electric device among other objects. Is the electric device on at any point?

Options:

- A. no
- B. yes
- C. I don't know

Visual Evidence: The electric device appears to be on at some point during the video. This can be inferred from the person's hand movements and the visible light on the device. The hand is shown holding the device in a way that suggests it is in operation, and there is a noticeable light on the device, which is typically an indicator that it is powered on. Additionally, the person's actions, such as adjusting the device and pointing towards it, suggest that it is functioning and being used actively.

Model Response: Let me think about this. The video shows a person holding an electric device, which appears to be a hair clipper, and a small object that could be a comb. The person is examining both items closely, and there is no indication that the electric device is turned on. The setting is a kitchen, and the person is not interacting with the device in a way that suggests it is in use. The focus is on the objects and the person's hands, not on the device's operation.

Question: Which object did the person take after they lied on the bed?

Options:

- A. The phone/camera.
- B. The towel.
- C. The broom.
- D. The paper/notebook.

Visual Evidence: After lying on the bed, the person moved to a desk and picked up a paper/notebook. This is evident from the sequence of actions: first, the person is seen lying on the bed with a laptop, then they get up and walk to the desk where they pick up a paper/notebook. The desk is cluttered with various items, including papers, a clock, and other office supplies, which suggests a workspace environment.

Model Response: Let me think about this. The question asks which object the person took after lying on the bed. The video shows the woman lying on the bed and then getting up to go to the desk. The options provided are: A. The phone/camera. B. The towel. C. The broom. D. The paper/notebook. The woman is seen sitting at the desk. The most logical object to take after lying on the bed and moving to the desk would be something they need to work on or use for their task. Therefore, the object is likely the phone or camera.

Figure 11: Visual evidence generated through our *inverted prompting* approach, as well as the evidence reward values produced by the LLM Judge. These examples illustrate the specific and relevant visual details that directly support answers and anchor the reasoning process. Key visual evidence is underlined. Green highlighting indicates successful reference to visual evidence, while red indicates a failure to do so.



Question: What did the person do first? Options: A. Closed the closet/cabinet. B. Put down the food.

Owen2.5-VL-7B: Let me think. The person is seen standing in front of a refrigerator, which suggests they might have been retrieving something from it. However, the video then cuts to the person in a different location, which could be a kitchen, where they are handling a bottle and a jar. This implies that the initial action of retrieving something from the refrigerator might not be the first action in the sequence shown in the video. The answer is B. ✗

Video-R1-7B: Let me think about this for a moment. The question is asking what the person did first, and we have two options to consider: A. Closed the closet/cabinet, and B. Put down the food. First, let's break it down and analyze the sequence of actions in the video. The person is seen interacting with various objects in the kitchen, and there's a clear timeline of events. Wait, I need to focus on the initial action. The person was initially standing near the refrigerator, and then they moved towards the counter. They picked up a bottle and a jar, and then they started to prepare something. Hmm, it seems like the person first interacted with the refrigerator, <...>. However, the question is specifically about <...>. Oh, I see. The person first interacted with the refrigerator, and then they moved towards the counter. They didn't close the closet/cabinet immediately after entering the kitchen. They were more focused on the refrigerator and the counter. <...>. Therefore, the first action was related to the refrigerator. So, the person first interacted with the refrigerator, which implies they put down the food after taking something out or putting something in the refrigerator. Therefore, the correct answer is B. ✗

Video-VER-7B: Let me think about this for a moment. The person in the video is seen interacting with various objects in a kitchen setting. First, they appear to be reaching into a cabinet or closet, which suggests they are retrieving something. Then, they seem to be handling a bottle, possibly pouring its contents into a container. After that, they are seen holding a piece of food, which they appear to be preparing or examining. The question asks what the person did first, and the options provided are A. Closed the closet/cabinet and B. Put down the food. To answer this, I need to carefully analyze the sequence of actions in the video. **First, the person reaches into a cabinet or closet, indicating they are retrieving something. Second, they then handle a bottle, which implies they are using it for some purpose.** Finally, they are seen holding a piece of food, which they seem to be preparing or examining. Given this sequence, the first action the person took was reaching into the cabinet or closet to retrieve something. This aligns with option A. Hmm, let's verify this. The person did not put down any food at the beginning; they were still in the process of retrieving it from the cabinet. **This confirms that the correct answer is A.** ✓



Question: Does the video show a complete motorcycle? A. yes B. no

Owen2.5-VL-7B: Let me think about this. The image shows a motorcycle, but it appears to be a close-up shot, focusing on the front part of the bike. The front wheel, headlight, and part of the body are visible, but the rear wheel and other parts of the motorcycle are not shown. This suggests that the video might not show a complete motorcycle. The answer is B. ✗

Video-R1-7B: Let me think about this for a moment. The question is asking <...>. Now, let's break it down. The video seems to focus on a motorcycle, but it's important to consider what exactly is shown. First, the video shows a motorcycle in a garage, and it's illuminated by a bright light. The motorcycle is clearly visible, and it appears to be a scooter, given its design and features. The lighting highlights the details of the motorcycle, such as the headlights, the bodywork, and the wheels. However, the question is <...>. A complete motorcycle would typically include all parts and features that make it a fully functional vehicle. In this video, the motorcycle is shown in a static position, and while it is detailed and well-lit, it doesn't seem to be in a state that suggests it is ready for use or has all its parts assembled. Wait, let's consider the context. The video is likely a promotional or showcase video for the motorcycle. Such videos often focus on the design and features of the motorcycle rather than showing it in a complete state. The absence of any indication of the motorcycle being ready for use or having all parts assembled suggests that it is not a complete motorcycle. <...> Final answer: B. ✗

Video-VER-7B: Let me think about this. The video showcases a sleek, modern motorcycle prominently displayed in a dimly lit garage. The motorcycle is brightly illuminated by a spotlight, highlighting its vibrant orange and black color scheme and intricate design features. Let's break down the question and the video content carefully. The question asks if the video shows a complete motorcycle. To answer this, we need to consider <...>. First, the video starts with a close-up of the motorcycle, focusing on its headlight and front design. The camera then pans around the motorcycle, showing different angles and details. This suggests that the video is indeed showing the motorcycle from various perspectives, which is a common practice when showcasing a complete vehicle. Next, the video includes a wider shot of the motorcycle in the garage, **which further emphasizes the full view of the motorcycle.** The garage setting and the presence of boxes in the background do not detract from the completeness of the motorcycle; they simply provide context for the setting. The video does not cut away to any other objects or scenes that would suggest a partial view of the motorcycle. Instead, it maintains a focus on the motorcycle throughout, highlighting its design and features in a comprehensive manner. **Given this analysis, it is clear that the video does show a complete motorcycle. Answer is A.** ✓



Question: How many times did the person launch objects on the table? A. 2 B. 3 C. 5 D. 4

Owen2.5-VL-7B: Let me think about this. The person is seen launching objects on the table in the video. I can see that they have launched the object twice. The first time, they launch it and it bounces off the table. The second time, they launch it again and it bounces off the table as well. There are no other launches visible in the video. The answer is A. ✗

Video-R1-7B: Let me think about this carefully. The question is asking how many times the person launched objects on the table. To answer this, I need to recall the sequence of actions in the video. First, let's break it down: 1. The person launched an object, possibly a ball, onto the table. 2. The person then launched another object, possibly a different ball or a similar object, onto the table. Now, let's count the launches: - The first launch was clearly visible. - The second launch was also clearly visible. Hmm, it seems like there were two distinct launches. <...> Oh, I see. The person launched objects two times. The question is asking for <...>. Let's break it down one more time to be sure. **The person launched an object, then launched another object. That's two launches.** After this reflection, I am confident that the correct answer is two. Let's check the options: A. 2 B. 3 C. 5 D. 4 The correct answer is A. ✗

Video-VER-7B: Let me think. The video shows a person interacting with objects on a wooden table. The person uses their hands to launch small objects across the table. The person launches the objects multiple times, and the objects roll across the table in different directions. The video captures the motion and trajectory of the objects as they are launched. Let's break down the sequence of events in the video to determine the number of times the person launched objects on the table. 1. The person first places a small object on the table and then uses their hand to launch it. This is the first launch. 2. The person then places another small object on the table and launches it. This is the second launch. 3. The person places a third small object on the table and launches it. This is the third launch. **After reviewing the video, it is clear that the person launched objects three times.** The person did not launch any objects more than three times, and there were no additional launches beyond these three. Now, let's consider the options: A. 2 - This is incorrect because the person launched objects more than twice. B. 3 - This is correct because the person launched objects three times. C. 5 - This is incorrect because the person did not launch objects five times. D. 4 - This is incorrect because the person did not launch objects four times. **The correct answer is B, as the person launched objects three times.** ✓

Figure 12: Comparison of reasoning traces from baseline models and our Video-VER model reveals that baselines often introduce speculative or hallucinated details not grounded in the video. In contrast, Video-VER consistently maintains alignment between reasoning steps and evidence. Text highlighted in red indicates incorrect reasoning steps, while text highlighted in green marks the key logical steps that lead to the correct answer.



Question: How many buttons did you see the person successfully buttoning up and correctly aligning the buttons with the holes? A. 2 B. 3 C. 5 D. 4

Owen2.5-VL-7B: Let me think about this. The person is seen buttoning up a shirt, and it appears that they are successfully aligning the buttons with the holes. However, the video only shows a few moments of the buttoning process. It's not clear how many buttons were actually buttoned up and correctly aligned. The options provided are 2, 3, 5, and 4. Without seeing the entire process, it's difficult to determine the exact number. Hmm, the video only shows a few moments, so it's hard to be certain. Let's break it down: if we see 2 buttons being buttoned up, that would be option A. If we see 3, that would be B. If we see 4, that would be D. Option C, 5, seems unlikely based on the limited footage. Answer is A. ✗

Video-R1-7B: Let me think about this carefully. The question is asking about the number of buttons the person successfully buttoned up and correctly aligned with the holes. I need to recall the details of the video and count the buttons. First, let's break it down. The person was seen buttoning up a shirt, and I need to count the buttons that were successfully aligned. From the video, I remember the person buttoning up the shirt in a specific sequence. Wait, let me verify. The person started from the bottom and worked their way up. I counted the buttons one by one. The first button was successfully aligned, the second button was also aligned, and the third button was aligned as well. Hmm, I need to double-check. The fourth button was also aligned, and the fifth button was aligned too. Oh, I see, the person successfully buttoned up five buttons in total. <...>. That's five buttons in total. After this reflection, I am confident that the person successfully buttoned up five buttons. The correct answer should be the option that corresponds to five buttons. Let's verify one last time. The person did not button up any buttons incorrectly, and all five buttons were aligned correctly. Therefore, the answer is C. ✗

Video-VER-7B: Let me think. The video shows a person seated at a table, wearing a maroon blouse with a V-neckline. The person is seen buttoning up the blouse, carefully aligning each button with its corresponding hole. The process is methodical, with the person using both hands to ensure the buttons are properly aligned and secured. The background includes a curtain and a plastic bag on the table, adding context to the setting. The person successfully buttons up the blouse, completing the task with precision. Let's break down the video step by step to determine the number of buttons the person successfully buttoned up and correctly aligned with the holes. 1. The person starts by holding the blouse open, revealing the buttons. 2. The person then begins to button up the blouse, one button at a time. 3. The person carefully aligns each button with its corresponding hole and presses it down. 4. The person continues this process until the blouse is fully buttoned up. From the video, it appears that the person successfully buttoned up the blouse, and the number of buttons visible in the video is 4. The person aligned each button correctly with its hole and pressed it down, ensuring that the blouse was fully buttoned up. After careful consideration, the correct answer is D. ✓



Question: Which description is a more suitable match for the video? A. The woman closest to the camera is moving at the fastest speed. B. The woman closest to the camera is moving at the slowest speed.

Owen2.5-VL-7B: The video shows a group of women running on a track. The woman closest to the camera appears to be running at a steady pace, but there's no indication that she is moving at the fastest speed. The other women in the group are also running at a similar pace, and there's no clear evidence that the woman closest to the camera is moving at the slowest speed. Therefore, the most suitable match for the video would be option B. ✗

Video-R1-7B: Let me think about this for a moment. The question is asking <...>. First, let's break it down and consider the visual cues in the video. The woman closest to the camera appears to be running at a consistent pace, but there's no clear indication that she is moving at the fastest speed. In fact, the other runners seem to be maintaining a similar speed, and there's no evidence that the woman closest to the camera is lagging behind or speeding up. Now, let's consider the second option, <...>. Hmm, it seems that the woman closest to the camera is not moving at the fastest speed; she is moving at a similar pace to the other runners, which aligns with the second option. Final answer: B ✗

Video-VER-7B: Let me think about this. The video showcases a group of female athletes participating in a track and field event, specifically a hurdles race. The runners are seen in various stages of their stride, with their bodies leaning forward and their arms swinging rhythmically. <...> The runners are moving at a consistent pace, with some slightly ahead of others, suggesting a competitive race. The question asks <...>. First, let's consider the spatial details. The woman closest to the camera <...> appears to be slightly ahead of the others. <...> Next, let's consider the temporal details. The video captures the runners in various stages of their stride, and the woman closest to the camera is not lagging behind <...> is maintaining a steady pace, which is typical for a competitive race <...>. Therefore, the more suitable match for the video is that the woman closest to the camera is moving at a faster speed. Final answer: A ✓



Question: Is the person in the video holding metal wires? A. yes. B. no.

Owen2.5-VL-7B: Let me think about this. The video shows a person's hands working with a tool, and there are sparks flying, which suggests some kind of metalworking activity. However, the video does not clearly show <...>. The hands are manipulating something, but it's not explicitly <...>. The person is also seen handling a metal container, which could be related to the activity but doesn't necessarily indicate <...>. The video does not provide clear evidence of the person holding metal wires. The activity seems to involve metalworking, but the specific object being manipulated is not identified as metal wires. ✗

Video-R1-7B: Let me think about this for a moment. The question is asking <...>. To answer this, I need to carefully analyze the visual information provided in the video. First, let's break it down. The video shows a person working with some kind of tool, and there are sparks flying around. This suggests that the person is likely using a tool that involves cutting or grinding metal. The person is also seen holding a cylindrical object, which appears to be a metal container or a part of the tool. Now, let's consider the wires. The wires mentioned in the question are not explicitly shown in the video. The person is not holding any wires that are clearly visible. The focus is on the tool and the sparks, which are indicative of metalworking. Hmm, it seems that the person is not holding metal wires. The wires are not a prominent feature in the video, and the person is not manipulating any wires. The person is working with a tool that involves metal, but the wires are not the focus of the video. <...>, I am confident that the person is not holding metal wires. <...> Final answer: B ✗

Video-VER-7B: Let me think. <...> The video clearly shows a person working with wires, and the question asks if the person <...>. The person is indeed handling wires, and the wires appear to be metallic based on their sheen and the way they are being manipulated. The person's hands are carefully gripping the wires, and there is no indication that the wires are not metallic. The workshop setting further supports the idea <...>. Now, let's consider the options. Option A suggests that the person is holding metal wires, which aligns with the visual evidence in the video. Option B suggests that the person is not holding metal wires, which contradicts the visual evidence. The person's actions and the environment strongly support the idea that the wires are metallic. <...> Given the detailed analysis of the video and the question, the answer is A. ✓

Figure 13: Comparison of reasoning traces from baseline models and our Video-VER model reveals that baselines often introduce speculative or hallucinated details not grounded in the video. In contrast, Video-VER consistently maintains alignment between reasoning steps and evidence. Text highlighted in red indicates incorrect reasoning steps, while text highlighted in green marks the key logical steps that lead to the correct answer.



Question: How many chair(s) are in this room? **Solution:** 9

Qwen2.5-VL-7B: Let me think through this carefully. The room has a dining table with chairs around it. There are two chairs visible in the dining area. Additionally, there is a single chair in the living area, which is not part of the dining table. To conclude, the dining area has two chairs, and the living area has one chair. Adding these together gives us a total of 3 chairs in the room. ✗

Video-R1-7B: Let me think about this carefully. The question is asking about the number of chairs in the room. Now, I need to recall the details of the room from the video. First, I'll break down the room's layout. There's a dining table with chairs around it, and I can see a couple of chairs near the table. Then, there's a couch with a couple of cushions, and I don't see any chairs there. Wait, let's focus on the dining area. There's a table with a white tablecloth, and around it, there are chairs. I can clearly see four chairs around the table. Hmm, I need to double-check if there are any other chairs in the room. I don't see any other chairs in the living area or the kitchen area. The room is quite spacious, and I've gone through all the visible areas, and I'm confident there are no other chairs. Oh, I see. The room has four chairs around the dining table. There are no other chairs in the room. Let's break it down one more time to be sure. **The dining area has four chairs, and the rest of the room doesn't have any additional chairs. After this thorough analysis, I'm confident that the room has exactly 4 chairs.** Let me verify one last time. The dining table has four chairs, and there are no other chairs in the room. Yes, that's correct. So, the number of chairs in the room is four. ✗

Video-VER-7B: Let me think. The video showcases a cozy, multi-purpose room with a warm and inviting atmosphere. The room features a dining area with a wooden table and chairs, a comfortable sofa adorned with cushions, and a small table with books and decorative items. The walls are painted in a soft beige color, complemented by wooden beams and a skylight that allows natural light to flood the space. The room also includes a staircase leading to an upper level, adding to its charm. The overall ambiance is warm and welcoming, making it an ideal space for relaxation and socializing. Let's break down the video content to identify the number of chairs present in the room. The video starts with a view of the dining area, where a wooden table is set with plates and utensils. There are chairs around the table, but the exact number isn't immediately clear. As the camera pans around the room, it reveals more details. The dining area is adjacent to a living area with a sofa and a small table. The camera then moves to the staircase, which leads to an upper level. The staircase area has a few chairs placed near it, possibly for resting or reading. The camera continues to pan, showing the entire room, and it becomes evident that there are a total of 4 chairs in the room. The chairs are distributed around the dining table and near the staircase. Now, let's verify the count. **The dining table has 4 chairs, and there are 2 additional chairs near the staircase. This brings the total to 6 chairs.** ✗

Figure 14: A common failure case in which both the baseline models and our method produce incorrect reasoning traces due to missing visual context, caused by incomplete frame sampling.

F Failure Case

We illustrate a common failure case where both the baseline models and our Video-VER model generate incorrect reasoning traces. This occurs due to incomplete frame sampling, which omits critical visual context from the video tokens needed to answer the question accurately. See Figure 14.

G Limitations

Our Visual Evidence Reward framework and Video-VER model advance grounded video reasoning. As with any research, there are aspects that provide context for our findings and suggest avenues for future exploration.

First, the performance of video reasoning systems, including Video-VER, is closely tied to the nature of the input video and how it is processed. Our current investigations primarily focus on videos of moderate length. This focus considers the current ability of many state-of-the-art vision encoders to effectively process very long video sequences, and the common MLLM design where the language model reasons using visual tokens that are expected to contain all necessary information for the task. As a result, extending robust, fine-grained reasoning to scenarios with very long videos—especially those containing sparse critical information or complex temporal patterns—remains an important direction for future work, which will benefit from advances in long-sequence video encoding. Furthermore, the quality of the visual representation itself significantly influences performance, irrespective of video length. As highlighted in our failure case analysis (Figure 14), if essential visual details are missed, for instance, due to frame sampling choices or limitations in feature extraction, the reasoning process can be compromised. Our Visual Evidence Reward method ensures that reasoning is firmly based on the *available* visual data, and its effectiveness is therefore complemented by ongoing improvements in dynamic frame selection and visual feature extraction techniques.

Second, the LLM-based reward signal generation is a key component of our approach. We utilize Llama-3.1-70B-Instruct with robust prompting strategies and temperature-0 decoding to ensure reliable visual grounding assessment. The quality of the reward signal is inherently connected to the chosen LLM's capabilities. As with similar LLM-based evaluation paradigms in the field, ongoing research into optimizing these judge models and exploring alternative evaluation mechanisms will further enhance the precision and scalability of such reward mechanisms.

Third, regarding the generation of visual evidence for training, our approach employs a powerful external MLLM (Qwen2.5-VL-72B) in an offline manner. Our inventive inverted prompting strategy and binary reward design are specifically configured to maximize the relevance of this evidence and ensure robustness against potential imperfections from the teacher model. While this bootstrapping method proves effective for our training purposes, continued advancements in the capabilities of MLLMs to generate high-fidelity, nuanced visual descriptions will naturally offer opportunities to refine the training data for such reward mechanisms even further.

We view this work as a significant step towards overcoming visual thinking drift and achieving more robust, visually grounded video intelligence. Future directions include extending our Visual Evidence Reward framework to effectively process long-form videos (potentially incorporating advanced visual information aggregation techniques) and exploring its integration with even more complex multi-step reasoning tasks that demand deeply verifiable and contextually rich thought processes.

H Societal Impact

The advancements in video reasoning presented in this paper, particularly the Visual Evidence Reward framework designed to mitigate *Visual Thinking Drift* and enhance the grounding capabilities of models like Video-VER, offer significant societal potential, encompassing both promising benefits and important ethical considerations. On one hand, more accurate, reliable, and interpretable video understanding systems can yield substantial advantages across diverse domains, including improved accessibility for individuals with visual impairments through richer descriptions of visual media, enhanced educational tools that can better analyze instructional content, and more dependable automated content analysis due to a reduction in model-generated hallucinations.