

Video-R2: Reinforcing Consistent and Grounded Reasoning in Multimodal Language Models

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<https://github.com/mbzuai-oryx/Video-R2>

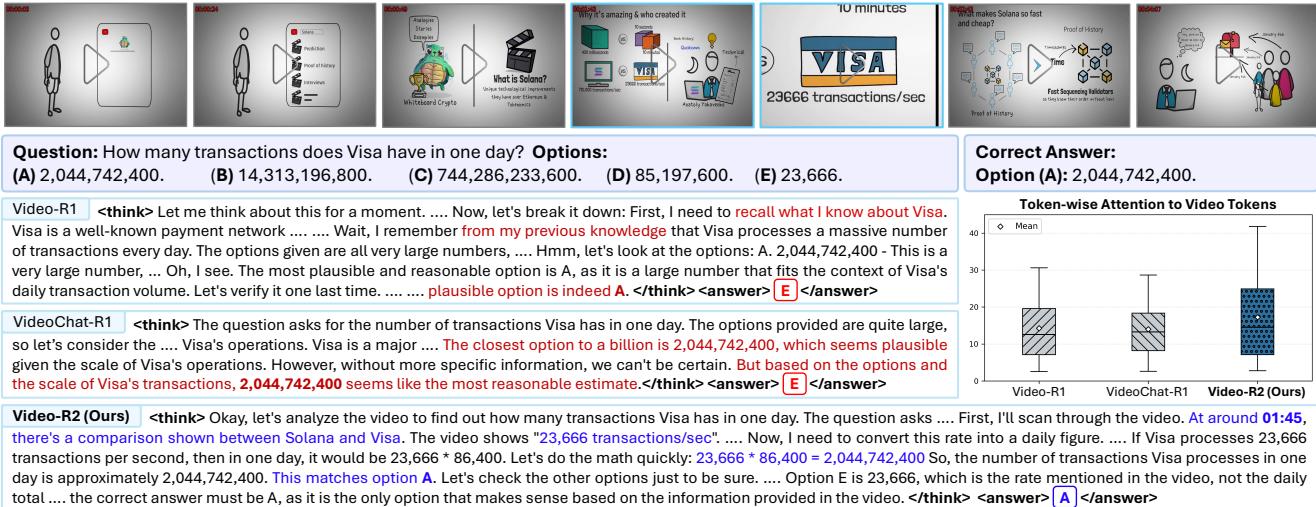


Figure 1. Inconsistent reasoning in prior video-LLMs and improved visual reliance with Video-R2. Given the video and the question, “How many transactions does Visa have in one day?”, both **Video-R1** [35] and **VideoChat-R1** [64] conclude option A during their reasoning but finally predict option E as answer, revealing inconsistent reasoning behavior where the model’s conclusion and final answer mismatch. This behaviour emerges because these models primarily rely on textual context and world knowledge, attending little to the video itself. In contrast, our **Video-R2** correctly identifies the on-screen visual cue at 01:45 (“23,666 transactions/sec”), performs temporal conversion, and arrives at the correct daily value. The box plot on the right shows the average attention from generated tokens to video tokens across all attention heads in the final transformer layer. Compared with baselines, **Video-R2** allocates higher and more distributed attention to video tokens, indicating stronger and more adaptive *visual reliance*. While prior models can produce plausible yet inconsistent reasoning, **Video-R2** reasons coherently and depends on actual video evidence. (Additional examples in Appendix C, D).

Abstract

Reasoning over dynamic visual content remains a central challenge for multimodal large language models. Recent thinking models generate explicit reasoning traces for interpretability; however, their reasoning often ‘appears’ convincing while being logically inconsistent or weakly grounded in visual evidence. We identify and formalize these issues through two diagnostic metrics: Think–Answer Consistency (TAC), which measures the alignment between reasoning and answers, and Video Attention Score (VAS), which captures the extent to which reasoning depends on visual versus textual cues. Analysis across 11 video reasoning benchmarks shows that current models rely heavily on lin-

guistic priors rather than visual content. To address this, we propose a reinforcement learning approach that enhances both temporal precision and reasoning consistency. Our approach combines timestamp-aware supervised fine-tuning with Group Relative Policy Optimization (GRPO) guided by a novel Temporal Alignment Reward (TAR). This dual-step post-training stage encourages temporally aligned and causally coherent video reasoning. The resulting model, **Video-R2**, achieves consistently higher TAC, VAS, and accuracy across multiple benchmarks, demonstrating that improvements in temporal alignment and reasoning coherence lead to more accurate and trustworthy video understanding.

1. Introduction

Recent progress in multimodal large language models (MLLMs) has advanced visual understanding [21, 23, 30, 60, 70, 71, 80, 81, 89, 141, 149]. However, reasoning over dynamic visual content remains a persistent challenge. Unlike static image tasks such as captioning or visual question answering, video reasoning requires the ability to infer temporal and causal relationships across sequences of frames [13, 16, 34, 40, 41, 45, 79, 102, 105, 138, 143, 147]. This demands not only frame-level recognition but also reasoning about how fine-grained visual elements (objects, actions, events) evolve and interact over time.

Recent *thinking* models such as Video-R1 [35], VideoChat-R1/1.5 [64, 127], and VideoRFT [114] address this challenge by generating explicit reasoning traces using <think> and <answer> formats. These traces aim to make the reasoning process transparent and interpretable. However, our analysis reveals a concerning trend: *the reasoning often sounds coherent but fails to correspond either to the final answer or to the actual visual evidence in the video*. This observation motivates a deeper look at how current SoTA models reason about videos and where they fail.

We begin by diagnosing two key issues that limit existing thinking models. *a) Inconsistency between reasoning and answers.* As shown in Fig. 1, the model may conclude one option in its reasoning but outputs a different answer, indicating poor internal alignment. We formalize this as **Think–Answer Consistency (TAC)** metric that measures whether the model’s reasoning logically supports its final answer. *b) Weak reliance on visual evidence.* Although the reasoning text often references the video, closer inspection shows minimal use of concrete visual details e.g., specific objects, actions, or timestamps. Attention analysis (Fig. 1, right) confirms that the current models overwhelmingly attend to text tokens, assigning minimal attention weights to visual tokens. To quantify this imbalance, we introduce the **Video Attention Score (VAS)**, which captures how strongly a model’s reasoning is grounded in visual evidence rather than linguistic priors. Fig. 1 illustrates both issues. Although current models often seem to reason from visual content, their reasoning remains largely text-driven rather than visually grounded. This shows that answer accuracy alone is insufficient to assess reasoning quality, motivating TAC and VAS as complementary diagnostic metrics.

To address these limitations, we propose a reinforcement learning framework that strengthens both temporal precision and reasoning consistency. Our method begins with supervised fine-tuning to teach the model timestamp-aware thinking, enabling it to generate intermediate reasoning steps linked to the video timeline. We then apply Group Relative Policy Optimization (GRPO) [100] using a new **Temporal Alignment Reward (TAR)** that encourages accurate temporal reasoning. TAR evaluates the alignment

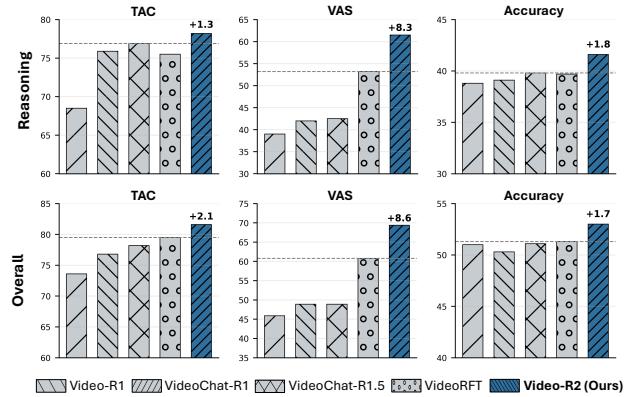


Figure 2. **Comparison of Video-R2** with recent video reasoning models, Video-R1 [35], VideoChat-R1/1.5 [64, 127], and VideoRFT [114], across three metrics: **TAC** (Think–Answer Consistency), **VAS** (Video Attention Score), and **Accuracy**. The upper row reports average scores over six reasoning benchmarks, VideoMathQA [97], Video-MMMU [44], MMVU [146], VSI-Bench [130], MINERVA [84], and SciVideoBench [31], while the lower row shows averages over all 11 benchmarks including the five generic ones, MVBench [62], VideoMME [36], TempCompass [75], MLUV [148], and LongVideoBench [122]. Video-R2 performs better across both reasoning and overall evaluations, achieving higher consistency (TAC) and video-focused reasoning (VAS) while maintaining competitive accuracy (Details in Sec. 4).

between predicted and reference timestamps and is applied only when the reasoning and the final answer are consistent. This combination allows the model to learn coherent and temporally accurate reasoning traces. We refer to the resulting model as **Video-R2**, the next step in the video reasoning family [28, 35, 64, 79, 114, 127].

Our approach enhances the capabilities of Video-R1 by improving temporal alignment and reasoning consistency, resulting in higher overall accuracy. As shown in Fig. 2, Video-R2 achieves consistent improvements across multiple video reasoning and non-reasoning benchmarks under a unified experimental setup. All methods are tested using the same number of frames, resolution, and input formatting across 11 established video understanding and reasoning benchmarks [31, 36, 44, 62, 75, 84, 97, 122, 130, 146, 148], along with our proposed TAC and VAS metrics. These results demonstrate that reinforcing temporal alignment and logical coherence leads to more reliable and grounded video reasoning without sacrificing performance.

Our main contributions are summarized as follows.

- We introduce two diagnostic metrics for video reasoning: **Think–Answer Consistency (TAC)** and **Video Attention Score (VAS)**, which measure logical coherence and perceptual focus in model reasoning. (Sec. 2)
- We propose a reinforcement learning framework with a new **Temporal Alignment Reward (TAR)** that promotes temporally precise and self-consistent reasoning. (Sec. 3)
- We curate a **timestamp-aligned reasoning dataset** by

filtering high-difficulty samples using an automated pipeline, followed by manual verification. This dataset provides the foundation for temporal alignment and reasoning supervision. (Sec. 4.1)

- We conduct a comprehensive comparison with existing video reasoning and non-reasoning models under a unified evaluation protocol, showing consistent gains in TAC, VAS and accuracy across multiple video understanding and reasoning benchmarks. (Sec. 4.3)

2. Reasoning Quality Metrics

Existing video understanding benchmarks primarily measure answer accuracy, which alone does not reflect how a model reaches its predictions [22, 31, 36, 44, 55, 62, 75, 82, 84, 87, 97, 117, 122, 124, 130, 146, 148]. As shown in Fig. 1, a model can produce the correct answer while its reasoning remains inconsistent or unrelated to the video. Such cases reduce interpretability and raise questions about the model’s actual reasoning ability. To assess reasoning quality more comprehensively, we introduce two complementary metrics: **Think–Answer Consistency (TAC)** and the **Video Attention Score (VAS)**. These metrics quantify distinct aspects of reasoning quality, namely logical coherence and visual dependence, providing a more comprehensive understanding of model behavior.

Think–Answer Consistency (TAC). TAC measures the logical alignment between the model’s reasoning and its final answer. A reasoning model usually responds in the format `<think> reasoning </think> <answer> final answer </answer>`. In many cases, the conclusion drawn in the reasoning section contradicts the final answer, suggesting that the model’s reasoning is disconnected from its actual decision. A high TAC value indicates coherent reasoning, where the model concludes the same output in both reasoning and answer, while a low TAC reflects reasoning inconsistencies that limit interpretability. We compute TAC only for the subset containing correctly answered samples, since consistency of incorrect answers can convey a false sense of better performance. For a model M and dataset D :

$$\text{TAC}(M, D) = \frac{1}{|D_{\text{correct}}|} \sum_{i \in D_{\text{correct}}} \mathbb{I}[\hat{a}_i^{\text{think}} = \hat{a}_i^{\text{answer}}], \quad (1)$$

where D_{correct} represents samples for which the model’s predicted final answer matches the ground truth. \hat{a}_i^{think} is the answer concluded in the reasoning trace (`<think>...</think>`), and $\hat{a}_i^{\text{answer}}$ is the explicit final answer of the model (`<answer>...</answer>`). The operator $\mathbb{I}[\cdot]$ is an indicator function that equals 1 when the condition inside the brackets holds true and 0 otherwise. $\text{TAC} \in [0, 1]$ thus represents the fraction of correct samples where the reasoning and final answer are consistent. The value of $(1 - \text{TAC})$ indicates the proportion of “uninterpretable correctness,” where the model outputs the right answer for unclear or contradictory reasons.

Video Attention Score (VAS). While TAC measures logical coherence, it does not capture whether the reasoning relies on the visual cues in the video. The **Video Attention Score (VAS)** quantifies how much the reasoning *claims* to rely on visual information rather than on textual patterns or prior knowledge. We employ an *LLM-as-a-Judge* framework, where a language model evaluates the reasoning trace based on predefined guidelines and assigns a visual-reliance score between 0 and 10, later normalized to the range $[0, 1]$. The LLM-judge considers cues such as explicit mentions of visual entities, spatial or temporal relations, and causal statements linked to observed actions. The complete judging prompt is provided in the Appendix D. Importantly, the *token-wise attention distributions* shown in Fig. 1 serve only as a visualization of the internal model behavior and are not used to compute VAS. VAS is independent of attention weights and provides a complementary, text-based proxy for visual reasoning. We can represent it as:

$$\text{VAS}(M, D) = \frac{1}{|D|} \sum_{i=1}^{|D|} s_i, \quad (2)$$

where $s_i \in [0, 1]$ is the normalized LLM-judge score assigned to the reasoning trace of sample i . Although VAS evaluates *claimed* rather than verified reliance on video evidence, it complements accuracy and TAC by quantifying how visually grounded a model’s reasoning appears.

Complementarity. TAC and VAS together form a two-axis evaluation of reasoning quality. TAC reflects the model’s internal logical coherence, while VAS captures its degree of visual focus. Both metrics correlate with intuitive model behavior and qualitative observations, revealing how well a model reasons rather than merely predicts. In the following section, we use these insights to design a reinforcement learning framework that directly promotes consistent and temporally aligned reasoning through the proposed Temporal Alignment Reward (TAR) with consistency gating.

3. RL with Temporal Alignment Reward

The reasoning quality metrics, TAC and VAS, reveal that models often produce reasoning traces that are only weakly grounded in video content or logically inconsistent with their final answers. To explicitly encourage temporally precise and consistent reasoning, we follow a two-stage post-training setup consisting of *supervised fine-tuning (SFT)* followed by *reinforcement learning (RL)* using GRPO [100]. Within the RL stage, we introduce a novel reinforcement signal called the **Temporal Alignment Reward (TAR)**, designed to promote reasoning traces where predicted timestamps are both temporally and semantically aligned with the reference reasoning while remaining logically consistent. The formulation of TAR is shown in Fig. 3.



Question: How many times does the person perform a cartwheel while holding the jump rope? **Options:** A. Three times, B. Four times, C. Once, D. Twice

Reference Reasoning

<think> Okay, I need to count how many times the person in the video does a cartwheel At around the **16-second mark**, she plants her hands on the floor and kicks her legs over, just like a cartwheel. Around **00:25**, she performs the exact same move, a cartwheel, this time **with her back to the camera** So, I counted a total of two The first one was at **00:16** and the second one was at **00:25**. This matches **option D.** </think> <answer> D. Twice </answer>

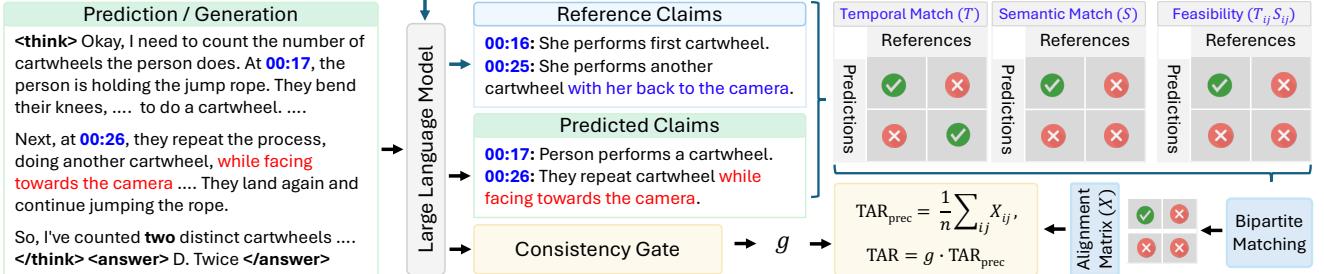


Figure 3. **Temporal Alignment Reward (TAR).** The figure illustrates how the proposed TAR is computed for a video reasoning example. We have a *reference reasoning* containing grounded timestamps and a *predicted reasoning* generated by our model. Both are processed by an LLM that extracts timestamp-sentence pairs, referred to as *claims*. The **Temporal Match** matrix (T) checks if a predicted timestamp lies within a temporal tolerance Δ of a reference timestamp (True if $|t_i^{\text{pred}} - t_j^{\text{ref}}| \leq \Delta$, otherwise False). The **Semantic Match** matrix (S) compares sentence similarities using embeddings; a True/tick indicates that the cosine similarity exceeds a threshold τ . A one-to-one bipartite matching is then applied over pairs satisfying both conditions to obtain the binary alignment matrix X , ensuring that each predicted claim aligns with at most one reference claim. The precision-based temporal alignment reward is computed as $\text{TAR}_{\text{prec}} = \frac{1}{n} \sum_{i,j} X_{ij}$. This score represents the fraction of predicted timestamps that are temporally and semantically valid. Finally, TAR is gated by the consistency indicator g that verifies if the reasoning and answer are coherent, yielding $\text{TAR} = g \cdot \text{TAR}_{\text{prec}}$. Rows correspond to predictions and columns to references. The example demonstrates how correct temporal matches contribute to higher rewards under logical consistency.

Claim extraction. For both the reference and predicted reasoning traces, we first extract timestamped *claims*. Each claim consists of a timestamp t and a short sentence u describing the observed visual event at that time. We denote the sets of reference and predicted claims as:

$$\mathcal{R} = \{(t_j^{\text{ref}}, u_j^{\text{ref}})\}_{j=1}^m, \quad \mathcal{P} = \{(t_i^{\text{pred}}, u_i^{\text{pred}})\}_{i=1}^n. \quad (3)$$

Where m and n are the number of reference and predicted claims respectively. These claims are automatically obtained using an LLM that identifies temporal mentions and associated descriptions within the reasoning text. We refer to the annotated reasoning as *reference reasoning* rather than ground truth, since it may not be fully exhaustive.

Temporal and semantic matching. To measure how well each predicted claim corresponds to the reference reasoning, we define two binary matrices that capture temporal and semantic agreement. The *temporal match matrix* $T \in \{0, 1\}^{n \times m}$ is defined as:

$$T_{ij} = \begin{cases} 1, & \text{if } |t_i^{\text{pred}} - t_j^{\text{ref}}| \leq \Delta, \\ 0, & \text{otherwise,} \end{cases} \quad (4)$$

where Δ is the temporal tolerance. The *semantic match matrix* $S \in \{0, 1\}^{n \times m}$ is given by:

$$S_{ij} = \begin{cases} 1, & \text{if } \text{sim}(e(u_i^{\text{pred}}), e(u_j^{\text{ref}})) \geq \tau, \\ 0, & \text{otherwise,} \end{cases} \quad (5)$$

where $e(\cdot)$ denotes the sentence embedding function and $\text{sim}(\cdot, \cdot)$ denotes the cosine similarity. The parameters Δ and τ represent the temporal and semantic thresholds, respectively, selected empirically (details in Appendix E, I). A valid match must satisfy both conditions.

One-to-one assignment. After computing the temporal and semantic matches between predicted and reference claims, we enforce a one-to-one alignment to establish correspondence between reasoning events. We formulate a bipartite matching problem that maximizes valid alignments while satisfying both temporal and semantic match constraints:

$$\max_{X \in \{0, 1\}^{n \times m}} \sum_{i,j} X_{ij}, \quad (6)$$

$$\text{s.t. } X_{ij} \leq T_{ij}S_{ij}, \quad \sum_j X_{ij} \leq 1, \quad \sum_i X_{ij} \leq 1, \quad (7)$$

where T_{ij} indicates whether the i -th predicted timestamp lies within the temporal tolerance Δ of the j -th reference timestamp, and $S_{ij} = \mathbb{I}\{\text{sim}(e(u_i^{\text{pred}}), e(u_j^{\text{ref}})) \geq \tau\}$ denotes semantic similarity above a threshold τ . Among all feasible pairs, we perform a greedy one-to-one matching that selects, for each predicted claim, the most similar unused reference claim above the threshold. The resulting binary matrix X represents the final alignment and ensures that duplicate predictions referring to the same reference event are counted only once when computing the reward.

Precision-based temporal alignment. Given the alignment matrix X , the precision-based alignment score is defined as:

$$\text{TAR}_{\text{prec}} = \frac{1}{n} \sum_{ij} X_{ij}, \quad (8)$$

where $X_{ij} = 1$ if the i -th predicted claim is both temporally and semantically matched to the j -th reference claim, and 0 otherwise. This score measures the fraction of predicted timestamps that are temporally and semantically supported by the reference reasoning. We adopt a precision-based formulation because with a sparse reference, recall is an unreliable signal that fails to penalize overgeneration. Precision instead provides a stable learning signal by rewarding only verifiable predictions and prioritizing strong support over exhaustive coverage. This precision score serves as the base component of TAR before applying the consistency gate.

Consistency gating. To ensure that temporal precision is only rewarded when reasoning is logically coherent, we apply a consistency gate. Let $g = \mathbb{I}[\text{TAC} = 1]$ denote the sample-level consistency indicator, where $\mathbb{I}[\cdot]$ is the indicator function that equals 1 if the conclusion from the model’s reasoning matches its predicted final answer (i.e., the sample is consistent) and 0 otherwise. The gated temporal alignment reward is then computed as:

$$\text{TAR} = g \cdot \text{TAR}_{\text{prec}}. \quad (9)$$

Total reward formulation. The total GRPO reward combines the accuracy, format, and the proposed consistency-gated temporal alignment reward. The final formulation is:

$$R_{\text{total}} = \lambda_{\text{acc}} R_{\text{acc}} + \lambda_{\text{fmt}} R_{\text{fmt}} + \lambda_{\text{tar}} \text{TAR}, \quad (10)$$

where R_{acc} equals 1 if the final answer is correct, R_{fmt} equals 1 if the model output follows the required `<think>` and `<answer>` structure, and the λ terms are weighting coefficients. This combined objective encourages the model to produce correct, well-structured, and temporally consistent reasoning traces. (Appendix B for implementation details).

Summary. In summary, the Temporal Alignment Reward measures how well the timestamps in the model’s reasoning align with reference reasoning, while the consistency gate ensures that improvements in timestamp precision contribute to coherent reasoning. Together with accuracy and format rewards, TAR provides a balanced reinforcement signal that enhances temporal precision, logical consistency, and visual focus in video reasoning.

4. Experiments

This section presents our dataset, implementation details, and quantitative evaluation of **Video-R2**. We describe how the data is collected, filtered, and refined to train timestamp-aware reasoning, followed by implementation and train-

ing specifics. Then, a comprehensive comparison is provided across 11 benchmarks, across generic and reasoning datasets, using TAC, VAS and answer accuracy metrics.

4.1. Dataset

Overview. The dataset used to train Video-R2 is designed to provide timestamp-aware reasoning supervision for both SFT and reinforcement learning. The data consists of video–question–answer triplets from multiple public sources, re-ranked and refined to emphasize reasoning-rich and temporally grounded examples. In total, the dataset contains 15,271 samples drawn from 11,816 unique videos.

Data collection. We collect video–question–answer pairs from five existing video QA datasets: **LLaVA-Video-178K** [145], **NeXtQA** [124], **ActivityNet-QA** [137], **PerceptionTest** [87], and **Clevrer** [134]. Together, these sources provide a diverse mixture of short to medium length videos covering everyday, causal, and temporal reasoning scenarios, resulting in approximately 200K QA pairs.

Difficulty ranking. To prioritize challenging examples that demand deeper temporal reasoning, we assign a difficulty score to each QA sample. Following the pipeline in Video-R1 [35], we first generate intermediate reasoning steps for each QA pair. An LLM then analyzes the reasoning trace associated with each question and estimates how difficult it is to derive the correct answer given the question’s context. Each sample receives a score between 0 and 10, where higher values indicate greater reasoning difficulty. The complete judging rubric and prompt are provided in the Appendix F.1. We observe that samples with higher difficulty scores often involve multi-step or temporally dependent reasoning, aligning with our goal of enhancing the model’s temporal reasoning ability. We select the 15K most difficult samples for training our model.

Reasoning regeneration and verification. We regenerate reasoning traces for all selected samples using Gemini-2.5-pro [25]. For each sample, the model receives both the question and the correct answer along with the video and is tasked with generating intermediate reasoning that explicitly references timestamps and describes relevant spatial and temporal details. Providing the correct answer reduces the likelihood of factual errors, but this setup may still produce occasional fabricated or misaligned reasoning. To ensure quality, we apply a two-stage filtering process: first, we automatically discard samples with inconsistent reasoning ($TAC = 0$), and second, we conduct human verification on a randomly selected subset of 500 samples. No factual errors or inconsistencies were found in this subset, confirming the overall reliability of the regenerated reasoning. While some minor imperfections may remain since full human verification is impractical at this scale, we observe the data to be of consistently high quality. Additional quality analysis and dataset examples are provided in the Appendix F.2, F.3.

Dataset statistics. The final dataset contains 15,271 QA pairs from 11,816 unique videos, with an average duration of 49 sec. Based on the difficulty ranking, we adopt a 70-30 split, using the top 30% most difficult samples for GRPO and the remaining 70% for SFT. This results in 10,467 samples (8,621 unique videos) for SFT and 4,804 samples (4,099 unique videos) for GRPO. Each reasoning trace averages about 450 tokens. (Appendix F.4 for more details).

4.2. Implementation Details

Video-R2 is built upon the non-reasoning Qwen2.5-VL-7B [8] MLLM and is trained following the standard reasoning-tuning pipeline comprising SFT and GRPO, consistent with prior video reasoning works [35, 64, 114, 127]. Please refer to Appendix B for training hyperparameters and additional implementation details.

Evaluation protocol. Previous reasoning models based on Qwen2.5-VL report results under varied configurations (e.g., Video-R1 [35] uses 16/32/64 frames, VideoRFT [114] uses 32 frames, and VideoChat-R1.5 [127] uses up to 2048 frames), making direct comparison of reported numbers difficult. To ensure fairness and reproducibility, we re-evaluate all reasoning models under a unified protocol using the lmms-eval [144] framework. Specifically, all models are tested with 2 FPS sampling, a maximum of 128 frames, and a per-frame maximum resolution of 360×420 px, using the official prompts provided in each paper. This standardized setup provides a balance between computation and visual coverage, enabling a fair and comprehensive comparison of reasoning ability and overall performance.

4.3. Results

We evaluate Video-R2 across 11 benchmarks, including five generic and six reasoning datasets, using three complementary metrics: Think–Answer Consistency (**TAC**), Video At-

tention Score (**VAS**), and final answer **Accuracy**.

Reasoning quality (TAC). Fig. 4 (left) shows TAC results across all benchmarks. Video-R2 ranks first on eight of the 11 benchmarks and achieves the highest overall TAC average, demonstrating logical alignment between the reasoning of the model and its final answers. Among recent reasoning models, VideoRFT [114] achieves the second-best TAC on average, which aligns with its use of semantic consistency reward that explicitly enforces alignment between the video description and SigLIP [140] visual embeddings. The gains of Video-R2 are attributed to the proposed temporal alignment reward (TAR), which encourages timestamp-accurate reasoning and filters temporally precise but logically inconsistent traces through consistency gating (ablation in Sec. 4.4). Overall, these results indicate that Video-R2 produces reasoning with stronger logical coherence between the `<think>` and `<answer>` content.

Reasoning quality (VAS). Fig. 4 (right) shows VAS results across all benchmarks. Video-R2 shows clear improvement over previously established reasoning models [35, 64, 114, 127], and ranks first across all 11 benchmarks. Compared with VideoRFT [114], which employs a semantic consistency reward, Video-R2 achieves an average VAS improvement of 8.6%, indicating that the proposed Temporal Alignment Reward (TAR) effectively enhances visual correspondence by reinforcing timestamp-referenced reasoning, leading to consistently higher VAS scores across benchmarks.

Benchmark accuracy. Tab. 1 presents results on 11 benchmarks and shows that Video-R2 achieves the best overall average in all three categories including generic, reasoning and combined. For generic benchmarks, Video-R2 reaches an average accuracy of 66.7, higher than the previous best of 65.6 from Video-R1 [35]. For reasoning-focused benchmarks, the gap is even clear, where Video-R2 achieves 41.6 compared to 39.8 from VideoChat-R1.5 [127] and 39.7

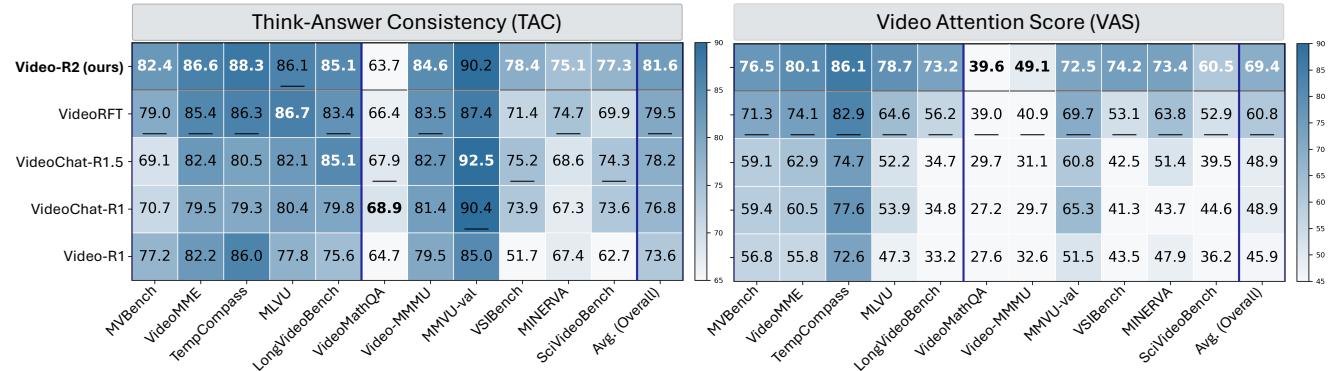


Figure 4. **Reasoning quality comparison on TAC and VAS metrics.** The left and right heatmaps show **TAC** and **VAS** across 11 benchmarks, including five generic [36, 62, 75, 122, 148] and six reasoning-focused [31, 44, 84, 97, 130, 146] datasets. The rightmost columns show the overall average. The **dark blue** vertical line separates the generic, reasoning, and average columns. Darker colors indicate higher scores, with the best results in **bold** and the second-best underlined for all benchmarks. Video-R2 achieves the best TAC on 8 out of 11 benchmarks and the best VAS on all 11 benchmarks compared with previous reasoning models. Overall, the proposed temporal alignment and consistency gating improve both logical coherence (TAC) and perceptual focus (VAS) in video reasoning multimodal models.

Model	Generic Benchmarks						Reasoning Benchmarks						Avg. (Reasoning)	Avg. (Overall)
	MVBF	VideoMME	TempCompass	MLU	Long VideoBench	Avg. (Generic)	VideoMathQA	Video-MMMU	MMVU-Val	VSiBench	MINERVA	SciVideoBench		
Non-Reasoning Models														
LLaVA-OV [59]	56.7	58.2	67.2	63.7	56.3	60.6	20.7	33.9	54.7	32.4	31.6	18.8	32.0	45.0
InternVL2.5 [19]	72.0	64.2	70.0	68.9	60.0	67.0	24.3	48.6	60.8	38.9	36.6	22.8	38.7	51.6
Qwen2.5-VL [89]	68.1	66.1	74.2	67.9	61.3	67.5	26.7	50.3	67.2	37.7	35.3	16.4	38.9	51.9
PerceptionLM [23]	77.1	58.3	72.7	66.2	60.9	67.0	22.1	39.9	56.5	34.3	35.6	18.9	34.5	49.3
InternVL3 [150]	75.4	66.3	72.2	71.2	58.8	68.8	29.1	50.3	66.1	42.1	34.1	29.4	41.9	54.1
Reasoning Models														
Video-R1 [35]	65.1	64.3	73.5	67.7	57.6	65.6	23.6	47.0	64.0	37.8	33.9	26.8	38.8	51.0
VideoChat-R1 [64]	63.6	64.1	74.5	62.5	54.3	63.8	24.3	52.0	64.8	33.0	33.8	26.5	39.1	50.3
VideoChat-R1.5 [127]	65.7	64.8	73.9	65.3	53.6	64.7	26.4	50.0	67.0	36.1	33.7	25.8	39.8	51.1
VideoRFT [114]	64.8	64.1	73.8	66.6	57.0	65.3	25.2	48.1	66.7	38.5	34.0	25.7	39.7	51.3
Video-R2 (Ours)	67.5	63.8	74.9	68.3	59.2	66.7	28.8	50.8	67.4	39.4	34.9	28.4	41.6	53.0

Table 1. **Accuracy comparison on generic and reasoning benchmarks.** Results are reported for both non-reasoning and reasoning models (7B/8B scale) across five generic [36, 62, 75, 122, 148] and six reasoning-focused [31, 44, 84, 97, 130, 146] benchmarks. Columns list per-benchmark accuracy along with averages for generic, reasoning, and overall performance, with the best results shown in **bold** and the second-best results underlined in each column. Our **Video-R2** achieves the highest averages across generic (66.7), reasoning (41.6), and overall (53.0), showing improved reasoning ability and balanced accuracy across multiple benchmarks.

from VideoRFT [114]. Overall, Video-R2 achieves an average of 53.0, higher than the second best of 51.3 achieved by VideoRFT. These results demonstrate that the proposed temporal alignment and consistency gating contribute to both stronger reasoning capability and robust predictive performance under a unified evaluation setup.

Comparison with non-reasoning models. For completeness, Tab. 1 also reports results from recent non-reasoning MLLMs, including LLaVA-OneVision [59], InternVL2.5 [19], Qwen2.5-VL [8], PerceptionLM [23], and InternVL3 [150]. These models achieve strong performance on generic benchmarks, reflecting their large-scale pretraining and broad visual coverage. For instance, InternVL2.5, Qwen2.5-VL, and PerceptionLM obtain average scores of 67.0, 67.5, and 67.0 on generic benchmarks, respectively, whereas Video-R2 achieves a comparable 66.7. However, on reasoning-focused benchmarks the gap becomes clear: InternVL2.5, Qwen2.5-VL and PerceptionLM average 38.7, 38.9 and 34.5, while Video-R2 achieves 41.6, indicating a clear improvement in reasoning ability through temporal alignment and consistency training. We also include recent InternVL3 [150] for completeness, which achieves slightly higher accuracy (41.9 on reasoning benchmarks vs 41.6 of ours) due to extended pretraining on larger datasets. Notably, **Video-R2** is trained on the non-reasoning base Qwen2.5-VL and achieves a higher overall average of 53.0 compared to 51.9, demonstrating that the proposed reasoning optimization effectively enhances reasoning perfor-

mance while maintaining general visual understanding.

Summary. Overall, Video-R2 achieves consistent improvements across all three evaluation metrics, reasoning coherence (TAC), visual correspondence (VAS), and accuracy, on a wide range of benchmarks. These findings confirm that explicitly rewarding temporal precision and logical consistency leads to more reliable and interpretable video reasoning. A detailed comparison of the *training data* used across prior methods versus ours and an extended technical discussion highlighting *key differences* between Video-R2 and prior approaches are provided in the Appendix G and H.

4.4. Ablations

To analyze the contribution of each training component, we conduct a step-by-step ablation over SFT, GRPO, and the proposed temporal alignment reward (TAR) w/ and w/o consistency gate (g). The results in Tab. 2 report averages for Accuracy, TAC, and VAS across all 11 benchmarks. The top row corresponds to the non-reasoning Qwen2.5-VL [8] baseline that directly predicts the final answer without intermediate reasoning; therefore, TAC and VAS cannot be computed. The second row, Qwen2.5-VL (CoT), shows the same model evaluated with chain-of-thought prompting, where it is asked to think before answer. We note that CoT decreases overall accuracy and yields the lowest TAC, suggesting that the non-reasoning model struggles to maintain coherence when forced to generate reasoning traces.

Effect of SFT. SFT over the non-reasoning baseline sig-

Method	Components				Accuracy ↑			TAC ↑			VAS ↑		
	SFT	RL	TAR	Cons. (g)	Generic	Reasoning	Overall	Generic	Reasoning	Overall	Generic	Reasoning	Overall
Qwen2.5-VL (non-reasoning)	-	-	-	-	67.5	38.9	51.9	-	-	-	-	-	-
Qwen2.5-VL (CoT)	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	59.6	37.0	47.3	63.2	49.1	55.5	53.2	36.9	44.3
+ SFT	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	60.9	38.8	48.9	96.5	97.1	96.8	76.8	63.7	69.7
+ SFT + GRPO	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	65.9	41.0	52.3	82.9	71.6	76.8	75.8	61.5	61.5
+ SFT + GRPO + TAR	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<u>66.5</u>	<u>41.2</u>	<u>52.7</u>	83.0	72.9	77.5	<u>78.4</u>	<u>62.9</u>	69.9
+ SFT + GRPO + TAR w/ Cons. (g)	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	66.7	41.6	53.0	<u>85.7</u>	<u>78.2</u>	<u>81.6</u>	78.9	61.5	69.4

Table 2. **Ablation on key components of Video-R2.** Checkmarks denote enabled modules: supervised fine-tuning (SFT), group relative policy optimization (GRPO), Temporal Alignment Reward (TAR), and consistency gating (g). Metrics are reported as average scores across five generic [36, 62, 75, 122, 148], six reasoning-focused [31, 44, 84, 97, 130, 146], and all benchmarks for **Accuracy**, **TAC**, and **VAS**. The results highlight the progressive improvements achieved by introducing temporal alignment and consistency gating in Video-R2.

nificantly improves both TAC and VAS, with TAC increasing from 55.5 to 96.8 and VAS from 44.3 to 69.7. This demonstrates that SFT effectively teaches the model to produce coherent, timestamp-aware reasoning in the `<think>-<answer>` format. Accuracy also improves slightly over the CoT baseline, confirming that reasoning supervision benefits both interpretability and predictive performance.

Effect of GRPO. Adding GRPO further improves accuracy ($48.9 \rightarrow 52.3$) but leads to a decrease in both TAC ($96.8 \rightarrow 76.8$) and VAS ($69.7 \rightarrow 61.5$). This behavior arises because the GRPO reward is only applied to the final answer; as a result, the model tends to rely on simpler *answer-based shortcuts* similar to those used by the non-reasoning baseline. Although this improves answer correctness, it reduces reasoning alignment and visual correspondence, highlighting the need for an additional reward component that explicitly targets reasoning quality.

Effect of TAR. Incorporating TAR improves both reasoning quality metrics: TAC improves from 76.8 to 77.5 overall, and VAS shows a notable increase from 61.5 to 69.9. These gains directly result from rewarding timestamp-verified reasoning claims, which encourage the model to rely more on visual and temporal evidence when reasoning.

Effect of consistency gating (g). Finally, enabling the consistency gate produces the overall best results, improving accuracy from 52.7 to 53.0, reasoning TAC jumps from 72.9 to 78.2, and overall TAC from 77.5 to 81.6. The gating ensures that temporally precise reasoning is rewarded only when the `<think>` conclusion aligns with the final `<answer>`, thus stabilizing training and reinforcing coherent reasoning. Additional ablations are in Appendix I, including (i) the effect of introducing a recall-based term in TAR, (ii) the stability of the proposed VAS metric using different LLM judges, (iii) sensitivity analyses for the semantic similarity (τ) and temporal thresholds (Δ).

The SFT consistency paradox. An interesting trend in

Tab. 2 is the high TAC observed after SFT, where the model achieves near-perfect consistency but relatively low accuracy. When trained with cross-entropy next-token prediction loss, the model learns to generate well-structured and logically coherent reasoning traces that, however, do not always lead to correct final answers. In contrast, GRPO increases answer accuracy by explicitly rewarding generations with correct answer but lowers reasoning consistency, indicating that *policy optimization tends to exploit answer-level shortcuts rather than improve actual reasoning behavior*. The introduction of the Temporal Alignment Reward (TAR) and the consistency gate (g) mitigates this trade-off, yielding a relatively balanced model that maintains coherence while improving accuracy. We further study this effect in Appendix I.1, showing that stronger consistency-oriented reward can close the TAC gap between SFT and GRPO but reduce accuracy, underscoring an open trade-off between interpretability and performance. **Video-R2** is a significant step toward addressing this challenge, though further research is required to fully resolve this balance.

5. Conclusion

Current video reasoning models often produce reasoning traces that are not consistent with their answers or grounded in visual content. We identify this gap and introduce two diagnostic metrics; Think–Answer Consistency (**TAC**) and Video Attention Score (**VAS**), to quantify these aspects. To address this gap, we introduce a reinforcement learning reward named Temporal Alignment Reward (**TAR**) with a consistency gate, which encourages temporally precise and logically consistent reasoning. The resulting **Video-R2** model improves reasoning quality and accuracy across multiple benchmarks, showing that explicit temporal alignment and consistency rewards lead to more reliable video reasoning. Our codes, data and model will be open-sourced.

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Video-R2: Reinforcing Consistent and Grounded Reasoning in Multimodal Language Models

Supplementary Material

Table of Contents

A. Related Works	10
A.1. Large Language Models	10
A.2. Multimodal Large Language Models	11
B. Implementation Details	12
B.1. Model and Training Stages	12
B.2. Evaluation Protocol	12
B.3. Compute and Environment	12
B.4. Hyperparameters	12
C. Think–Answer Consistency (TAC)	12
C.1. Prompt for Answer Extraction	12
C.2. TAC vs TAC-All	14
C.3. Qualitative Comparison	14
D. Video Attention Score (VAS)	15
D.1. Prompts for VAS Calculation	15
D.2. Qualitative Comparison	16
E. Temporal Alignment Reward (TAR)	16
E.1. Prompt for Claim Extraction	16
E.2. Prompt for Consistency Gating	17
E.3. TAR Calculation Examples	17
F. Dataset	18
F.1. Dataset Prompts	18
F.2. Dataset Quality Analysis	18
F.3. Dataset Examples	19
F.4. Dataset Stats	19
G. Comparison with Prior Methods	19
G.1. Training Dataset Based Comparison	19
H. Detailed Discussion on Novelty	19
I. Additional Ablations	21
I.1. Effect of Stronger Consistency Reward Factor	21
I.2. Introducing Recall Term in TAR	21
I.3. Stability of VAS Metric	22
I.4. Sensitivity Analysis	22
I.5. Comparison using Reported Numbers	23
J. Prompts Used in Training and Evaluation	23

A. Related Works

A.1. Large Language Models

The trajectory of modern AI has been shaped by the rapid evolution of Large Language Models (LLMs), beginning with the Transformer architecture [112]. This innovation enabled autoregressive models such as GPT-1 [90], GPT-2 [91], and the paradigm-shifting GPT-3 [12], which showcased powerful in-context learning. Complementary masked-language models like BERT [32] advanced language understanding tasks, while T5 [95] unified multiple NLP tasks under a text-to-text formulation. The scaling era then followed, with PaLM [24] and Chinchilla [42] investigating the limits of compute-optimal scaling, and models like Gopher [94] pushing the envelope of dataset curation.

Open weights efforts. The open-weights movement accelerated progress by making strong LLMs broadly available. Meta’s LLaMA series [38, 109, 110] demonstrated that high performance is possible with carefully curated open data. Other competitive families soon followed: Mistral and its Mixture-of-Experts variant Mixtral [51, 52], Falcon [5], Orca [83], the Qwen series (Qwen / Qwen1.5 [7], Qwen2 [128], Qwen2.5 [89] and Qwen3 [129]), DeepSeek series (DeepSeek LLM [9], Deepseek-MoE [26], Deepseek-V2 [68], and Deepseek-V3 [69]), Microsoft’s Phi series (Phi-1 [39], Phi-1.5 [65], Phi-3 [1], and Phi-4 [2]), and Google’s Gemma family [107]. Together, these models have created a vibrant ecosystem of both proprietary and open alternatives to GPT, Gemini and Claude.

Reasoning in LLMs. Reasoning has emerged as a central focus of LLM development. Prompting-based strategies like Chain-of-Thought (CoT) prompting [120], Self-Consistency [118], and Tree-of-Thoughts (ToT) [131] enable models to produce intermediate reasoning steps. More interactive frameworks, such as ReAct [132] and Reflexion [103], extend reasoning with tool use and self-reflection. Recently, the “O1/R1” family of reasoning-first models has gained prominence: DeepSeek-R1 [29] demonstrated that reinforcement learning with outcome and format rewards can substantially improve mathematical reasoning; Qwen-3 [129] introduced explicit reasoning-tuned variants; and OpenAI’s o1/o3/o4 [49, 86] represents proprietary advances in this space. Some relevant open-source efforts include Vision-R1 [48], VLM-R1 [101], and Video-R1 [35], which adapt reasoning-first reinforcement learning to multimodal and temporal settings.

A.2. Multimodal Large Language Models

Early vision-language models: The connection between vision and language started with dual-stream models such as ViLBERT [76] and LXMERT [106], where images and text were processed separately before being combined. Single-stream models like VisualBERT [63] and UNITER [18] instead fused the two modalities in a shared space. Later, contrastive learning methods became dominant. CLIP [92] and ALIGN [50] showed that training on large collections of image-text pairs can give strong zero-shot recognition abilities. MetaCLIP [126] followed the same contrastive objective as CLIP but focused on transparent and reproducible data curation, making it more open and reliable. SigLIP [140] and SigLIP-2 [111] further improved contrastive training by refining the learning objectives and scaling the training data. More recently, the Perception Encoder [11] introduced a scalable family of vision encoders that achieve state-of-the-art performance across image, video, vision-language, and dense prediction tasks.

Image-focused MLLMs. The landscape of image-focused Multimodal Large Language Models (MLLMs) is defined by both powerful proprietary systems, such as OpenAI’s GPT-4V [85], and a rapidly growing ecosystem of open models. Foundational open-source work established two main ways to connect pre-trained vision encoders to LLMs. The first uses adapter modules, such as the Q-Former in BLIP-2 [61] and MiniGPT-4 [149], which serve as a translator between visual features and the LLM. The second uses a much simpler projection approach, where the visual features are mapped directly into the LLM’s embedding space with just a linear layer or a small neural layer, as seen in LLaVA [70]. These designs significantly lowered the barrier for MLLM creation and inspired a wave of successors such as LLaVA-v1.5 [71], LLaVA-NeXT Interleave [60], and InstructBLIP [27].

Building on these strong foundations, a number of strong open model families have emerged, pushing the state of the art through scaling and architectural refinement. The Qwen-VL [8, 113], InternVL [19–21, 37, 115, 150], and LLaMA 3.2 Vision [38] and Phi-Vision [1, 3] series represent large-scale efforts that achieve top results on broad vision-language benchmarks. Other notable efforts include Molmo [30], and Pixtral [4] which also deliver highly competitive performance.

Alongside scaling, research has focused on enhancing specific capabilities. To improve efficiency and accessibility, models like MiniCPM-V [133] have been developed with smaller parameter counts. For handling high-resolution imagery and complex document understanding, models such as Idefics2 [58] and InternLM-XComposer2-4KHD [33] have introduced specialized techniques. CogVLM [116] explored deeper fusion strategies between the vision and language backbones. For fine-

grained understanding that connects language to specific image regions, several models have introduced grounding capabilities. The Kosmos family [47, 88] enabled referring to objects via bounding boxes, a concept extended by Ferret 1/2 [135, 142] to ground any-shape regions and by GLaMM [96] to provide pixel-level segmentation. Together, these systems highlight the rapid and diverse growth of image-focused MLLMs.

Video-focused MLLMs. Extending to video, early works such as Video-ChatGPT [80], Video-LLaMA [141], and Video-LLaVA [67] adapted image-based models to temporal sequences. Specialized models then appeared, including TimeChat [98], MovieChat [104], LLaMA-VID [66], VideoChat2 [62], ChatUniVi [53], and VTimeLLM [45]. More recent contributions focus on efficiency and broader coverage: BT-Adapter [72], ST-LLM [73], IG-VLM [56], GoldFish [6], VideoGPT+ [81], and Mobile-VideoGPT [99]. Methods such as LongVLM [121], FTFV-LVLM [14], and LLaVA-MR [78] address token reduction, long-context reasoning, and efficient retrieval, which are critical for scaling video-based multimodal systems.

Joint image-video MLLMs. A recent trend is to design models that handle both images and videos within a single framework. LLaVA-OneVision [59] shows that a unified architecture can support single-image, multi-image, and videos together. The Qwen-VL series [8, 113] extends this idea with stronger dynamic resolution and long-context abilities, while the InternVL family [19, 150] achieves state-of-the-art results in both document and video understanding. Perception Language Model (PLM) [11] builds on the Perception Encoder [11] to align powerful vision encoders with language models, enabling competitive performance across image and video benchmarks. These works suggest a shift toward general-purpose multimodal assistants that can seamlessly move between static and temporal visual inputs.

Reasoning in MLLMs. Beyond recognition and understanding, recent works aim to equip MLLMs with explicit reasoning. For images, LLaVA-O1 [125], LLaMA-V-o1 [108], Vision-R1 [48], VLM-R1 [101], Visionary-R1 [123], and Perception-R1 [136] introduce reasoning-first training strategies. For videos, methods include Video-R1 [35], VideoChat-R1 [64], VideoChat-R1.5 [127], VideoORFT [114], TW-GRPO [28], ReVisual-R1 [15], VideoAgent [119], VersaVid-R1 [17], and Vad-R1 [46], each adapting reinforcement or process-level rewards to temporal reasoning. A complementary line explores “visual chain-of-thought” reasoning, such as AURORA [10], which introduces intermediate perception tokens (depth maps, segmentation masks) to bridge perception and symbolic reasoning.

Benchmarks for Multimodal Reasoning. The advancement of multimodal reasoning has been enabled by increasingly diverse benchmarks. For images, MM-Bench [74],

MMMU [139], AI2D [54], and MathVista [77] target visual knowledge, diagram, and math reasoning. For videos, general-purpose benchmarks such as MVBench [62], Video-MME [36], TempCompass [75], MLVU [148], and LongVideoBench [122] assess broad multimodal understanding, while reasoning-focused datasets including VideoMathQA [97], Video-MMMU [44], MMVU [146], VSIBench [130], MINERVA [84], and SciVideoBench [31] evaluate spatio-temporal reasoning. Together, these benchmarks highlight both the steady gains and the persistent gap to human-level multimodal reasoning.

B. Implementation Details

B.1. Model and Training Stages

Video-R2 is initialized from the non-reasoning backbone Qwen2.5-VL-7B [8]. Following prior reasoning-based approaches such as Video-R1 [35], VideoChat-R1 [64], and VideoRFT [114], training follows two stages:

1. **Supervised Fine-Tuning (SFT)** to learn timestamp-aware reasoning in the <think> and <answer> format.
2. **Group Relative Policy Optimization (GRPO)** to refine temporal alignment and logical consistency through the proposed Temporal Alignment Reward (TAR, Sec. 3).

Video Processing Videos are uniformly sampled at 2 FPS. A maximum of 128 frames are used during SFT, and 32 frames during GRPO. Evaluation uses a maximum of 128 frames for all the reasoning models. Frames are resized to a maximum of 360×420 px resolution during both training and evaluation. For videos requiring audio cues, subtitles are generated via WhisperX-Large-v3 [93] and rendered at the bottom of frames during training. To facilitate temporal reasoning, we overlay frames with timestamps (HH:MM:SS format) at the top-left corner during training. Timestamp visibility is dynamically adjusted (light-on-dark or dark-on-light) for optimal legibility. During evaluation, only timestamps (displayed at the top-left corner) are preserved, while subtitles are omitted to ensure that reasoning relies solely on visual and temporal cues.

Supervised Fine-Tuning (SFT). SFT is performed for one epoch using LoRA [43] adapters (rank $r=64$) applied to both the attention and the feed-forward layers. Training uses a global batch size of 32 and learning rate of $1e^{-5}$, with bf16 precision and a maximum context length of 32K tokens. LoRA-based adaptation preserves the pretrained multimodal knowledge of the base Qwen2.5-VL model while enabling efficient reasoning specialization on the relatively small SFT dataset (we use only $\simeq 10K$ samples for SFT).

Reinforcement learning (GRPO). Followed by SFT, reinforcement learning using GRPO is conducted for one epoch with group size $K=8$ (eight candidate generations per sample), global batch size of 8, learning rate $1e^{-6}$, and KL anchor coefficient $\beta=0.04$ for training stability. All re-

ward components including accuracy reward, format reward, and the proposed consistency-gated temporal alignment reward (TAR), are equally weighted (1:1:1) as described in Sec. 3. Reward computation uses Qwen3-Next-80B-A3B [129] as the LLM for both claim extraction and consistency gating, served via VLLM [57] framework for efficient inference. For text similarity, we use sentence-transformers/all-MiniLM-L6-v2 model from Sentence Transformers.

B.2. Evaluation Protocol

All reasoning and non-reasoning models are evaluated under a unified configuration using lmms-eval [144]. Videos are sampled at 2 FPS (maximum 128 frames, 360×420 px resolution). Each reasoning model uses its official prompt template as given in the respective paper, and non-reasoning baselines follow the best configurations reported in their respective papers. Inference uses greedy decoding for all models. Subtitles are excluded during the evaluation to prevent linguistic leakage and ensure a purely visual reasoning evaluation. More details are provided in Sec. 4.2.

B.3. Compute and Environment

All experiments are conducted on $8\times$ AMD Instinct™ MI210 accelerators (64 GB each, 512 GB total) using PyTorch 2.7 and ROCm 6.4. We use bf16 precision throughout both training and evaluation. VLLM [57] is used to efficiently serve the Qwen3-Next-80B-A3B [129] LLM during reinforcement learning. SFT uses 10,467 samples and completes in approximately 3.8 hours, while GRPO uses 4,804 samples and completes in about 54.4 hours. Evaluation on all 11 benchmarks with a maximum of 128 frames and a maximum of 1024 output tokens takes around 27.5 hours. We use Qwen3-Next-80B-A3B, which maintains a balance between efficiency and accuracy with a total of 80B parameters and only 3B active parameters, as the LLM judge in the Video Attention Score (VAS) calculation, as well as for the extraction of answers from thinking traces in the Think-Answer Consistency (TAC) calculation. The complete training and evaluation codebase, dataset, and model checkpoints will be open-sourced for reproducibility.

B.4. Hyperparameters

A detailed summary of all key hyperparameters for both the training stages and the evaluation is provided in Table A1.

C. Think–Answer Consistency (TAC)

C.1. Prompt for Answer Extraction

To compute the Think–Answer Consistency (TAC) metric, we extract the answer predicted in model’s,

1. Reasoning trace (<think>...</think> block).
2. Final output (<answer>...</answer> block).

Category	Setting	Value	Notes
Base model	Backbone	Qwen2.5-VL-7B	Non-reasoning base model
	Training stages	SFT → GRPO	Standard reasoning-tuning pipeline
Frame sampling	FPS	2	2 FPS → Uniform frame sampling
	Max frames	128 / 32 / 128	SFT / GRPO / Eval
	Frame resolution	360×420 px	Applied to all datasets
Visual preprocessing	Subtitles	WhisperX Large-v3	Printed bottom during training only
	Timestamps	HH:MM:SS format	Top-left (train and eval)
	Color scheme	Light-on-dark / dark-on-light	Improves visibility and grounding
SFT configuration	Epochs	1	
	Batch size	32	
	Learning rate	1e-5	Cosine LR scheduler
	Weight decay	0.01	
	Max tokens (context)	32K	Precision: bf16
	Adapter type	LoRA ($r=64$)	Applied to Q/K/V/FFN modules
	Training time	3.8 hours	8×AMD Instinct™ MI210
GRPO configuration	Epochs	1	
	Group size (K)	8	Number of candidate generations
	KL coefficient (β)	0.04	Anchor regularization strength
	Batch size	8	
	Learning rate	1e-6	
	Reward weights	$\lambda_{\text{acc}} = \lambda_{\text{fmt}} = \lambda_{\text{tar}} = 1$	Accuracy, format, TAR components
	Hyperparameters	$\Delta = 2, \tau = 0.75$	Temporal and semantic thresholds
Evaluation	Judge model	Qwen3-Next-80B-A3B	Served via VLLM API
	Sentence Embeddings	a11-MiniLM-L6-v2	Used for claim similarity matching
	Training time	54.4 hours	8×AMD Instinct™ MI210
	Benchmarks	11 total	5 generic + 6 reasoning
	Framework	lmms-eval	Official prompts for all models
	Decoding	Greedy	temperature=0
	Frames used	2 FPS, max 128	No subtitles during evaluation
Environment	Metrics	TAC, VAS, Accuracy	Consistent setup for all methods
	Judge model	Qwen3-Next-80B-A3B	Used for VAS
	Max output tokens	1024	Max generation length of 1024
	Evaluation time	27.5 hours	8×AMD Instinct™ MI210

Table A1. Comprehensive summary of all hyperparameters used for Video-R2 training and evaluation. The table details configuration choices across both supervised fine-tuning (SFT) and reinforcement learning (GRPO) stages, including visual preprocessing, frame sampling, model adaptation, and evaluation protocols. These settings ensure reproducible results across all benchmark evaluations.

We use deterministic parsing prompts that instruct LLM to extract the final choice directly from the model’s output.

(1) Parsing from Reasoning Traces. To extract the answer implied by the reasoning trace, we use a stricter prompt that scans for the last explicit conclusion mentioned within the `<think>...</think>` section. Refer to [Prompt A](#).

(2) Parsing from Final Answers. The [Prompt B](#) provides the prompt we use to extract the final answer from the model’s `<answer>...</answer>` block.

Prompt A: TAC - Prompt for Answer Extraction from `<think>...</think>`

System Prompt:

You are a strict extractor.

Task: Read ONLY the Reasoning text appended at the end of the user message and output a SINGLE LETTER corresponding to the option that the Reasoning explicitly concludes as the final answer.

Rules (follow in order):

1. Look ONLY at the Reasoning text. Ignore the options text for decision-making.
2. If the Reasoning contains an explicit final choice (e.g., “Therefore, D”, “Answer: A”), output that letter. If multiple explicit finals appear, output the LAST one.
3. If the Reasoning labels a single option as correct (e.g., “D is correct”), output that letter. If multiple appear, output the LAST one.
4. If the Reasoning states the correct option by its text (e.g., “the correct answer is ‘red car’”), match that text exactly to the provided options and output the corresponding letter. Prefer the LAST explicit conclusion.
5. Do NOT judge correctness or infer meaning. Output only the explicit final conclusion.
6. Output a single uppercase letter (A–Z). No punctuation, no explanations.

User Prompt:**If `is_mcq_task = True`:**

Options:

- A.
B.
C.

Reasoning:

`text inside <think>...</think> block`

MCQ output format:

- Return ONLY one capital letter A–Z on a single line.
- Do NOT include any other characters or spaces.

Else (open-ended task):

Reasoning:

`text inside <think>...</think> block`

Open-form output format:

- If numeric, return ONLY the number.
- If textual, return ONLY the minimal text answer.
- Output must be a single line with no extra characters.

5. Treat case-insensitive tokens like option c, (c), [c], C as the letter C when MCQ is requested.

User Prompt:**If `is_mcq_task = True`:**

Options:

- A.
B.
C.

Text to parse (final answer snippet):

`text inside <answer>...</answer> block`

MCQ output format:

- Return ONLY one capital letter A–Z on a single line.
- Do NOT include any other characters or spaces.

Else (open-ended task):

Text to parse (final answer snippet):

`text inside <answer>...</answer> block`

Open-form output format:

- If numeric, return ONLY the number.
- If textual, return ONLY the minimal text answer.
- Output must be a single line with no extra characters.

Usage. Both **Prompt A** and **B**, are used to extract \hat{a}_{think} and \hat{a}_{answer} for each sample, which are compared to compute the TAC metric as defined in Eq. 1 of the main paper:

$$\text{TAC}(M, D) = \frac{1}{|D_{\text{correct}}|} \sum_{i \in D_{\text{correct}}} \mathbb{I}[\hat{a}_i^{\text{think}} = \hat{a}_i^{\text{answer}}].$$

C.2. TAC vs TAC-All

In Eq. 1 of the main paper, the Think–Answer Consistency (TAC) metric is computed only over correctly answered samples, denoted as D_{correct} , to avoid cases where logically consistent but incorrect reasoning could inflate the score. For completeness, we also evaluate a variant, **TAC-All**, which measures the same consistency but across *all* evaluation samples (D). This variant provides an absolute measure of reasoning stability independent of answer accuracy, capturing how consistently a model maintains internal alignment between its reasoning and final prediction regardless of the correctness.

As shown in Tab. A2, both TAC and TAC-All show a similar trend across all benchmarks. Our model, Video-R2, maintains strong logical alignment under both metrics, achieving the highest scores across most of the benchmarks. While TAC focuses on interpretable correctness, TAC-All confirms that Video-R2 produces coherent reasoning traces even for incorrect predictions.

C.3. Qualitative Comparison

Figs. A1-A3 show qualitative differences in reasoning consistency across models, focusing on the Think–Answer Consistency (TAC) behavior of Video-R1 [35], Vide-

Prompt B: TAC - Prompt for Answer Extraction from `<answer>...</answer>`**System Prompt:**

You are a deterministic parsing agent.

Task: Read ONLY the provided text and emit a SINGLE-LINE answer in the exact format requested.**Hard rules (apply all):**

1. Do not infer or reason beyond the text. If the text lacks a valid answer, output exactly: UNKNOWN.
2. Output must contain no explanations, no extra words, no labels, no code fences, no quotes, no brackets.
3. Strip leading/trailing whitespace. No trailing punctuation unless required by format (e.g., a %).
4. Normalize internal whitespace to single spaces.

Model	Generic Benchmarks						Reasoning Benchmarks							Avg. (Reasoning)	Avg. (Overall)
	MVBBench	VideoMME	TempCompass	MLVU	LongVideoBench	Avg. (Generic)	VideoMathQA	Video-MMMU	MMVU-Val	VSiBench	MINERVA	SciVideoBench			
Think–Answer Consistency (TAC)															
Video-R1 [35]	77.2	82.2	86.0	77.8	75.6	79.8	64.7	79.5	85.0	51.7	67.4	62.7	68.5	73.6	
VideoChat-R1 [64]	70.7	79.5	79.3	80.4	79.8	77.9	68.9	81.4	<u>90.4</u>	73.9	67.3	73.6	75.9	76.8	
VideoChat-R1.5 [127]	69.1	82.4	80.5	82.1	85.1	79.9	<u>67.9</u>	82.7	92.5	<u>75.2</u>	68.6	<u>74.3</u>	<u>76.9</u>	78.2	
VideoRFT [114]	<u>79.0</u>	<u>85.4</u>	<u>86.3</u>	86.7	<u>83.4</u>	<u>84.1</u>	66.4	<u>83.5</u>	87.4	71.4	74.7	69.9	75.5	<u>79.5</u>	
Video-R2 (Ours)	82.4	86.6	88.3	<u>86.1</u>	85.1	85.7	63.7	84.6	90.2	78.4	75.1	77.3	78.2	81.6	
Think–Answer Consistency (TAC) - All															
Video-R1 [35]	75.7	82.4	84.2	78.8	77.4	79.7	82.6	80.2	81.8	79.4	79.7	81.9	80.9	80.4	
VideoChat-R1 [64]	74.8	81.5	78.4	82.9	84.2	80.4	62.2	81.2	<u>89.1</u>	91.5	81.8	84.9	81.8	81.2	
VideoChat-R1.5 [127]	72.6	83.2	78.5	84.1	88.2	81.3	86.0	79.7	89.5	84.2	83.2	76.0	83.1	82.3	
VideoRFT [114]	77.4	86.2	82.6	87.2	84.8	<u>83.6</u>	75.5	86.8	86.0	86.1	<u>83.3</u>	<u>88.0</u>	<u>84.3</u>	<u>84.0</u>	
Video-R2 (Ours)	82.7	87.6	86.3	<u>86.7</u>	<u>85.8</u>	85.8	<u>83.1</u>	86.4	87.8	<u>90.6</u>	84.9	89.2	87.0	86.5	

Table A2. **Comparison between TAC and TAC-All.** TAC is computed only over correctly answered samples (D_{correct}), while TAC-All considers all predictions (D_{all}) regardless of correctness. The upper block reproduces the TAC results corresponding to the left heatmap of Fig. 4, whereas the lower block reports TAC-All. Both metrics exhibit similar relative trends, confirming that Video-R2 maintains strong reasoning-answer consistency even for incorrect responses.

oRFT [114], and our proposed **Video-R2**. In each example, we visualize the video, question, options, correct answer, and reasoning traces generated by all models. While prior reasoning models such as Video-R1 and VideoRFT often produce logically inconsistent reasoning, where the reasoning trace concludes one option but the final `<answer>` outputs another, our Video-R2 maintains internal alignment between reasoning and answer, demonstrating high TAC.

- **Example 1 (Fig. A1):** A video-game scenario where Video-R1 and VideoRFT misalign between reasoning and final answer, while Video-R2 maintains consistency and predicts the correct answer (“Smoke”).
- **Example 2 (Fig. A2):** Counting acrobatic rolls in a dance performance. Both baselines exhibit reasoning-answer mismatch, whereas Video-R2 accurately counts and maintains logical coherence.
- **Example 3 (Fig. A3):** A soccer clip identifying the cause of a yellow card. Baselines misinterpret the reasoning context, producing contradictory answers, while Video-R2 produces consistent and correct reasoning grounded in the visual evidence.

D. Video Attention Score (VAS)

D.1. Prompts for VAS Calculation

To compute the Video Attention Score (VAS), we evaluate the degree to which the reasoning text (`<think>...</think>` block) *claims* to rely on visual evidence from the video. The scoring prompt guides a

large language model (LLM) to assign a 0-10 score. The complete prompt configuration is shown in **Prompt C**.

Prompt C: VAS - Prompt for Visual Attention Scoring
from `<think>...</think>`

System Prompt:

You are an expert judge of ***claimed visual grounding*** in video QA chain-of-thought. You will receive an Input (question/options/prompt) and a model Response that includes `<think>...</think>` and `<answer>...</answer>` tags.

Your task: Evaluate how much the reasoning inside `<think>` and `</think>` only **claims** to rely on concrete visual evidence from the video versus using text patterns, prior knowledge, or guessing. You do not have the video; score what the reasoning asserts, not whether those assertions are true or the final answer is correct.

What counts as visual grounding signals (positive cues):

1. Concrete, specific references to visible entities and attributes (colors, positions, counts, on-screen text/OCR).
2. Spatio-temporal descriptions tied to the video (“first/then,” “left/right,” “foreground/background,” scene changes).
3. Actions/interactions clearly described as seen (“picks up,” “points at,” “walks behind”).
4. Visual logic chained to the question (“Because the sign reads ‘Gate B’ and the arrow points left...”).
5. Mentions like “the video shows,” “the video states,” or “the video indicates...” count as **moderate visual grounding** ***if**** they reference specific factual content (e.g., numbers, object names, or events), even without

spatial detail.

What counts as non-visual or weak grounding (negative cues):

1. Generic mentions of “the video” with no specific content (“the video talks about cars”).
2. Option pattern matching, stereotypes/common knowledge, or generic phrases (“based on the context,” “usually...”).
3. Restating the question or options with “I see” but no concrete visual detail.
4. Timestamp name-dropping without linked content, irrelevant flourish, or contradictions.

Edge cases:

- If multiple `<think>` blocks exist, judge the first.
- If `<think>` is missing or empty → score 0.
- Ignore `<answer>` when scoring.

Scoring (0-10, integer):

1. 10 (Excellent): Dense, highly specific, step-by-step visual reasoning directly addressing the question.
2. 7–9 (Strong): Clearly video-based with several specific claims tied to what’s shown, even if phrased verbally (“the video states...”).
3. 4–6 (Moderate): Claims to recall or cite specific video facts (numbers, entities, or comparisons) but lacks spatial or temporal detail.
4. 1–3 (Weak): Minimal visual content; mostly generic or option-pattern reasoning with only token mentions of the video.
5. 0 (None): No visual grounding; guessing, meta-reasoning only, or `<think>` absent.

Output: Return JSON only with keys “score” (0–10 integer) and “rationale” (2–3 concise sentences citing the most important cues; do not mention lack of video).

User Prompt:

Evaluate ATTENTION-TO-VIDEO in the model’s reasoning. Score only the text inside `<think>...</think>`, not the final `<answer>` and not answer correctness.

You do not have access to the video. Judge whether the reasoning *claims* to use concrete visual evidence (what is seen, where it appears, how it changes) versus relying on generic patterns, options, or prior knowledge.

Use this rubric (0–10):

1. 10: Dense, specific visual descriptions (entities, attributes, counts, on-screen text, spatial relations, temporal order) directly supporting the question.
2. 7–9: Clearly video-based reasoning with multiple specific claims tied to what the video shows, even if phrased as “the video states...” or “the video shows...”.
3. 4–6: Claims to recall or cite specific video facts (numbers, labels, or entities) but lacks spatial or visual detail.

4. 1–3: Minimal visual content; generic “the video talks about...” or option-based logic.
5. 0: No visual grounding; guessing, meta-reasoning only, or missing `<think>` block.

Input: `{input_text}`

Response: `{response_text}`

Reply ONLY with JSON like: `{"score": int, between 0 and 10, "rationale": "2 to 3 sentences"}`

D.2. Qualitative Comparison

Figs. A4-A6 show how Video Attention Score (VAS) captures the claimed visual grounding quality of model reasoning. Each example compares reasoning traces from Video-R1 [35], VideoRFT [114], and our **Video-R2**, highlighting how visual specificity and temporal grounding differ across models. While baseline models often describe generic contexts or rely on prior knowledge, our Video-R2 consistently references concrete visual details, such as timestamps, spatial positions, and detailed object descriptions, resulting in significantly higher VAS.

- **Example 1 (Fig. A4):** A boy playing guitar in Central Park. Video-R1 and VideoRFT reasoning remain abstract or irrelevant, lacking any visual grounding, whereas Video-R2 cites timestamps (0:50) and mention visual details such as “blonde hair,” “black t-shirt,” and “sitting on a bench,” achieving a VAS of 9/10.
- **Example 2 (Fig. A5):** A medical consultation scene. Both baselines fail to describe visual evidence: one relying on generic assumptions, the other misinterpreting unrelated footage, while Video-R2 grounds its reasoning in specific visual cues (white coat, stethoscope, and wall background) for a VAS of 9/10.
- **Example 3 (Fig. A6):** A construction worker picking an object from a plastic box. Baselines forms a theory without observation of visual details, while Video-R2 identifies the exact moment (6:45–6:50) and object features (“thin, sharp, needle-like”) for perfect visual grounding with a VAS of 10/10.

E. Temporal Alignment Reward (TAR)

E.1. Prompt for Claim Extraction

To compute the Temporal Alignment Reward (TAR), we first extract timestamped *claims* from both the reference and model-generated reasoning. Each claim represents a localized event or observation within the `<think>...</think>` block, expressed as a timestamp and its corresponding textual description. The extraction process is handled by an LLM-based parser that ensures temporal precision and semantic clarity. The prompt is provided in [Prompt D](#).

Prompt D: TAR - Prompt for Claim Extraction

System Prompt:

You are a precise temporal information extraction assistant.

Goal: Given ONLY the provided text, extract every timestamp mention and produce a compact JSON object mapping each timestamp (key) to ONE short sentence (value) describing what happens at that time according to the text.

Output format (STRICT):

1. Return ONLY a JSON object. No prose, no code fences, no explanations.
2. Keys: timestamps exactly as mentioned, normalized to MM:SS or HH:MM:SS with leading zeros.
 - Single time example: "00:42"
 - Range examples: "00:42-00:45", "01:45-02:01"
3. Order keys by start time ascending.
4. If the text uses phrases like "around the 16-second mark" or "at about 1:02", convert to "00:16" or "01:02".
5. If a single continuous action is described across adjacent times (e.g., 00:07 and 00:08), you MAY consolidate into a range "00:07-00:08" with one concise sentence.
6. If the same timestamp appears multiple times, merge into a single key and summarize succinctly.
7. If no timestamps are present, return .

Content rules:

1. Derive sentences ONLY from the given text. No hallucinations.
2. Each value is a brief, plain-language clause (≤ 10 words), sentence case, ending with a period.
3. Prefer action-focused wording ("Performer executes a cartwheel while holding the jump rope.").

User Prompt:

Extract timestamped events from the following text and return ONLY the JSON object as specified.

STRICT KEYS FORMAT:

1. Use ONLY zero-padded MM:SS or HH:MM:SS.
2. For ranges, use a single hyphen: "MM:SS-HH:MM:SS".
3. Do NOT output plain seconds without a colon (e.g., "6" or "020" is forbidden).
4. Do NOT output words like "end", "EOF", "+", or any trailing symbols.
5. If the text mentions decimal seconds (e.g., 01.77s or 3.5s), round to the nearest second BEFORE emitting.
6. Normalize phrases like "around 16 seconds" to "00:16".
7. Keys must be unique and ordered by start time ascending.
8. If no timestamps are present, return exactly.

VALUES:

1. Each value is ONE short clause (≤ 10 words), sentence case, action-focused, ends with a period.
2. Derive strictly from the provided text (no hallucinations).

Return ONLY the JSON object. No code fences, no explanations.

The reasoning text is:
{the reasoning text}

E.2. Prompt for Consistency Gating

The consistency gating step in Temporal Alignment Reward (TAR) ensures that temporal alignment contributes to the reward only when the reasoning (<think>...</think>) and the final conclusion (<answer>...</answer>) agree. The LLM determines whether the reasoning supports the same conclusion as given in the final answer and outputs a binary TRUE or FALSE signal used to gate the TAR computation.

Prompt E: TAR - Prompt for Consistency Gating

System Prompt:

You are a meticulous auditor. Determine whether the reasoning (THINK) and the final answer (ANSWER) are logically consistent with each other for the given question. Ignore style, verbosity, or extra details; focus strictly on whether the conclusion in THINK matches and supports the final ANSWER for the same question.

User Prompt:

QUESTION:
{question}
THINK (model's internal reasoning):
{reasoning}
ANSWER (model's final answer):
{answer}

TASK:

- 1) Output ONLY one of the **TRUE** or **FALSE** on the first line.
 - **TRUE** ⇒ THINK and ANSWER are consistent and express the same conclusion.
 - **FALSE** ⇒ THINK contradicts or does not support the ANSWER (e.g., mismatched conclusion).
- 2) On the next line(s), give a brief justification (1–3 sentences) summarizing the key evidence supporting your decision.

E.3. TAR Calculation Examples

Figs. A7-A16 show end-to-end TAR computation (using candidate generations during GRPO), including claim extraction, temporal and semantic matching, and reward calculation. We show diverse cases. Brief summaries:

- **Example 1 (Fig. A7):** Counting cartwheels. Consistent reasoning with one match and one miss.
- **Example 2 (Fig. A8):** Counting cartwheels. Temporal mismatch, low similarity score.
- **Example 3 (Fig. A9):** OCR on spatula text ("ELITE"). Consistent reasoning, perfect alignment.
- **Example 4 (Fig. A10):** OCR on spatula text ("ELITE").

- OCR error and TAC gate failure, TAR is zero.
- **Example 5 (Fig. A11-A12):** Ribbon-adjustment tutorial. Partial alignment from one matched step.
 - **Example 6 (Fig. A13-A14):** Ribbon-adjustment tutorial. Inconsistent reasoning, no alignment and gated to zero.
 - **Example 7 (Fig. A15):** Horse riding practice. No predicted timestamp.
 - **Example 8 (Fig. A16-A17):** Horse riding practice. Partial alignment with one match and one miss.

F. Dataset

F.1. Dataset Prompts

Prompt for Difficulty Ranking: To identify samples requiring deeper temporal reasoning, we assign a difficulty score to each video QA pair based on the complexity of its assistant response. The complete prompt used for this difficulty evaluation is provided in [Prompt F](#).

Prompt F: Dataset - Prompt for Difficulty Ranking

You are an expert model evaluator. Evaluate how difficult it would be for a vision-language model to generate the assistant responses in the following conversation.

The conversation is:

User: <user message>

Assistant: <assistant message>

Now, analyze the assistant responses:

Write the difficulty score in the format:

Difficulty score: X, where X is a number from 1 (easy) to 10 (very hard).

Prompt for Reasoning Generation To regenerate timestamp-aware reasoning traces for each question-answer pair, we use the Gemini-2.5-Pro [25] model to produce reasoning traces that explicitly reference key temporal cues. The model follows the instructions provided in [Prompt G](#), which ensures consistent reasoning style and timestamp annotation across the dataset.

Prompt G: Dataset - Prompt for Reasoning Generation

Instructions

Adopt the persona of someone carefully thinking through the following video-based question. Your goal is to show your reasoning process as a natural, internal monologue.

Formatting Rules:

1. **Thinking Block:** Write your entire thought process within <think> and </think> tags. It should sound like you’re talking to yourself to figure out the answer. Use conversational phrases like “Okay, let’s see...”, “Hmm, that’s inter-

esting.” “Wait a minute...”, “That makes sense because...”

2. **NO LISTS:** Your thought process must be written in prose (a flowing paragraph or two). **Do not use numbered lists, bullet points, or a formal step-by-step breakdown.** This should feel like a stream of consciousness.
3. **Answer Block:** After the <think> block, provide the final, concise answer inside <answer> and </answer> tags.
4. **Key Frame Block:** After the answer, include a <key_frame> block where you point out the specific timestamp(s) of the critical video frames without which the question cannot be answered. The timestamps should be as precise as possible (e.g., “00:12”, “01:05–01:08”). If no key frame is required, leave the block empty.

Here is your question:

<question>

The final answer is provided below. Use it as a reference to guide your thinking process, ensuring it logically leads to the correct conclusion. Also, make sure to highlight the key frame(s) that were essential for answering.

<answer>

F.2. Dataset Quality Analysis

The dataset used for training Video-R2 combines samples from five public video QA datasets: LLaVA-Video-178K [145], NeXtQA [124], ActivityNet-QA [137], PerceptionTest [87], and Cleverer [134]. It contains a total of 15,271 samples collected from 11,816 unique videos, annotated to provide timestamp-aware grounded supervision for both the SFT and GRPO stages.

Data verification. To ensure high quality of the data, the verification was performed in two stages. First, all samples with $TAC = 0$ were automatically discarded. Second, a randomly selected subset of 500 samples (approximately 3% of the total) was manually verified, checking both the correctness of the reasoning and its agreement with the provided answer. The goal of this verification was to assess reasoning quality of the data, focusing specifically on the correctness and answer consistency.

Timestamp accuracy. During early inspection, we find that the predicted timestamps sometimes do not match the video. To fix this issue, we print timestamps directly on the video frames during reasoning regeneration, which greatly improves temporal precision. After printing timestamps, small offsets still appear in some cases, usually within ± 2 seconds of the real event in the video. These small differences are within the acceptable time range and do not affect the effectiveness of temporal supervision (see Tab. 2 of the main paper for the ablation on SFT and GRPO).

Overall quality. While full manual verification of all 15,271 samples is not possible at our scale, the verified subset shows high reasoning accuracy and consistent temporal alignment. Including ground truth final answers during rea-

Split	Core Stats						Resolution		Datasets Source				
	Samples	Unique Videos	Avg. Duration (s)	Avg. Reasoning Words	Avg. Reasoning Timestamps	$\vee 720\text{ p}$	$\wedge 720\text{ p}$	LLaVA-Video-178K	NeXtQA	ActivityNet-QA	PerceptionTest	Clevrer	
SFT	10,467	8,621	47.3	328.6	2.54	5,993	2,628	4,635	1,185	2,553	520	1,574	
GRPO	4,804	4,099	57.8	305.8	2.22	2,493	1,606	2,198	614	1,328	472	192	
Combined	15,271	11,816	48.9	321.4	2.44	7,977	3,839	6,833	1,799	3,881	992	1,766	

Table A3. **Dataset statistics for SFT, GRPO, and combined.** We report the number of samples, unique videos, average video duration, average reasoning length in words, and average number of timestamps per reasoning trace. Resolution counts are split below and at least 720p. The last five columns list per source counts for LLaVA-Video-178K, NeXtQA, ActivityNet-QA, PerceptionTest, and Clevrer.

soning generation reduces possible annotation noise, and TAC-based filtering further ensures strong internal consistency across the dataset. Although small ambiguities may remain, they have little effect on downstream performance, as shown by steady improvements in TAC, VAS, and accuracy during model training (see Fig. 4, Tab. 1 and Tab. 2 of the main paper for the quantitative results).

F.3. Dataset Examples

Figs. A18-A20 show a few samples from the dataset, covering both simple and complex temporal reasoning cases. Each visualization shows the video context, question, options and generated reference reasoning.

- **Example 1 (Fig. A18):** Cooking video with fine-grained temporal reasoning on appearance change after adding ingredients.
- **Example 2 (Fig. A19):** Causal reasoning in a synthetic simulation, identifying which event did not contribute to a collision.
- **Example 3 (Fig. A20):** Reasoning across repeated motion cycles (throwing and removing darts) with strong temporal alignment.

F.4. Dataset Stats

Tab. A3 provides a breakdown of the stats for the Supervised Fine-Tuning (SFT) and Group Relative Policy Optimization (GRPO) subsets of our dataset. The overall dataset contains 15,271 video-question-answer samples collected from five public sources: LLaVA-Video-178K [145], NeXtQA [124], ActivityNet-QA [137], PerceptionTest [87], and Clevrer [134].

Across all splits, the dataset maintains balanced coverage of video lengths and resolutions, with roughly one-third of videos above 720p. The average reasoning trace spans around 320 words, indicating detailed yet concise temporal reasoning. The presence of multiple datasets ensures di-

versity in domain and task type, facilitating generalization across multiple reasoning tasks.

G. Comparison with Prior Methods

G.1. Training Dataset Based Comparison

Tab. A4 compares our dataset and results with prior video reasoning models. Unlike previous works that depend on much larger training sets (about 100K-400K samples), our model reaches higher TAC, VAS, and accuracy while using only 15.2K samples in total. This shows that data quality and temporal supervision are more important than dataset size. Our dataset (**A+M**) combines automatically generated reasoning annotations with manual checks for about 3% of all samples, making it more reliable. Using timestamp-aware reasoning and TAC-based filtering also improves consistency, allowing more effective learning from a smaller dataset. In contrast, earlier models mainly use automatically generated (**A**) reasoning traces, which can lead to inconsistency or weak visual grounding.

H. Detailed Discussion on Novelty

Comparison with Video-R1. Video-R1 [35] employs a two-stage training pipeline similar to ours, consisting of supervised fine-tuning (SFT) followed by group relative policy optimization (GRPO). Its key novelty lies in the temporal-GRPO (T-GRPO), which compares model performance on ordered versus shuffled frames. While this provides a proxy for ensuring that the model explores the temporal sequence present in the video frames, no direct reinforcement is applied on the reasoning traces. In contrast, our approach introduces the Temporal Alignment Reward (TAR), which operates at the claim level by aligning timestamped reasoning to reference claims with consistency gathering, resulting in fine-grained temporal credit assignment.

Comparison with VideoChat-R1. VideoChat-R1 [64] fo-

Model	Dataset Info				TAC			VAS			Accuracy		
	SFT Dataset Size	RL Dataset Size	Combined Dataset Size	Reasoning Annotation Type	Avg. (Generic)	Avg. (Reasoning)	Avg. (Overall)	Avg. (Generic)	Avg. (Reasoning)	Avg. (Overall)	Avg. (Generic)	Avg. (Reasoning)	Avg. (Overall)
Video-R1 [35]	165K	260K	260K	A	79.8	68.5	73.6	53.2	39.9	45.9	65.6	38.8	51.0
VideoChat-R1 [64]	-	18K	-	-	77.9	75.9	76.8	57.3	42.0	48.9	63.8	39.1	50.3
VideoChat-R1.5 [127]	-	80K	80K	A	79.9	76.9	78.2	56.7	42.5	48.9	64.7	39.8	51.1
VideoRFT [114]	102K	310K	412K	A	84.1	75.5	79.5	69.8	53.2	60.8	65.3	39.7	51.3
Video-R2 (Ours)	10.4K	4.8K	15.3K	A+M	85.7	78.2	81.6	78.9	61.5	69.4	66.7	41.6	53.0

Table A4. **Training dataset comparison with prior video reasoning models.** All baselines rely primarily on large-scale, automatically generated (**A**) reasoning datasets, whereas our dataset (**A+M**) combines automatic annotation with partial manual verification of approximately 3% of the total samples (500 out of 15,271). Despite being trained on an order of magnitude fewer samples, Video-R2 achieves higher TAC, VAS, and accuracy across both generic and reasoning benchmarks, indicating that dataset quality and consistency contribute more strongly to reasoning performance than raw dataset scale. Dashes (-) indicate unavailable information or unused stage.

cuses on improving video perception through reinforcement fine-tuning with GRPO. Its reward functions are task-specific and are all verifiable, such as intersection-over-union (IoU) for temporal range grounding, accuracy for classification, and recall for captioning. Although this yields strong perceptual grounding, it does not evaluate the reasoning process of the model. Our method differs by directly rewarding temporally aligned reasoning through predicted and reference claims, offering an explicit link between reasoning steps and video content.

Comparison with VideoChat-R1.5. VideoChat-R1.5 [127] introduces Visual Test-Time Scaling (VTTS) and Iterative Perception, where the model iteratively refines its output at test time. The improvement primarily comes from the test-time scaling, not from reward formulation. Unlike VideoChat-R1.5, our method strengthens temporal reasoning during training via a temporal alignment reward and a consistency gating, leading to more coherent and grounded reasoning traces.

Comparison with VideoRFT. VideoRFT [114] introduces a semantic consistency reward that aligns generated video descriptions with visual embeddings using SigLIP [140]. It works at a coarse level of text-video similarity and focuses

on visual matching rather than detailed reasoning or timing accuracy. In contrast, our method directly supervises the reasoning process by aligning timestamped claims in the reasoning text with reference claims through the proposed Temporal Alignment Reward (TAR). Further, instead of conditioning on answer correctness as in VideoRFT, our gating mechanism is based on Think–Answer Consistency (TAC), which enforces logical agreement between reasoning and answer before applying any temporal reward. This design focuses learning on fine-grained temporal reasoning instead of broad video-text similarity, representing a conceptually distinct reinforcement formulation.

Summary. Overall, **Video-R2** unifies timestamp-aware supervision and reinforcement fine-tuning through a precision-based Temporal Alignment Reward (TAR) combined with a consistency gate (g). Unlike prior works that focus on perceptual or embedding-level correspondence, our method explicitly rewards temporally accurate and logically consistent reasoning at the claim level. This joint supervision reinforces both the temporal correspondence and internal coherence of the reasoning process. To the best of our knowledge, **Video-R2** is the first to employ consistency-gated temporal alignment as a reinforcement objective for

Method	Reward Type	Granularity	Consistency Handling
Video-R1 [35]	T-GRPO (ordered vs. shuffled)	Sequence	Answer-gated
VideoChat-R1 [64]	Task-verifiable (IoU / Acc)	Task-level	None
VideoChat-R1.5 [127]	VTTS Iterative Perception	Inference-level	None
VideoRFT [114]	Semantic Consistency (SigLIP)	Description-span	Answer-gated
Video-R2 (Ours)	TAR (Precision-based)	Claim-level	TAC-gated

Table A5. **Comparison of reward formulation and consistency design across recent video reasoning models.** Unlike previous approaches that focus on task-specific or semantic alignment rewards, our method introduces a novel claim-level precision-based temporal alignment reward combined with TAC-gated consistency enforcement, providing fine-grained supervision of reasoning alignment.

Model	Generic Benchmarks						Reasoning Benchmarks						Avg. (Reasoning)	Avg. (Overall)
	MV-Bench	VideoMME	TempCompass	MLVU	Long-VideoBench	Avg. (Generic)	VideoMathQA	Video-MMMU	MMVU-Val	VSiBench	MINERVA	SciVideoBench		
Accuracy														
Video-R2 (Ours)	67.5	63.8	74.9	68.3	59.2	66.7	28.8	50.8	67.4	39.4	34.9	28.4	41.6	53.0
→ Stronger Consistency Reward	62.9	60.3	71.9	63.7	54.2	62.6	20.0	49.3	64.3	35.7	33.5	26.0	38.1	49.3
→ Recall Term in TAR	67.0	62.9	74.2	68.6	<u>57.4</u>	<u>66.0</u>	<u>22.6</u>	47.9	<u>66.9</u>	<u>37.9</u>	35.5	28.5	<u>39.9</u>	51.8
Think-Answer Consistency (TAC)														
Video-R2 (Ours)	82.4	86.6	88.3	86.1	85.1	85.7	63.7	84.6	<u>90.2</u>	78.4	75.1	<u>77.3</u>	78.2	81.6
→ Stronger Consistency Reward	98.7	98.3	99.0	98.9	99.0	98.8	96.1	99.0	98.5	98.1	98.5	98.0	98.0	98.4
→ Recall Term in TAR	89.6	88.9	88.6	<u>89.0</u>	<u>89.3</u>	<u>89.1</u>	77.8	92.0	86.8	85.4	82.3	73.7	83.0	85.8
Video Attention Score (VAS)														
Video-R2 (Ours)	76.5	80.1	86.1	<u>78.7</u>	<u>73.2</u>	<u>78.9</u>	39.6	49.1	72.5	74.2	<u>73.4</u>	60.5	61.5	69.4
→ Stronger Consistency Reward	83.1	83.5	88.8	85.3	81.5	84.4	<u>43.4</u>	51.9	78.0	79.7	78.0	65.9	66.2	74.5
→ Recall Term in TAR	<u>78.2</u>	<u>80.5</u>	<u>86.2</u>	76.8	72.7	<u>78.9</u>	44.5	<u>50.8</u>	<u>76.3</u>	<u>76.9</u>	72.9	62.7	64.0	70.8

Table A6. **Ablations on stronger consistency reward and recall term in TAR.** The first variant adds a TAC-based reward directly to the total reward instead of consistency gating, producing a nearly *perfect TAC* (98.4%) and *strong visual grounding* (VAS) but reduced accuracy. This highlights a trade-off similar to the *SFT consistency paradox*, where optimizing for internal coherence alone yields a highly consistent but not necessarily stronger model. The second variant introduces a recall term in the Temporal Alignment Reward, computing TAR_{F1} instead of precision-only TAR. While this slightly enhances visual attention (VAS), accuracy drops especially on the reasoning benchmarks, as overgeneration of timestamps is encouraged. These experiments confirm that the precision-based, TAC-gated TAR in **Video-R2** offers the most balanced optimization of accuracy, consistency (TAC), and visual grounding (VAS).

video reasoning, offering a path toward more interpretable and causally grounded multimodal reasoning. A summary of comparison with recent video reasoning methods is provided in Tab. A5 for completeness.

I. Additional Ablations

I.1. Effect of Stronger Consistency Reward Factor

To study the effect of stronger consistency-oriented optimization, we modify the reward function to explicitly include the **Think-answer consistency (TAC)** as an additional reward component rather than using it as a gating condition. In this configuration, the Temporal Alignment Reward is computed without the consistency gate (e.g. TAR_{prec}), and a separate TAC-based term is added to the total reward for GRPO:

$$R_{\text{total}} = \lambda_{\text{acc}} R_{\text{acc}} + \lambda_{\text{fmt}} R_{\text{fmt}} + \lambda_{\text{tar}} TAR_{\text{prec}} + \lambda_{\text{tac}} R_{\text{TAC}}, \quad (11)$$

where $R_{\text{TAC}} \in [0, 1]$ directly measures the alignment between the model’s reasoning ($\langle \text{think} \rangle \dots \langle / \text{think} \rangle$) and final answer ($\langle \text{answer} \rangle \dots \langle / \text{answer} \rangle$). Removing the gating allows the model to be explicitly rewarded for self-consistency, irrespective of the other reward components.

As shown in Tab. A6, this variant achieves *nearly perfect TAC* (98.4%) and the *highest VAS* across all benchmarks,

but at a clear cost to overall accuracy. This behavior reflects a strong parallel to the *SFT consistency paradox* discussed in the main paper, where optimizing solely for internal coherence yields highly structured reasoning but not necessarily a stronger model. We attribute this to the model overemphasizing logical self-agreement while underexploring corrective reasoning signals. Nevertheless, we note that combining this stronger consistency reward with larger-scale data (on the order of hundreds of thousands or millions of samples) may produce highly consistent and accurate models: a promising direction for future exploration.

I.2. Introducing Recall Term in TAR

We further explore whether incorporating a recall component into the Temporal Alignment Reward (TAR) improves video reasoning. In this variant, we compute both precision- and recall-based temporal alignment scores before applying the TAC gate. The recall component (TAR_{rec}) is defined as:

$$TAR_{\text{rec}} = \frac{1}{m} \sum_{ij} X_{ij}, \quad (12)$$

where m is the number of reference claims. We then combine the precision (TAR_{prec}) and recall components (TAR_{rec}) using the harmonic mean:

$$TAR_{F1} = \frac{2 \times TAR_{\text{prec}} \times TAR_{\text{rec}}}{TAR_{\text{prec}} + TAR_{\text{rec}}}. \quad (13)$$

Model	Generic Benchmarks						Reasoning Benchmarks						Avg. (Reasoning)	Avg. (Overall)
	MV/Bench	VideoMME	TempCompass	MLVU	LongVideoBench	Avg. (Generic)	VideoMathQA	Video-MMMU	MMVU-Val	VSiBench	MINERVA	SciVideoBench		
Pearson Correlation Coefficient (PCC)														
Video-R1 [35]	0.740	0.777	0.666	0.777	0.684	0.729	0.664	0.752	0.782	0.744	0.733	0.657	0.722	0.725
VideoChat-R1 [64]	0.689	0.768	0.690	0.779	0.745	0.734	0.762	0.707	0.753	0.756	0.819	0.728	0.754	0.745
VideoChat-R1.5 [127]	0.654	0.762	0.727	0.781	0.634	0.711	0.750	0.762	0.731	0.720	0.736	0.654	0.726	0.719
VideoRFT [114]	0.709	0.715	0.646	0.796	0.657	0.705	0.649	0.707	0.682	0.731	0.759	0.676	0.701	0.702
Video-R2 (Ours)	0.670	0.656	0.613	0.704	0.610	0.651	0.675	0.693	0.698	0.540	0.671	0.579	0.643	0.646
Average	0.692	0.736	0.668	0.767	0.666	0.706	0.700	0.724	0.729	0.698	0.744	0.659	0.709	0.708

Table A7. **Stability of Video Attention Score (VAS) metric across different LLM judge models.** Pearson Correlation Coefficient (PCC) between VAS scores computed using Qwen3-Next-80B-A3B (default) and Qwen3-32B across all benchmarks and reasoning models. Average PCC values exceed 0.7 in both generic and reasoning categories, confirming a strong and statistically significant linear correlation (p -values = 10^{-35} – 0.0). This demonstrates that VAS is stable with respect to the choice of LLM judge, and model rankings remain consistent across judge models. For full reproducibility and alignment with the reported results, we recommend using Qwen3-Next-80B-A3B as the default LLM judge for VAS computation.

This TAR_{F1} replaces the precision-only term in the total reward, while the consistency gating remains active.

$$R_{\text{total}} = \lambda_{\text{acc}} R_{\text{acc}} + \lambda_{\text{fmt}} R_{\text{fmt}} + \lambda_{\text{tar}}(g \cdot \text{TAR}_{F1}). \quad (14)$$

The results in Tab. A6 show that adding the recall term slightly improves temporal completeness (higher VAS) but lowers accuracy, especially on reasoning benchmarks. This drop likely because the recall component encourages over-generation of timestamps, rewarding redundant or loosely aligned reasoning claims. This observation aligns with the inherent incompleteness of reference annotations, where not every relevant event is exhaustively labeled, thus, overfitting to recall may not yield better reasoning quality. Empirically, the precision-based TAR used in Video-R2 remains more stable and better aligned with reasoning quality.

I.3. Stability of VAS Metric

To assess the robustness of our proposed Video Attention Score (VAS) metric against the choice of large language model (LLM) used as the judge, we compute VAS using two different models: **Qwen3-Next-80B-A3B** (our default) and **Qwen3-32B**. The default model features a larger total parameter count but fewer active parameters, offering an optimal balance between speed and evaluation accuracy, while the Qwen3-32B is a dense 32B parameter model used in its non-reasoning mode. For each benchmark and reasoning model, we calculate sample-level VAS scores using both LLMs and measure their linear correlation through the *Pearson Correlation Coefficient (PCC)*. This process is repeated across all 11 benchmarks (five generic and six reasoning) for five reasoning models, resulting in a comprehensive cross-model stability analysis in Tab. A7.

As shown in Tab. A7, all PCC values remain high, with

overall averages exceeding 0.7, indicating a strong linear correlation between the VAS computed by the two LLMs. This demonstrates that the relative ranking of models across benchmarks remains consistent even when the judge model changes, confirming that VAS is a stable and reliable indicator of visual grounding strength. Further, the corresponding p -values for all correlations were effectively zero (in the range of 10^{-35} – 0.0), showing that these correlations are statistically significant. While Qwen3-32B produces consistent rankings, we recommend using **Qwen3-Next-80B-A3B**, which is openly available, to ensure complete reproducibility of all reported VAS values and maintain exact correspondence with our main results.

I.4. Sensitivity Analysis

Sensitivity of τ , Δ , and λ_{tar} . The hyperparameters used in the Temporal Alignment Reward (TAR), the semantic similarity threshold (τ), the temporal tolerance (Δ), and the TAR weighting factor (λ_{tar}), are selected empirically. The search objective focuses solely on maximizing answer accuracy; reasoning quality metrics such as TAC or VAS are not considered during this process. To avoid overfitting and ensure efficient tuning, experiments are conducted on a representative subset of 1,000 randomly sampled instances from the 4.8K GRPO dataset and evaluated using a subset of the generic benchmarks. This setup follows standard machine learning practice, where hyperparameters are optimized on a held-out subset rather than the full training dataset.

For τ and Δ , a sequential search is performed. First, τ is fixed at 0.75, and four different Δ values are tested. Next, using the best Δ , τ is varied across four candidate settings. From these runs, $\Delta = 2$ s and $\tau = 0.75$ provide the best overall score on generic benchmarks. The selected values

Model	Max Frames	Generic Benchmarks					Avg. (Generic)	Reasoning Benchmarks					Avg. (Reasoning)	Avg. (Overall)	
		MVBench	VideoMME	TempCompass	MLVU	LongVideoBench		VideoMathQA	Video-MMMU	MMVU-Val	VSiBench	MINERVA			
Accuracy (Reported)															
Video-R1 [35]	64	64.8	61.4	73.2	-	-	-	52.4	63.8	<u>37.1</u>	-	-	-	-	
VideoChat-R1 [64]	NA	66.2	-	-	-	-	-	-	-	-	-	-	-	-	
VideoChat-R1.5 [127]	2048	70.6	65.2	-	70.1	61.4	-	-	49.6	-	-	-	-	-	
VideoRFT [114]	32	62.1	59.8	<u>73.7</u>	-	-	-	-	<u>51.1</u>	68.5	36.8	-	-	-	
Video-R2 (Ours)	128	67.5	<u>63.8</u>	74.9	<u>68.3</u>	<u>59.2</u>	66.7	28.8	50.8	<u>67.4</u>	39.4	34.9	28.4	41.6	53.0
Accuracy (Reproduced)															
Video-R1 [35]	128	65.1	<u>64.3</u>	73.5	67.7	<u>57.6</u>	<u>65.6</u>	23.6	47.0	64.0	37.8	33.9	<u>26.8</u>	38.8	51.0
VideoChat-R1 [64]	128	63.6	64.1	<u>74.5</u>	62.5	54.3	63.8	24.3	52.0	64.8	33.0	33.8	26.5	39.1	50.3
VideoChat-R1.5 [127]	128	65.7	64.8	73.9	65.3	53.6	64.7	<u>26.4</u>	50.0	<u>67.0</u>	36.1	33.7	25.8	39.8	51.1
VideoRFT [114]	128	64.8	64.1	73.8	66.6	57.0	65.3	25.2	48.1	<u>66.7</u>	<u>38.5</u>	<u>34.0</u>	25.7	39.7	51.3
Video-R2 (Ours)	128	67.5	63.8	74.9	68.3	59.2	66.7	28.8	50.8	<u>67.4</u>	39.4	34.9	28.4	41.6	53.0

Table A8. **Comparison with previously reported numbers and evaluation under a unified protocol.** Upper section shows the accuracy values as reported in the original papers of prior methods, which vary significantly in evaluation settings, frame counts, resolutions, and benchmark coverage. Lower section presents results of all models re-evaluated under our standardized setup (2 FPS, 128 frames, 360×420 px), ensuring consistency across benchmarks. Our unified evaluation eliminates confounding factors and allows fair cross-model comparison. All datasets, trained models, and code for training and evaluation will be publicly released to support reproducibility.

also align qualitatively with observations in Figs. A7–A17.

For λ_{tar} , values 0.5, 1.0, 1.5 are tested while keeping all other coefficients fixed. Setting $\lambda_{\text{tar}} = 1.0$, equal to the weights of the accuracy and format rewards, results in the best overall performance. These hyperparameters are determined using limited subsets rather than the complete dataset or all benchmarks. The final values, $\tau = 0.75$, $\Delta = 2$ s, and $\lambda_{\text{tar}} = 1.0$, remain fixed in all subsequent experiments.

I.5. Comparison using Reported Numbers

Tab. A8 compares the performance of recent video reasoning models using the accuracy values reported in their respective papers, alongside our results obtained under the proposed unified evaluation protocol. This comparison highlights the inconsistencies that arise from differing evaluation settings and underscores the need for a standardized evaluation protocol.

Reported numbers across existing methods are not directly comparable due to several confounding factors. (1) Different methods evaluate using widely varying maximum frame counts, ranging from 32 frames in VideoRFT [114] to 2048 frames in VideoChat-R1.5 [127]. (2) Frame resolution also differ across implementations and are often unspecified. (3) The benchmark coverage itself varies, as some methods report results on only a subset of the benchmarks. These discrepancies make a direct quantitative comparison between methods unreliable and can hide the underlying progress in reasoning ability.

To address these inconsistencies, we evaluate all prior

reasoning models using their official prompts under our unified evaluation protocol, which standardizes frame sampling (2 FPS, up to 128 frames, 360×420 px resolution) and ensures consistent benchmarking across all 11 datasets. This controlled setup allows an accurate and fair assessment of reasoning quality, free from evaluation bias. Refer to the lower half of Tab. A8 for the results obtained from our evaluation protocol.

Our unified protocol, along with the complete datasets, models, and training and evaluation code, will be publicly released with detailed documentation to facilitate full reproducibility and future research on video reasoning.

J. Prompts Used in Training and Evaluation

Both during training and evaluation, we append a fixed post prompt to encourage explicit reasoning within `<think>...</think>` and a final answer within `<answer>...</answer>` block. The exact post prompt is:

Post Prompt used in training and evaluation

Please think about this question as if you were a human pondering deeply. Engage in an internal dialogue using expressions such as 'let me think', 'wait', 'Hmm', 'oh, I see', 'let's break it down', etc, or other natural language thought expressions. It's encouraged to include self-reflection or verification in the reasoning process. Provide your detailed reasoning between the `<think>` and `</think>` tags, and then give your final answer between the `<answer>` and `</answer>` tags.



Question: What does the player see upon exiting the building?

Options: A. A rocket B. Fire C. Smoke

D. His Teammates

Correct Answer: C. Smoke

Video-R1

<think> Let me think about this for a moment. The question is asking what the player sees upon exiting the building. To answer this, I need to carefully analyze the sequence of events in the video.

Firstly, the player is inside a building, and there's a map visible at the top left corner of the screen. The player seems to be in a strategic position, possibly preparing to move out. Now, when the player exits the building, I need to focus on what appears immediately after that action.

Wait, let's break it down step by step. The player exits the building, and the next thing we see is a significant change in the environment. There's a noticeable shift from the interior of the building to an outdoor area. The outdoor area has some structures and possibly other players or objects around.

Hmm, now I need to consider the options given. Option A, "A rocket," doesn't seem likely because there's no rocket visible in the immediate vicinity. Option B, "Fire," also doesn't fit because there's no fire evident in the scene. Option C, "Smoke," could be a possibility, but it's not explicitly mentioned in the video description.

Oh, I see. The most logical and common sight upon exiting a building in a game like this would be to see other players or teammates. This aligns with the typical behavior of players in such games, where they often engage with their team members after exiting a building.

Let's verify this one last time. The player exits the building, and the next logical action would be to interact with his teammates, either to coordinate or to engage in combat. This fits perfectly with the context of the game and the typical behavior of players.

Therefore, the best answer is D, "His teammates."

Let's double-check one last time. Yes, the player sees his teammates upon exiting the building, which is the most logical and common scenario in this type of game. </think> <answer> C </answer>

VideoRFT

<think> To determine what the player sees when exiting the building, let's review the video content step-by-step. The video begins with the player inside a building, holding a weapon and moving cautiously. The player is wearing a headset and appears focused on the game. The map shows "Sniper's Nest" and "Bombsite A," indicating the player is likely in a tactical shooter like Counter-Strike: Global Offensive (CS:GO).

The player exits the building and moves into an open area with stone walls and arches, typical of CS:GO maps. The environment is clear, with no immediate signs of smoke or fire. The player's teammates are not visible in the immediate vicinity, but they could be elsewhere on the map.

The key elements to consider are the visual details provided in the video. Upon exiting the building, the player encounters an open area with stone walls and arches. **There is no indication of smoke or fire in the immediate surroundings.** The player's teammates are not visible in the immediate area, but they could be elsewhere on the map.

Given the options:

- A. A rocket: No rocket is visible in the video.
- B. Fire: No fire is visible in the video.
- C. Smoke: No smoke is visible in the video.
- D. His teammates: While the player's teammates are not visible in the immediate area, they could be elsewhere on the map.

Since the video does not show any of these elements, the most logical answer based on the available information is that the player sees his teammates, even though they are not visible in the immediate area. Therefore, the answer is D. </think> <answer> C </answer>

Video-R2 (Ours)

<think> Okay, let's analyze what happens in the video when the player exits the building.

The player is inside a building, holding a pistol. They look out through a window and see a street scene outside. Then they move through the doorway into a courtyard area. The key moment is right after they step out onto the courtyard. At **00:18**, there's a very clear shot of the player's view. They are standing in front of a stone wall, looking across the courtyard towards another building. **The most prominent thing visible is a large plume of smoke rising from the ground near that building.** This is the visual cue for the answer.

Now, let's evaluate the options:

- A. A rocket. No, there's no rocket visible. It's just a cloud of smoke.
- B. Fire. While the smoke could be from a fire, the term "fire" is too specific. The video doesn't show flames or any indication of a burning object. It's just a general cloud of smoke.
- C. Smoke.** Yes, this matches exactly what I saw. The player clearly sees a large cloud of smoke billowing up from the ground.
- D. His teammates. The player is alone at first. They don't see anyone else until later in the video, but the question asks what they *see* upon exiting, not what they *do*. So, seeing teammates isn't the correct answer.

Based on the visual evidence provided by the video, the player sees **smoke** when they exit the building. </think> <answer> C </answer>

Figure A1. TAC comparison Example 1.



Question: How many rolls does the girl do in her performance?

- Options:**
- A. More than 5 but less than or equal to 10.
 - B. Less than or equal to 5.
 - C. More than 10 but less than or equal to 15
 - D. More than 15

Correct Answer: A. More than 5 but less than or equal to 10.

Video-R1

<think> Let me think about this for a moment. The question is asking about the number of rolls the girl does during her performance. To answer this, I need to carefully observe the video and count the rolls she performs. Firstly, let's break it down. A roll is a specific type of movement where the body rotates around its longitudinal axis. In the video, the girl performs various acrobatic moves, including flips and spins, which can be considered rolls.

Now, let's count the rolls:

1. She starts with a roll from a standing position.
2. She performs another roll while doing a flip.
3. She does a roll while doing a cartwheel.
4. She performs a roll while doing a backflip.
5. She does a roll while doing a forward roll.

After counting these, it seems like there are approximately 5 rolls. However, there might be more subtle rolls that are not immediately apparent. Wait, let's verify. The girl does indeed perform several rolls, and the count seems to be around 5. There are no indications of more than 10 rolls, so we can rule out options A, C, and D. Hmm, the most accurate answer based on the observed rolls and the given options is that the girl does less than or equal to 5 rolls. Oh, I see. The correct answer should be the one that matches the observed number of rolls, which is less than or equal to 5. Let's break it down one last time to ensure. The girl does 5 rolls, and there are no indications of more than 5 rolls. Therefore, the correct answer is B.

Final answer: B

Let's double-check. Yes, the girl does less than or equal to 5 rolls, and there are no indications of more than 5 rolls. </think> <answer> A </answer>

VideoRFT

<think> To determine how many rolls the girl performs in her acrobatic routine, let's review the video step-by-step. The video begins with Mackenzie entering the stage wearing a colorful outfit and a party hat, with the text "MACKENZIE'S SOLO DANCE STYLE: ACRO" displayed. She then proceeds to perform various acrobatic moves, including cartwheels, handstands, and flips. The key is to identify the number of rolls she executes during her routine. A roll typically involves rotating the body around the vertical axis. In the video, Mackenzie performs several rolls, which can be counted as follows:

- At the start, she does a cartwheel, which includes one roll.
- Later, she transitions into a handstand, which also counts as a roll.
- Towards the end, she performs another handstand, adding another roll.
- Finally, she ends with a roll before exiting the stage.

Counting these rolls, we have: 1. Cartwheel (roll), 2. Handstand (roll), 3. Handstand (roll), 4. Final roll

Thus, the total number of rolls performed by Mackenzie is four. Given the options provided, the closest match is B. Less than or equal to 5. Since four is within this range, the answer is B. </think> <answer> A </answer>

Video-R2 (Ours)

<think> Okay, let's analyze the video to figure out how many rolls the girl performs. The question asks for the number of rolls she does during her dance routine. First, I need to watch the entire performance carefully. She starts by walking onto the stage, then begins her dance. I'll pay close attention to any flips or rolls she executes.

At around 00:08, she does a roll from a handstand position. This is the first one. Then, at 00:13, she does another roll, this time from a different angle. That's two rolls so far. Next, at 00:16, she does a third roll, this time from a kneeling position. So now we have three rolls. After that, at 00:20, she does a fourth roll, this time from a standing position. Now it's four. Then, at 00:24, she does a fifth roll, this time from a kneeling position again. So, five rolls. Finally, at 00:27, she does a sixth roll, this time from a handstand. That makes six rolls in total.

So, the girl performs a total of six rolls. Let's look at the options:

- A. More than 5 but less than or equal to 10.
- B. Less than or equal to 5.
- C. More than 10 but less than or equal to 15.
- D. More than 15.

Based on my count, the number of rolls is exactly 6, which fits perfectly into option A. It's more than 5 and less than or equal to 10. The other options are either too high or too low. Therefore, the correct answer must be A. </think> <answer> A </answer>

Figure A2. TAC comparison Example 2.



Question: What does the Woking player do to get the first yellow card?

- Options:**
- A. He shouts at the referee.
 - B. He wastes time before a throw-in.
 - C. He knocks over a Wrexham player.
 - D. He makes a rude gesture to the Wrexham manager.
 - E. He dives in the penalty box.

Correct Answer:
C. He knocks over a Wrexham player.

Video-R1

<think> Let me think about this for a moment. The question is asking what specific action by the Woking player resulted in the first yellow card. Firstly, let's consider each option:

- A. He shouts at the referee - This doesn't seem likely because shouting at the referee isn't typically grounds for a yellow card.
- B. He wastes time before a throw-in - This could be possible, but there's no clear evidence in the video that he did this.
- C. He knocks over a Wrexham player - This seems plausible. In soccer, knocking over a player can lead to a foul and potentially a yellow card.
- D. He makes a rude gesture to the Wrexham manager - This is unlikely because making a rude gesture to the manager isn't a standard reason for a card.
- E. He dives in the penalty box - This is also unlikely because diving in the penalty box is not a common reason for a yellow card.

Now, let's focus on option C. The video shows a sequence where a Woking player appears to knock over a Wrexham player. This action is clearly visible and can be interpreted as a foul. The referee then issues a yellow card to the Woking player for this action. Hmm, after considering all the options and the visual evidence from the video, it's clear that the most logical and observable action leading to the first yellow card is the Woking player knocking over a Wrexham player. Oh, I see. The correct answer should be the one that aligns with the most evident and observable action in the video. Let's break it down one last time to verify. The Woking player knocking over a Wrexham player is the most direct and observable reason for the yellow card.

Final answer: C

Let's double-check the video one more time to ensure there's no other action that could have led to the yellow card. After verification, it's confirmed that the Woking player knocking over a Wrexham player is the correct action. </think> <answer> **B** </answer>

VideoRFT

<think> To determine which action results in the Woking player receiving the first yellow card, let's review the sequence of events from the video. The match begins with Wrexham leading 1-0 against Woking, and the scoreboard shows WRE 1-0 WOK. The video highlights various moments, including a goal by Summerfield at 18' and another by Jarvis at 47'. The key moment for the yellow card is when Woking's player, wearing a yellow jersey, is shown receiving a caution. This occurs during a specific play where the player is seen diving into the penalty box, causing a foul. The referee then issues the yellow card, indicating that the player's action was deemed unsporting behavior.

Given the options provided:

- A: Shouting at the referee (not shown)
- B: Wasting time before a throw-in (not shown)
- C: Knocking over a Wrexham player (not shown)
- D: Making a rude gesture to the Wrexham manager (not shown)
- E: Diving in the penalty box (matches the video)

The correct answer is clearly E, as the video explicitly shows the player diving into the penalty box, resulting in a foul and the referee issuing a yellow card. Therefore, the correct answer is E. </think> <answer> **C** </answer>

Video-R2 (Ours)

<think> Okay, let's analyze the video to find out why the Woking player gets the first yellow card. The question asks for the specific action that leads to the card. First, I need to identify when the first yellow card is shown. I'll scan through the video. At 01:12, there's a replay of a foul. A Woking player in a yellow jersey is seen knocking over a Wrexham player in a red jersey near the corner flag. The referee points to his card, and the player is shown a yellow card. This seems like a clear foul.

Now, let's look at the options:

- A. He shouts at the referee. No, he doesn't shout; he just runs off after being booked.
- B. He wastes time before a throw-in. This doesn't fit the context. The incident happens during play, not before a throw-in.
- C. He knocks over a Wrexham player. Yes, this matches what I saw. The player in yellow is clearly seen tripping or knocking over the player in red.
- D. He makes a rude gesture to the Wrexham manager. There's no mention of a manager or any gesture towards him. This is incorrect.
- E. He dives in the penalty box. This also doesn't match. The incident is outside the penalty area, and diving is not the action shown.

So, the most logical conclusion is that the yellow card was given for a foul. The key moment is the tackle at 00:12. The player in yellow is definitely the one who committed the foul. Therefore, the correct answer must be related to this action. Option C is the best description of the action that led to the card. </think> <answer> **C** </answer>

Figure A3. TAC comparison Example 3.



Question: Which hair color does the little boy have while playing the guitar in the video?

- Options: A. Black B. Golden C. White D. Grey

Correct Answer: B. Golden

Video-R1

<think> Let me think about this for a moment. The question is asking about the hair color of the little boy who plays the guitar in the video. Now, let's break it down step by step. First, I need to recall the scene where the little boy is playing the guitar. In my mind's eye, I can visualize the boy sitting on a bench, strumming his guitar. He has long hair that falls over his shoulders. Now, what color is this hair? Let's consider the options:
 A. Black - This would mean the hair is dark and possibly jet black.
 B. Golden - This would suggest a light, golden hue.
 C. White - This would imply the hair is white, which is not typical for a young boy.
 D. Grey - This would indicate the hair is grey, which is also not common for a child.

Hmm, when I think of a young boy playing the guitar, the most likely hair color would be something warm and inviting. The golden color fits well with the idea of a young, carefree boy enjoying music. It's a color that often associated with warmth and happiness. Oh, I see. The golden color aligns perfectly with the typical appearance of a young boy in a casual setting like this. It's a color that stands out and adds to the overall charm of the scene. Wait, I should double-check if there's any other detail in the video that might contradict this. So, after all this reflection, I am confident that the correct answer is B. Let's verify one last time. Yes, the golden hair fits the scene and the typical appearance of a young boy. </think> <answer> B </answer>

Video Attention Score (VAS): 1/10 (One out of Ten)

Rationale: The reasoning uses stereotypes ('typical appearance', 'warm and inviting') rather than concrete visual details from the video. It references no specific attributes, lighting, positions, or on-screen cues, only generic assumptions about youth and hair color.

VideoRFT

<think> To determine the hair color of the little boy playing the guitar in the video, let's review the visual content step-by-step. The video begins with a blue screen featuring the Viator logo and text, followed by a scene of Central Park in New York City. A woman in a light blue shirt is seen talking to tourists, pointing out various locations. The video then shows people walking along paths, including a person holding a blue umbrella.

Next, the video transitions to a scene where a man in a red shirt and another in a checkered shirt are standing together. The man in the red shirt has short dark hair, while the man in the checkered shirt has longer hair. The video then shifts to a close-up of a mosaic with the word "IMAGINE" surrounded by geometric patterns. Finally, the video concludes with a sign for the Central Park TV and Movie Sites Walking Tour.

The key moment is when the video shows a person holding a blue umbrella. This individual is wearing a light blue shirt and black shorts. The video then cuts to a scene where a man in a red shirt and another in a checkered shirt are standing together. The man in the red shirt has short dark hair, while the man in the checkered shirt has longer hair. However, there is no mention of a little boy playing the guitar in any of these scenes. Therefore, the answer is not provided in the video content.

Given the options A. Black, B. Golden, C. White, and D. Grey, none of these match the hair color of the man in the red shirt, who has short dark hair. Since the video does not show a little boy playing the guitar, the answer is not present in the video content. </think> <answer> B </answer>

Video Attention Score (VAS): 0/10 (Zero out of Ten)

Rationale: The reasoning claims to describe visual content but completely fails to mention a little boy playing the guitar, which is the core of the question. It describes unrelated scenes (woman talking, mosaic, signs) and incorrectly concludes the boy is absent, offering no visual evidence for any hair color.

Video-R2 (Ours)

<think> Okay, let's analyze the video for the question "Which hair color does the little boy have while playing the guitar in the video?" First, I need to find the scene where a boy is playing the guitar. The video starts with a title card, then shows a panoramic view of Central Park. After that, there's a shot of a woman talking to a group of people. Then, at 0:38, a man in a red shirt is shown pointing at something off-screen. Following that, around 0:41, a woman holding a blue umbrella walks by. At 0:42, a man in a plaid shirt is shown. Then, at 0:45, a man in a white shirt is shown. Finally, at 0:50, a young boy with blonde hair appears. He is wearing a black t-shirt and is sitting on a bench, playing a guitar.

Now, I can see his hair color clearly. It's a light, golden blonde. Let's check the options:

- A. Black - No, he's not black.
 B. Golden - Yes, this matches my observation.
 C. White - No, it's not white.
 D. Grey - No, it's not grey.

So, the correct answer must be B. The key moment is when the boy is shown playing the guitar at 0:50. </think> <answer> B </answer>

Video Attention Score (VAS): 9/10 (Nine out of Ten)

Rationale: The reasoning explicitly cites a timestamp (0:50) and describes the boy's appearance with specific visual details: 'blonde hair,' 'black t-shirt,' and 'sitting on a bench playing a guitar,' directly tying the observation to the video. It also references preceding scenes to establish temporal context.

Figure A4. VAS comparison Example 1.



Question: Where is the young medical doctor discussing health issues with the patient?
Options: A. In a park B. Inside Office C. In a hospital ward D. At the patient's home

Correct Answer: B. Inside Office

Video-R1

<think> Let me think about this for a moment. The question is asking where the medical doctor is discussing health issues with the patient. Now, let's break it down. Firstly, the setting of the discussion is crucial. The options provided are quite different, so we need to consider each one carefully.

Option A: In a park - This seems unlikely because parks are not typically places where medical consultations take place. It's not a professional environment for healthcare discussions.

Option B: Inside office - This could be a possibility. Offices are common places for doctors to conduct medical consultations. They provide a private and professional space for patients to discuss their health issues.

Option C: In a hospital ward - While hospitals do have wards, they are usually more clinical and less private than an office. It's possible, but it's not the most likely option.

Option D: At the patient's home - This is also a possibility, but it's less common for doctors to visit patients' homes for consultations. It's more convenient for the doctor to go to the office.

Hmm, after considering all the options, the most logical and common place for a medical consultation would be inside the doctor's office. It provides a private and professional environment, which is ideal for discussing health issues. Oh, I see. The question is asking for the most likely and common place, and based on the options, the inside office is the most fitting. Let's verify this one last time. Yes, the inside office is the most logical and common place for a medical consultation. It provides the necessary privacy and professionalism required for such discussions. So, the correct answer should be the inside office. </think> <answer> B </answer>

Video Attention Score (VAS): 0/10 (Zero out of Ten)

Rationale: The reasoning mentions no specific visual details from the video, no descriptions of setting, objects, text, or actions seen. It relies entirely on generic assumptions about typical medical consultation environments, with no claim of observing anything in the video itself.

VideoRFT

<think> To determine where the medical doctor is discussing health issues with the patient, let's analyze the given options: park, inside office, hospital ward, or at the patient's home. The video begins with a beach scene featuring baby turtles, followed by underwater footage of a turtle swimming. It then transitions to a scene of a bird flying over a tree and later shows a sea turtle swimming near coral reefs. The video concludes with aerial views of clouds and mountains, and a close-up of a butterfly on a leaf. The key elements here are the initial beach scene and the subsequent underwater footage. The video then shifts to a bird flying over a tree, which could be part of the same sequence. However, the question specifically asks about the doctor's location during the health discussion. Given that the video starts with a beach scene and transitions to underwater footage, it's likely that the doctor's office is not near the beach. The options provided are park, inside office, hospital ward, or at the patient's home. Since the video doesn't show any outdoor scenes after the initial beach, the most logical choice is the inside office (option B). The video then shows a sea turtle swimming near coral reefs, but this is unrelated to the doctor's location. The final scenes focus on clouds and mountains, which are also not relevant to the doctor's setting. Therefore, the correct answer is B, inside office. The other options — park, hospital ward, or patient's home — are less likely because the video doesn't show any outdoor scenes after the initial beach. The park option is unlikely since the video doesn't depict any park scenes. The hospital ward option is possible, but the video doesn't show any hospital scenes either. </think> <answer> B </answer>

Video Attention Score (VAS): 0/10 (Zero out of Ten)

Rationale: The reasoning mentions no visual evidence of the doctor, patient, or any healthcare setting; instead, it describes unrelated video content (turtles, birds, clouds) and guesses the answer by eliminating options based on absence of imagery, which is not visual grounding.

Video-R2 (Ours)

<think> Okay, let's analyze the video clips to figure out where the medical consultation is taking place. First, I need to identify the scene that shows the medical interaction. The video starts with baby turtles on a beach, which is clearly not the location of the doctor's office. Then, there's a shot of a bird flying over clouds, also not relevant. Next, we see a dense forest with butterflies, which is another unrelated location. The next clip at 05:04 is a close-up of a woman wearing glasses and a white coat, who is speaking to someone off-camera. She has a stethoscope around her neck, which is a strong indicator that she is a medical professional. This is the first time I've seen any kind of medical setting. The background is a simple, light-colored wall, which is typical for a doctor's office. There are no patients visible, but the context strongly suggests a consultation is happening. The woman's attire and the setting are very consistent with what one would expect in a medical office.

Now, let's look at the options.

(A) In a park - This is incorrect because the setting is indoors, not outdoors.

(B) Inside office - This seems like a good possibility based on the visual evidence.

(C) In a hospital ward - While hospitals do have offices, the environment looks more like a general practice or clinic rather than a ward.

(D) At the patient's home - The setting doesn't look residential; it's too clean and professional.

Given the visual clues, especially the white coat and the plain wall, option (B) "Inside office" is the most logical conclusion. The consultation is taking place within the confines of a medical office. </think> <answer> B. Inside office </answer>

Video Attention Score (VAS): 9/10 (Nine out of Ten)

Rationale: The reasoning explicitly references specific visual cues from the video: the woman wearing a white coat and stethoscope (05:04), the light-colored wall background. It chains these observations to the question with clear visual logic, even noting the temporal sequence of clips.

Figure A5. VAS comparison Example 2.



Question: What did I pick from the plastic box?

Options: A. Pen B. Paper C. Needle D. scissors

Correct Answer: C. Needle

Video-R1

<think> Let me think about this for a moment. The question is asking what I picked from the plastic box, and the options provided are A (pen), B (paper), C (needle), and D (scissors). Firstly, let's consider the context. The image shows a person working on a construction project, and there's a plastic box visible in the scene. The contents of the box aren't explicitly shown, but we can infer some possibilities based on common tools used in construction.

Now, let's break it down:

- A pen: This is a common tool used for marking measurements and notes, which might be relevant in construction.
- B paper: White paper is used for notes, it's not a tool itself and doesn't require picking up from a box.
- C needle: This seems unlikely because needles are not typically used in construction.
- D scissors: Scissors are used for cutting materials, but they are usually handheld and don't need to be picked up from a box.

Hmm, the most logical option given the context and the typical tools used in construction is a pen. It's a common tool that would be picked up from a box to mark measurements. Oh, I see. The most likely answer is A (pen). Let's verify this by considering the other options again. The paper and needle are less likely, and scissors are not typically picked up from a box in this context. After this reflection, I am confident that the correct answer is A (pen). Let's break it down one last time to ensure. The pen is the most logical and commonly used tool in construction that would be picked up from a box. </think>

<answer> C </answer>

Video Attention Score (VAS): 1/10 (One out of Ten)

Rationale: The reasoning mentions 'the image shows a person working on a construction project' and 'a plastic box visible,' but makes no specific claims about what is seen inside the box or any visual evidence of the picked object. It relies on generic inference about construction tools rather than concrete visual details from the video.

VideoRFT

<think> To determine what was picked from the plastic box, let's review the video content step-by-step. The video shows a person working on a wooden structure outdoors, wearing a gray sweatshirt with "NOLLELANDS" on it. They use various tools like a tape measure, pencil, and circular saw, and interact with materials such as wood planks and nails. The key action is picking something from a plastic box. The options provided are pen, paper, needle, or scissors. Initially, the person is seen holding a yellow tape measure and measuring a wooden beam. Later, they use a circular saw to cut a plank. The video also shows them handling nails and other materials. However, there is no visual evidence of a plastic box containing any of these items. The only box mentioned is a white one, but its contents are not specified.

Given the options, the most plausible item that could be picked from a plastic box is a pen (option A). While the video does not explicitly show a pen being picked from a box, it is a common tool used in construction. If the person had a pen in their pocket or on the workbench, it could have been picked up from a box. Paper (option B) could be a tool or material, but the video does not indicate any paper being picked from a box. Alternatively, a needle (option C) might be used for sewing, but the video does not show any sewing activity. Scissors (option D) are not shown in the video at all.

Since the video does not provide clear evidence of any of these items being picked from a plastic box, the safest assumption based on the given options is that the person picked a pen (option A). </think> <answer> C </answer>

Video Attention Score (VAS): 2/10 (Two out of Ten)

Rationale: The reasoning mentions visual elements like 'wooden structure,' 'tape measure,' and 'circular saw,' but falsely claims to observe a 'plastic box' whose contents are 'not specified,' then guesses based on option plausibility rather than visual evidence. It admits 'no visual evidence' of the box's contents, making the final inference non-visual.

Video-R2 (Ours)

<think> Okay, let's analyze the video to figure out what was picked from the plastic box.

First, I need to identify when the person picks something from the box. The video shows a man working on a wooden structure. He climbs up a ladder, gets some wood, and then goes back down. At around 6:45-6:50, he reaches for a plastic container on the ground near the ladder. He opens it and takes out a small object. The camera is focused on his hands, so I can clearly see him picking up a needle.

Now, let's look at the options.

- (A) pen - No, it's not a pen. It's too thin and pointed.
- (B) paper - No, there's nothing flat and rectangular like a piece of paper.
- (C) needle - Yes, that matches exactly what I saw. It's a thin, sharp object.
- (D) scissors - No, they're not sharp and they have two blades.

So, based on the visual evidence, the item picked from the box is definitely a needle. The question asks for the correct option, and (C) Needle is the only one that fits the description. </think> <answer> C. Needle </answer>

Video Attention Score (VAS): 10/10 (Ten out of Ten)

Rationale: The reasoning provides dense, specific visual evidence: it cites a precise timestamp (6:45-6:50), describes the subject's action (reaches for, opens, picks up), notes the camera focus on hands, and details the object's visible attributes (thin, pointed, sharp) to rule out other options.

Figure A6. VAS comparison Example 3.



Question: How many times does the person perform a cartwheel while holding the jump rope?

Options: A. Three times B. Four times C. Once D. Twice

Reference Reasoning

<think>

Okay, I need to count how many times the person in the video does a cartwheel while holding the jump rope. I'll watch the video carefully from the beginning and keep a tally.

The video starts, and the person begins her jump rope routine. There are a lot of advanced tricks right away. I'm looking for a specific gymnastic move: a cartwheel.

Alright, here comes the first one. At around the **16-second mark**, she plants her hands on the floor and kicks her legs over, just like a cartwheel. She's holding the jump rope handles the entire time and the rope passes under her body as she completes the move. So that's one cartwheel.

I'll keep watching. She continues with her routine, moving across the floor. She turns her back to the camera... and there's another one! Around **00:25**, she performs the exact same move, a cartwheel, while holding the rope. Her back is to the camera this time, but it's clearly the same skill. That makes two cartwheels.

Now I'll watch the rest of the video to make sure there aren't any more. She keeps jumping with different leg movements and turns, but no more cartwheels. The routine ends, and she walks away.

So, I counted a total of two cartwheels performed with the jump rope. The first one was at **00:16** and the second one was at **00:25**. This matches option D.

</think> <answer> D. Twice </answer>

Model's Prediction

<think>

Okay, I need to count the number of cartwheels the person does while holding the jump rope. I'll watch the video carefully and keep track.

At **00:16**, the person is holding the jump rope. They bend their knees, then twist their body and throw their legs up to do a cartwheel. This is the first one.

After the cartwheel, they land and immediately continue jumping rope without dropping the rope. They spin the rope over their head.

Next, at **00:26**, they repeat the process, doing another cartwheel while still holding the jump rope.

They land again and continue jumping rope.

So, I've counted two distinct cartwheels performed while holding the jump rope. The question is clear about the sequence of events. The answer is D.

</think> <answer> D. Twice </answer>

Reference Claims

00:16: She performs a cartwheel while holding the jump rope handles and the rope passes under her body.

00:25: She performs another cartwheel while holding the jump rope, with her back to the camera.

Predicted Claims

00:16: The person holds the jump rope, bends their knees, twists, and performs a cartwheel.

00:26: The person repeats the cartwheel while continuing to hold the jump rope.

Temporal Alignment Reward (TAR) - Calculation

- 1) P(**00:16**): Sim: 0.77 > 0.75, Match
- 2) P(**00:26**): Sim: 0.67 < 0.75, No Match

$$\text{Precision} = \frac{\# \text{match}}{\# \text{pred_claims}}, \quad \text{Consistency } (g) = 1$$

$$\text{Reward (TAR)} = g \times P = 1 \times 0.5 = 0.5$$

Temporal Match (T^T)			Semantic Match (S^T)				
	Prediction			Prediction			
Timestamps	00:16	00:26	Timestamps	00:16	00:26		
Ref.	00:16	True	False	Ref.	00:16	0.77	0.68
	00:25	False	True		00:25	0.66	0.67

Figure A7. TAR calculation Example 1.



Question: How many times does the person perform a cartwheel while holding the jump rope?

Options: A. Three times B. Four times C. Once D. Twice

Reference Reasoning

<think>

Okay, I need to count how many times the person in the video does a cartwheel while holding the jump rope. I'll watch the video carefully from the beginning and keep a tally.

The video starts, and the person begins her jump rope routine. There are a lot of advanced tricks right away. I'm looking for a specific gymnastic move: a cartwheel.

Alright, here comes the first one. At around the **16-second mark**, she plants her hands on the floor and kicks her legs over, just like a cartwheel. She's holding the jump rope handles the entire time and the rope passes under her body as she completes the move. So that's one cartwheel.

I'll keep watching. She continues with her routine, moving across the floor. She turns her back to the camera... and there's another one! Around **00:25**, she performs the exact same move, a cartwheel, while holding the rope. Her back is to the camera this time, but it's clearly the same skill. That makes two cartwheels.

Now I'll watch the rest of the video to make sure there aren't any more. She keeps jumping with different leg movements and turns, but no more cartwheels. The routine ends, and she walks away.

So, I counted a total of two cartwheels performed with the jump rope. The first one was at **00:16** and the second one was at **00:25**. This matches option D.

</think> <answer> D. Twice </answer>

Model's Prediction

<think>

Okay, I need to identify the moments when the person performs a cartwheel while holding a jump rope. I'll watch the video carefully and count them.

At **00:15**, the person starts doing a handstand on their toes, and then they throw the jump rope over them. Immediately after, at **00:17**, they perform a cartwheel while still holding the rope. This is the first one.

Now, I'll look for any other instances. At **00:30**, the person performs a similar trick, but this time they jump and flip over the rope. This counts as a cartwheel with the rope, but it's not a handstand-to-cartwheel like the first one.

So, I've identified two distinct cartwheels where they are holding the jump rope. The first is the handstand-to-cartwheel at **00:17**, and the second is the jump-and-flip cartwheel at **00:30**.

Therefore, the total count is two. The question asks if it happens "twice," and my observation confirms that. The other options, one and four, are incorrect based on what I saw in the video.

</think> <answer> D. Twice </answer>

Reference Claims

00:16: She performs a cartwheel while holding the jump rope handles and the rope passes under her body.

00:25: She performs another cartwheel while holding the jump rope, with her back to the camera.

Predicted Claims

00:17: Performer executes a cartwheel while holding the jump rope after a handstand.

00:30: Performer performs a cartwheel while holding the jump rope with a jump-and-flip motion.

Temporal Alignment Reward (TAR) - Calculation

- 1) P(**00:17**): Sim: 0.69 < 0.75, **No Match**
- 2) P(**00:30**): **Timestamp: No Match**

$$\text{Precision} = \# \text{match} / \# \text{pred_claims}, \quad \text{Consistency}(g) = 1$$

$$\text{Reward (TAR)} = g \times P = 0.0$$

Temporal Match (T^t)			Semantic Match (S^t)		
			Prediction		
Timestamps			Timestamps	00:17	00:30
Ref.	00:16	True	False	Ref.	00:16
	00:25	False	False		0.69
				00:25	0.72
					0.64
					0.65

Figure A8. TAR calculation Example 2.



Question: What is written on the wooden spatula used in the video?

Options: A. CHEF B. ELITE C. PREMIUM D. COOK

Reference Reasoning

<think>

Okay, I need to figure out what's written on the wooden spatula in the video. I'll watch the video carefully and focus on the spatula.

The video starts with a close-up shot of a pot with a curry-like substance. A wooden spatula is in the pot, with its handle pointing towards the left. I can see some red text stamped on the handle. Let me pause it right at the beginning, around **00:01-00:02**. The text is inside a red rectangular box. It looks like a five-letter word. The first letter is clearly an 'E'. The last letter is also an 'E'. The letters in between look like 'L', 'I', and 'T'. So, the word appears to be 'ELITE'.

Let me check the provided options.

A is 'CHEF'. That doesn't match; the word starts with an 'E'.
 B is 'ELITE'. This matches my observation perfectly.
 C is 'PREMIUM'. That's too long and starts with a 'P'.
 D is 'COOK'. That's too short and starts with a 'C'.

So, based on the visual evidence, especially in the first few seconds, the word on the spatula is definitely 'ELITE'. The view is quite clear, even though there's a bit of wear on the stamp. I'm confident with this answer.

</think> <answer> B. 'ELITE' </answer>

Model's Prediction

<think>

Okay, the user wants me to identify what's written on the wooden spatula. I need to carefully examine the video and look for a spatula.

First, let's scan the video from the beginning. At **00:02**, there's a wooden spatula being used to stir the sauce in the pot. The video is zoomed in on the pot, so the spatula is right there. Now I need to look at what's written on it. The video shows a close-up of the spatula moving through the sauce. I can clearly see the words written on the spatula's wooden handle. They are in a darker color, probably black or dark brown, against the lighter wooden surface. The text is in a sans-serif font and is oriented horizontally. It says "ELITE" in bold capital letters.

Let me double-check the other options. None of the other words like 'CHEF', 'PREMIUM', or 'COOK' are visible on the spatula. The most prominent text is indeed 'ELITE'.

So, my conclusion is that the correct answer is 'ELITE'. I can confidently confirm that the text is clearly visible on the spatula being used in the video.

</think> <answer> B. 'ELITE' </answer>

Reference Claims

00:01-00:02: A wooden spatula with red stamped text 'ELITE' is visible in the pot.

Predicted Claims

00:02: A wooden spatula is used to stir the sauce in the pot, with 'ELITE' clearly written on its handle.

Temporal Match (T^T)

Semantic Match (S^T)

Temporal Alignment Reward (TAR) - Calculation

	Prediction			Prediction	
Timestamps	00:02		Timestamps	00:02	
Ref	00:01-02	True	Ref	00:01-02	0.79

- 1) P(**00:17**): Sim: 0.79 > 0.75, Match
 $P = \#match / \#pred_claims, \text{ Consistency } (g) = 1$
Reward (TAR) = g \times P = 1 \times 1 = 1.0

Figure A9. TAR calculation Example 3.



Question: What is written on the wooden spatula used in the video?

Options: A. CHEF B. ELITE C. PREMIUM D. COOK

Reference Reasoning

<think>

Okay, I need to figure out what's written on the wooden spatula in the video. I'll watch the video carefully and focus on the spatula.

The video starts with a close-up shot of a pot with a curry-like substance. A wooden spatula is in the pot, with its handle pointing towards the left. I can see some red text stamped on the handle. Let me pause it right at the beginning, around **00:01-00:02**. The text is inside a red rectangular box. It looks like a five-letter word. The first letter is clearly an 'E'. The last letter is also an 'E'. The letters in between look like 'L', 'I', and 'T'. So, the word appears to be 'ELITE'.

Let me check the provided options.

A is 'CHEF'. That doesn't match; the word starts with an 'E'.

B is 'ELITE'. This matches my observation perfectly.

C is 'PREMIUM'. That's too long and starts with a 'P'.

D is 'COOK'. That's too short and starts with a 'C'.

So, based on the visual evidence, especially in the first few seconds, the word on the spatula is definitely 'ELITE'. The view is quite clear, even though there's a bit of wear on the stamp.

I'm confident with this answer.

</think> <answer> B. 'ELITE' </answer>

Model's Prediction

<think>

Okay, the question is about the text on the wooden spatula. I need to look very closely at the video to find it. The video starts with a close-up of a pot with a wooden spatula inside. The spatula is dark brown and has some red writing on it. It's a bit hard to make out, but the first word is definitely "to". The video shows the spatula being used to stir some kind of sauce or soup. At around **00:00**, the text on the spatula becomes clearer as it's being used to stir a large amount of chickpeas into the sauce. **The complete text on the spatula seems to be "to it now".** Now, I'll look at the options.

Option A is 'CHEF'. This doesn't seem right; the text isn't about being a chef.

Option B is 'ELITE'. That doesn't look like it at all.

Option C is 'PREMIUM'. That's also incorrect for the same reason.

Option D is 'COOK'. This is a plausible option. The action is clearly cooking, so a spatula with the word "COOK" on it would make sense. The word "to" makes the most sense in this context as part of the instruction.

I'll check the video again to confirm. Ah, yes, the text on the spatula is definitely "to it now". And that does sound like a cooking instruction. **"To it now" means add it immediately. So, option D is correct.**

</think> <answer> B. 'ELITE' </answer>

Reference Claims

00:01-00:02: A wooden spatula with red stamped text 'ELITE' is visible in the pot.

Predicted Claims

00:00: The text on the spatula becomes clearer as it's used to stir chickpeas into the sauce.

Temporal Match (T^T)

Semantic Match (S^T)

Temporal Alignment Reward (TAR) - Calculation

Prediction

Prediction

1) P(**00:17**): Sim: 0.56 < 0.75, **X No Match**

Timestamps **00:00**

Timestamps **00:00**

$P = \#match / \#pred_claims, \text{ Consistency } (g) = 0$

Ref

00:01-02

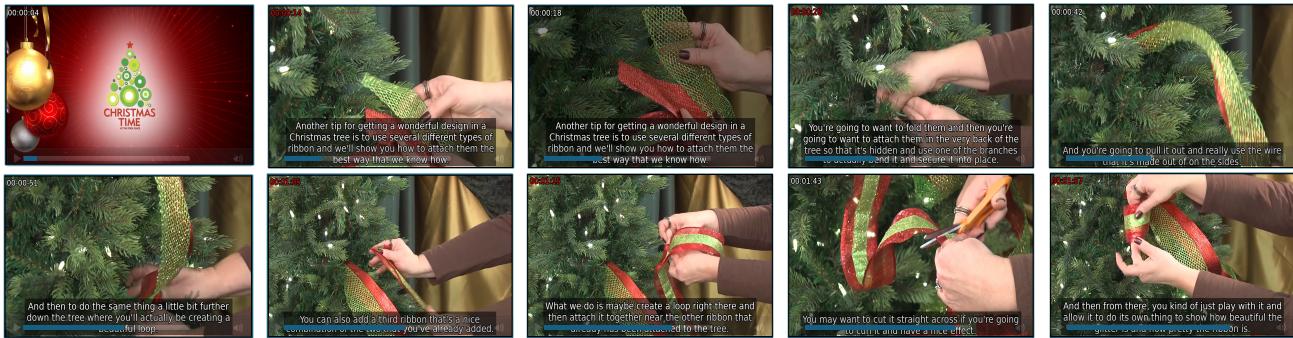
True

Ref **00:01-02**

0.56

Reward (TAR) = $g \times P = 0.0 \times 0.0 = 0.0$

Figure A10. TAR calculation Example 5.



Question: How does the person adjust the ribbons on the tree?

Options:

- A. With moderate speed and precision
- B. Quickly and carelessly
- C. Rapidly and haphazardly
- D. Slowly and meticulously

Reference Reasoning

<think>

The user wants me to describe how the person in the video adjusts the ribbons on the tree. I need to observe her actions and pace carefully.

Okay, I'm watching the demonstration. Starting around **00:20**, she takes the ribbons and tucks them deep into the tree. She doesn't just stuff them in; she carefully wraps a tree branch around the ribbon to secure it. This is a very deliberate and precise movement.

Then, from **00:32** onwards, she pulls the ribbons out to form a loop. She smooths them out, twists them so they lay nicely on top of each other, and gently shapes the loop. Her hands are moving with purpose, but not quickly. She's clearly focused on getting the shape just right.

Later, around **1:05**, she adds a third ribbon to create a more complex bow or accent. She forms a loop, twists it, and attaches it near the other ribbons. Again, the process is very controlled. She fluffs it to make it look "intentional," as she says.

The final part, from **1:45**, really highlights her method. She decides to curl the end of a streamer. She doesn't just scrunch it up. She starts at the very end and slowly, tightly rolls the ribbon around her fingers. This is a very detailed and careful action, not something you can do quickly if you want it to look good. She then gently pulls it apart to create a perfect spiral.

Based on these observations, the words that come to mind are "careful," "deliberate," "precise," and "slow." She's not rushing at all.

Let's evaluate the options.

A. "With moderate speed and precision." The precision is there, but I'd say her speed is slower than moderate.

B. "Quickly and carelessly." This is definitely incorrect. Her actions are the opposite of careless.

C. "Rapidly and haphazardly." Also incorrect. Her method is very systematic, not haphazard.

D. "Slowly and meticulously." This seems to be the best fit.

"Meticulously" means showing great attention to detail, which she does in every step, from securing the ribbon to curling the end. Her pace is consistently slow and focused. This option accurately captures the essence of her technique.

</think> <answer> D. Slowly and meticulously </answer>

Model's Prediction

<think>

Okay, let's analyze the video to understand how the person is adjusting the ribbons on the tree.

At **00:04**, she says, "Another tip for getting a wonderful design in a Christmas tree is to use several different types of ribbon and we'll show you how to attach them the best way that we know how." This sets the stage for an instructional, careful approach.

Then, at **00:09**, she begins attaching the ribbons. Her hands are visible, and she's seen carefully folding a piece of ribbon and placing it on the back of the tree. The speed isn't emphasized in the video.

The next shot, **00:22**, shows her pulling a gold ribbon through the branches. She manipulates it with care, ensuring it's placed correctly and not too tight. This is an example of her meticulous adjustment.

Further along, at **00:46**, she attaches a red and green ribbon. She creates a loop and then another piece, placing them around the tree. The whole process is shown in a way that emphasizes the technique. She doesn't rush through the steps; she takes time to ensure the loops are secure and positioned well.

Later, at **01:15**, she attaches more ribbons. Her movements are deliberate and slow, as she wants the placement to look nice. The text on screen even suggests, "And then from there, you may want to even loop it around, or you could actually cut with your scissors."

The entire video is a tutorial, and the person demonstrates how to make each ribbon look its best. The actions are shown in a way that clearly shows the precision and care she takes. She isn't adjusting things quickly or haphazardly. The words "meticulously" and "slowly" seem the most fitting description of her adjustment process.

So, putting all this together, the most accurate option is D. Slowly and meticulously. Her actions are deliberate and careful, not hasty or careless. They are shown in a way that allows viewers to see the details and learn from her technique.

</think> <answer> D. Slowly and meticulously </answer>

Figure A11. TAR calculation Example 5 (page 1 of 2).



Question: How does the person adjust the ribbons on the tree?

- Options:**
- A. With moderate speed and precision
 - B. Quickly and carelessly
 - C. Rapidly and haphazardly
 - D. Slowly and meticulously

Reference Claims

- 00:20:** She takes the ribbons and tucks them deep into the tree, wrapping a branch around to secure them.
- 00:32:** She pulls the ribbons out to form a loop, smooths and twists them to lay nicely on top of each other.
- 01:05:** She adds a third ribbon, forms a loop, twists it, and attaches it near the other ribbons, then fluffs it.
- 01:45:** She slowly rolls the end of a streamer around her fingers to create a perfect spiral.

Predicted Claims

- 00:04:** She explains the technique for using multiple ribbons on a Christmas tree.
- 00:09:** She begins attaching ribbons by folding and placing them on the back of the tree.
- 00:22:** She pulls a gold ribbon through the branches with careful manipulation.
- 00:46:** She attaches a red and green ribbon, creating secure loops around the tree.
- 01:15:** She attaches more ribbons with deliberate, slow movements for precise placement.

Temporal Match Matrix (T^T)

		Predicted Claims				
Timestamps		00:04	00:09	00:22	00:46	01:15
Ref. Claims	00:20	False	False	True	False	False
	00:32	False	False	False	False	False
	01:05	False	False	False	False	False
	01:45	False	False	False	False	False

Semantic Match Matrix (S^T)

		Predicted Claims				
Timestamps		00:04	00:09	00:22	00:46	01:15
Ref. Claims	00:20	0.71	0.88	0.79	0.78	0.57
	00:32	0.59	0.75	0.65	0.63	0.65
	01:05	0.69	0.69	0.66	0.72	0.73
	01:45	0.32	0.40	0.42	0.43	0.38

Temporal Alignment Reward (TAR) - Calculation

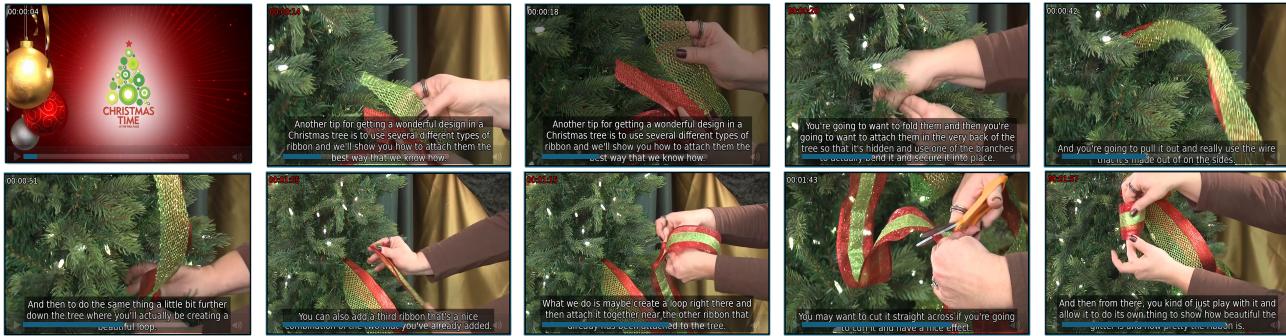
- 1) P(00:04): Timestamp: **X No Match** 2) P(00:09): Timestamp: **X No Match** 3) P(00:22): Sim: 0.79 > 0.75 **Match**
 4) P(00:46): Timestamp: **X No Match** 5) P(01:45): Timestamp: **X No Match**

Precision = #match / #pred_claims,

Consistency (g) = 1.

Reward (TAR) = $g \times P = 1 \times (1/5) = 0.20$

Figure A12. TAR calculation Example 5 (page 2 of 2).



Question: How does the person adjust the ribbons on the tree?

- Options:**
- A. With moderate speed and precision
 - B. Quickly and carelessly
 - C. Rapidly and haphazardly
 - D. Slowly and meticulously

Reference Reasoning

<think>

The user wants me to describe how the person in the video adjusts the ribbons on the tree. I need to observe her actions and pace carefully.

Okay, I'm watching the demonstration. Starting around **00:20**, she takes the ribbons and tucks them deep into the tree. She doesn't just stuff them in; she carefully wraps a tree branch around the ribbon to secure it. This is a very deliberate and precise movement.

Then, from **00:32** onwards, she pulls the ribbons out to form a loop. She smooths them out, twists them so they lay nicely on top of each other, and gently shapes the loop. Her hands are moving with purpose, but not quickly. She's clearly focused on getting the shape just right.

Later, around **1:05**, she adds a third ribbon to create a more complex bow or accent. She forms a loop, twists it, and attaches it near the other ribbons. Again, the process is very controlled. She fluffs it to make it look "intentional," as she says.

The final part, from **1:45**, really highlights her method. She decides to curl the end of a streamer. She doesn't just scrunch it up. She starts at the very end and slowly, tightly rolls the ribbon around her fingers. This is a very detailed and careful action, not something you can do quickly if you want it to look good. She then gently pulls it apart to create a perfect spiral.

Based on these observations, the words that come to mind are "careful," "deliberate," "precise," and "slow." She's not rushing at all.

Let's evaluate the options.

- A. "With moderate speed and precision." The precision is there, but I'd say her speed is slower than moderate.
- B. "Quickly and carelessly." This is definitely incorrect. Her actions are the opposite of careless.
- C. "Rapidly and haphazardly." Also incorrect. Her method is very systematic, not haphazard.
- D. "Slowly and meticulously." This seems to be the best fit.

"Meticulously" means showing great attention to detail, which she does in every step, from securing the ribbon to curling the end. Her pace is consistently slow and focused. This option accurately captures the essence of her technique.

</think> <answer> D. Slowly and meticulously </answer>

Model's Prediction

<think>

Okay, the question asks how the person adjusts the ribbons on the Christmas tree. I'll watch the video and analyze their actions.

At **00:26**, she starts to adjust a green ribbon. She's clearly not rushing. She's carefully folding and positioning the ribbon. Then, at **00:30**, she's sliding the ribbon through branches. Her movements are deliberate and measured. The same precision is shown when she attaches the ribbons (**00:45**) and later when she creates loops and curls with the ribbon (**01:17**). There's no sense of urgency or haphazardness in her actions. She seems to take her time to ensure the ribbons are securely and aesthetically placed.

Now, let's look at the options. "With moderate speed and precision" fits perfectly. The video doesn't show her rushing; it shows her working at a consistent, moderate pace, performing each step carefully and accurately. This is a positive description, but it might be too mild.

"Quickly and carelessly" is incorrect because she's certainly not quick. Her actions are deliberate, which is the opposite of careless. So, that's out.

"Rapidly and haphazardly" is also wrong. She's not doing anything haphazardly. Her actions are planned, and she's methodically making a design. "Rapidly" is wrong because she's not working quickly; she's working at a steady pace. The option "Slowly and meticulously" also seems plausible. She is moving slowly and with great care, which is a very precise description. However, "moderate speed and precision" seems to capture the overall pace and attention to detail better than "slowly." The video doesn't provide information about the speed being very slow, it just shows it to be moderate.

Therefore, based on the careful and steady pace shown in the video, the most accurate description is "**with moderate speed and precision**." The person is adjusting the ribbons in a deliberate, precise manner.

</think>

<answer> D. Slowly and meticulously </answer>

Figure A13. TAR calculation Example 6 (page 1 of 2).



Question: How does the person adjust the ribbons on the tree?

- Options:**
- A. With moderate speed and precision
 - B. Quickly and carelessly
 - C. Rapidly and haphazardly
 - D. Slowly and meticulously

Reference Claims

00:20: She takes the ribbons and tucks them deep into the tree, wrapping a branch around to secure them.

00:32: She pulls the ribbons out to form a loop, smooths and twists them to lay nicely on top of each other.

01:05: She adds a third ribbon, forms a loop, twists it, and attaches it near the other ribbons, then fluffs it.

01:45: She slowly rolls the end of a streamer around her fingers to create a perfect spiral.

Predicted Claims

00:26: She starts to adjust a green ribbon with careful folding and positioning.

00:30: She slides the ribbon through branches with deliberate and measured movements.

00:45: She attaches the ribbons with the same precision.

01:17: She creates loops and curls with the ribbon.

Temporal Match Matrix (T^T)

		Predicted Claims			
Timestamps		00:26	00:30	00:45	01:17
Ref. Claims	00:20	False	False	False	False
	00:32	False	True	False	False
	01:05	False	False	False	False
	01:45	False	False	False	False

Semantic Match Matrix (S^T)

		Predicted Claims			
Timestamps		00:26	00:30	00:45	01:17
Ref. Claims	00:20	0.58	0.69	0.63	0.53
	00:32	0.68	0.61	0.65	0.70
	01:05	0.69	0.67	0.76	0.77
	01:45	0.44	0.41	0.31	0.49

Temporal Alignment Reward (TAR) - Calculation

- 1) P(00:26): Timestamp: **No Match** 2) P(00:30): Sim: 0.61 < 0.75 **No Match** 3) P(00:45): Timestamp: **No Match**
 4) P(01:17): Timestamp: **No Match**

Precision = #match / #pred_claims,

Consistency (g) = 0.

Reward (TAR) = g x P = 0.0 x 0.0 = **0.0**

Figure A14. TAR calculation Example 6 (page 2 of 2).



Question: Why did the rider on the white horse pass by the jump obstacle without engaging with it?

Options: A. The jump obstacle was broken

C. The rider was practicing control and turns

B. The horse was tired

D. The rider was waiting for instructions

Reference Reasoning

<think>

Okay, I need to figure out why the rider on the white horse rides past the jump instead of going over it. I'll watch the video and evaluate the different possibilities.

The video shows a young rider on a white horse in an indoor arena. There are other riders present, so it looks like a group lesson. From the start, the rider is trotting along the edge of the arena. Around 00:09, she approaches a jump set up against the far wall. However, she doesn't line the horse up to jump it. Instead, she just continues to ride straight along the wall, passing by the side of the obstacle.

Let's consider the options.

A. The jump obstacle was broken. I don't see anything wrong with the jump. It looks like a standard, simple cross-rail or low vertical. It seems perfectly usable. So, this is unlikely.

B. The horse was tired. The horse doesn't appear tired. It's moving at a steady trot and then later in the video, around 00:27, it picks up a nice, energetic canter. It doesn't seem sluggish or unwilling to move. So I can probably rule this one out too.

D. The rider was waiting for instructions. This is a possibility in a lesson environment. However, she isn't just standing around. She's actively riding a specific path around the arena. It seems more like she *is* following instructions, and those instructions are to ride the pattern she's riding, not to jump.

C. The rider was practicing control and turns. This makes the most sense. Her entire ride in the video clip is focused on navigating the arena, making turns, and maintaining a steady pace. **From 00:27 to 00:33**, we see her cantering in a large, controlled circle. This kind of work is called "flatwork" and is essential for developing control, balance, and communication with the horse. The jump is just in the arena, but it's not the focus of her current exercise. She is passing it by because her task is to ride the rail and practice her turns and canter, not to jump obstacles. The focus is on maneuverability and pace, which is fundamental training. This explanation fits all her actions in the video.

</think>

<answer> C. The rider was practicing control and turns.

</answer>

Model's Prediction

<think>

Okay, let's analyze the video to answer this question. The rider on the white horse is the main focus, and the jump obstacle is clearly visible in the background. The video starts with the rider on the white horse, and as it moves, the jump obstacle is shown. The rider on the white horse makes a turn and then passes by the obstacle. This action is repeated a couple of times.

The question is why the rider avoided the obstacle. Let's look at the options.

Option A, "The jump obstacle was broken," is incorrect. I can clearly see the obstacle is intact and still in its place. The rider just passed it by without jumping over it.

Option B, "The horse was tired," doesn't seem to be the reason. The horse is moving at a steady pace and doesn't appear to be struggling or showing signs of fatigue. The rider is in control and guiding the horse in a straight line.

Option C, "The rider was practicing control and turns," seems to be the most plausible answer. The rider is clearly demonstrating a control exercise on the white horse. The video shows the rider taking a sharp turn and then riding directly past the obstacle. The other riders in the video also ride past the obstacle in a controlled manner. This exercise is likely about controlling the horse's speed, direction, and reaction to obstacles, which is a common training activity.

Option D, "The rider was waiting for instructions," is also possible, but the context is a bit different. The exercise is being demonstrated, and the focus is on the rider's own technique. The video seems to be a practice session, not a formal competition where waiting for instructions would be the primary focus.

Let's confirm by watching the video closely. The rider on the white horse is the first to pass the obstacle, and then others do the same. This seems to be a standard exercise to improve control over the horse, which aligns perfectly with option C.

</think>

<answer> C. The rider was practicing control and turns.

</answer>

Temporal Alignment Reward (TAR) - Calculation

The temporal alignment reward (TAR) will be **zero (0)** as there are no timestamp present in the prediction.

Figure A15. TAR calculation Example 7.



Question: Why did the rider on the white horse pass by the jump obstacle without engaging with it?

- Options:**
- A. The jump obstacle was broken
 - B. The horse was tired
 - C. The rider was practicing control and turns
 - D. The rider was waiting for instructions

Reference Reasoning

<think>

Okay, I need to figure out why the rider on the white horse rides past the jump instead of going over it. I'll watch the video and evaluate the different possibilities.

The video shows a young rider on a white horse in an indoor arena. There are other riders present, so it looks like a group lesson. From the start, the rider is trotting along the edge of the arena. Around **00:09**, she approaches a jump set up against the far wall. However, she doesn't line the horse up to jump it. Instead, she just continues to ride straight along the wall, passing by the side of the obstacle.

Let's consider the options.

A. The jump obstacle was broken. I don't see anything wrong with the jump. It looks like a standard, simple cross-rail or low vertical. It seems perfectly usable. So, this is unlikely.

B. The horse was tired. The horse doesn't appear tired. It's moving at a steady trot and then later in the video, around **00:27**, it picks up a nice, energetic canter. It doesn't seem sluggish or unwilling to move. So I can probably rule this one out too.

D. The rider was waiting for instructions. This is a possibility in a lesson environment. However, she isn't just standing around. She's actively riding a specific path around the arena. It seems more like she *is* following instructions, and those instructions are to ride the pattern she's riding, not to jump.

C. The rider was practicing control and turns. This makes the most sense. Her entire ride in the video clip is focused on navigating the arena, making turns, and maintaining a steady pace. **From 00:27 to 00:33**, we see her cantering in a large, controlled circle. This kind of work is called "flatwork" and is essential for developing control, balance, and communication with the horse. The jump is just in the arena, but it's not the focus of her current exercise. She is passing it by because her task is to ride the rail and practice her turns and canter, not to jump obstacles. The focus is on maneuverability and pace, which is fundamental training. This explanation fits all her actions in the video.

</think>

<answer> C. The rider was practicing control and turns.

</answer>

Model's Prediction

<think>

Okay, I need to figure out why the rider on the white horse, the one wearing a white shirt, decided to avoid the jump obstacle.

First, I'll watch the video carefully. The video shows a person leading a white horse into a large indoor riding arena. Then, another person on a horse is shown from behind. The white horse is being ridden by someone wearing a white shirt and dark pants. At the **00:09** mark, this rider turns the horse and rides straight past the jump obstacle, which is a small white triangle-like object. The rider continues riding away from the obstacle.

Now, let me analyze the options provided.

Option A says the jump was broken. However, the video clearly shows the jump standing upright with the obstacle intact. So, this is incorrect.

Option B suggests the horse was tired. While it's possible the horse was tired, I can't see any signs of fatigue in its movements. The horse looks well-controlled and energetic. So, I'll eliminate that option.

Option C states the rider was practicing control and turns. This seems most plausible. The video begins with a close-up of a rider on a horse, and the next shot shows the rider leading the horse. Then, the camera focuses on the horse and rider from behind, which allows me to see their movements more clearly. The rider on the white horse makes a sharp turn, which is shown at the **00:02** mark. The rider then rides directly past the jump obstacle without touching it. This action seems to be a demonstration of the rider's skill in maneuvering the horse. They are not trying to jump; they are simply controlling the horse's path. This makes C a very strong contender.

Option D says the rider was waiting for instructions. There are no visible signs of another person directing the rider. The video starts with the rider leading the horse and then pans to show the main action. It's just a single rider, and they are clearly performing the turn and ride-by themselves. So, the rider wasn't waiting for instructions.

Therefore, the most logical conclusion is that the rider on the white horse was practicing control and turns, demonstrating their ability to direct the horse's movement. They used the jump obstacle as an obstacle to showcase their riding skills.

</think>

<answer> C. The rider was practicing control and turns.

</answer>

Figure A16. TAR calculation Example 8 (page 1 of 2).



Question: Why did the rider on the white horse pass by the jump obstacle without engaging with it?

- Options:**
- A. The jump obstacle was broken
 - B. The horse was tired
 - C. The rider was practicing control and turns
 - D. The rider was waiting for instructions

Reference Claims

00:09: The rider approaches a jump but continues straight along the wall, passing by the obstacle.

00:27: The horse picks up a steady canter.

00:27-00:33: The rider canters in a large, controlled circle as part of flatwork training.

Predicted Claims

00:02: Rider makes a sharp turn with the white horse.

00:09: Rider turns the horse and rides straight past the jump obstacle.

Temporal Match (T^T)

Semantic Match (S^T)

Temporal Alignment Reward - Calculation

		Predicted Claims				Predicted Claims	
Timestamps		00:02	00:09	Timestamps		00:02	00:09
Ref Claims	00:09	False	True	Ref Claims	00:09	0.38	0.76
	00:27	False	False		00:27	0.51	0.44
	00:27-33	False	False		00:27-33	0.36	0.39

1) P(00:02): Timestamp: **No Match**

2) P(00:09): Sim: 0.76 > 0.75 **Match**

$P = \#match / \#pred_claims$, Consistency (g) = 1.

Reward (TAR) = $g \times P = 1.0 \times (1/2) = 0.5$

Figure A17. TAR calculation Example 8 (page 2 of 2).



Question: What change occurs in the pan after the person adds the green herbs?

- Options:**
- A. The dish becomes thicker
 - B. The dish starts to boil
 - C. The dish changes color
 - D. The dish now has visible green herbs

Reference Reasoning

<think>

Okay, I need to figure out what change happens in the pan right after the person adds the green herbs.

First, let's look at the pan at the very beginning, at **00:00**. The dish is a brownish-orange color, simmering on the stove. I don't see any green in it.

Now, I'll watch what the person does. Starting around **00:01**, she takes a small white bowl with chopped green herbs and begins sprinkling them into the pan. She continues to do this for several seconds.

What does the pan look like after she's done, say around **00:08**? The dish itself is still the same brownish-orange color, but now it's covered with little green pieces of the herbs she just added. They are very easy to see.

Let's check the options.

- A. "The dish becomes thicker." I can't really tell if the consistency changed. It looks like it's still simmering the same way. There's no visual cue that it got thicker.
- B. "The dish starts to boil." It was already simmering or gently boiling before she added the herbs, so this isn't a change that *occurred* because of the herbs.
- C. "The dish changes color." This is partially true in that a new color (green) has been introduced. However, the base sauce color is still the same brownish-orange. The whole dish didn't change from orange to green, for example. Option D seems more specific and accurate.
- D. "The dish now has visible green herbs." This is definitely true. Before, there were none. After, there are plenty. This is the most direct and observable change that happened as a result of her action.

Comparing C and D, D is the most precise description of what happened. The most obvious change is the appearance of the green herbs themselves. So, D is the best answer.

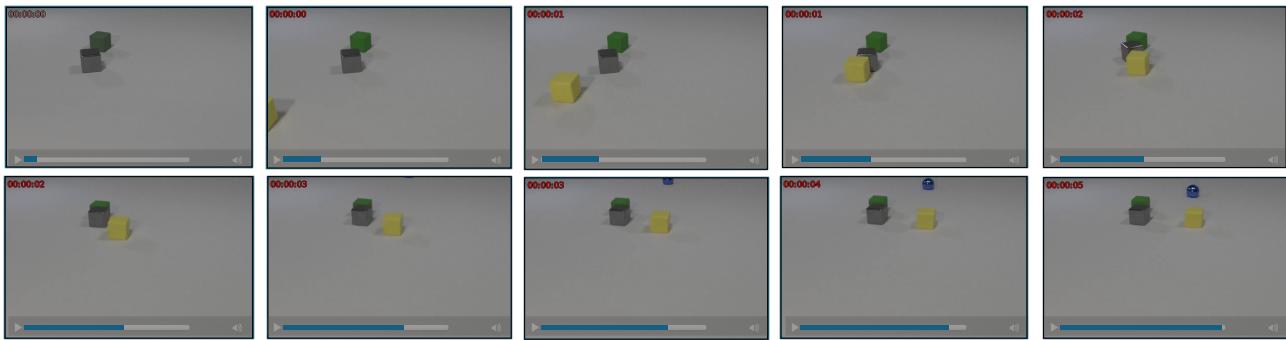
</think>

<answer>

- D. The dish now has visible green herbs**

</answer>

Figure A18. Dataset Example 1



Question: Which of the following is not responsible for the gray object's colliding with the green cube?

- Options:**
- A. The sphere's entrance
 - B. The presence of the yellow rubber cube
 - C. The yellow object's colliding with the gray cube
 - D. The yellow cube's entering the scene

Reference Reasoning

<think>

Okay, let's analyze this video to figure out the answer. The question asks what is *not* responsible for the gray cube colliding with the green cube. So I'm looking for the event that did *not* cause that specific collision.

First, I'll watch the sequence of events.

At the beginning, we see a green cube and a gray cube sitting next to each other. Then, around **00:00-00:01**, a yellow cube slides in from the left. At **00:01**, the yellow cube hits the gray cube. Immediately after that, at **00:02**, the impact from the yellow cube pushes the gray cube into the green cube. So, that's the collision the question is about. After this collision has already happened, around **00:03**, a blue sphere starts to enter the frame from the top background.

Now I'll evaluate the options based on this timeline.

A. The sphere's entrance: The sphere only starts to appear at **00:03**. The collision between the gray and green cubes already happened at **00:02**. An event that happens *after* another event cannot be its cause. So, the sphere's entrance is definitely not responsible for the collision. This looks like a strong candidate for the correct answer.

B. The presence of the yellow rubber cube: Well, if the yellow cube wasn't present in the scene, it couldn't have hit the gray cube. So its presence is a necessary condition for the collision to happen. This *is* a responsible factor.

C. The yellow object's colliding with the gray cube: This is the direct, immediate cause. The yellow cube strikes the gray cube, transferring its momentum and pushing the gray cube into the green one. This is clearly responsible.

D. The yellow cube's entering the scene: The yellow cube had to enter the scene first before it could do anything else. Its entrance is the first step in the chain of events that leads to the final collision. So, this is also a responsible factor.

Comparing the options, A is the only one that is completely unrelated to the causal chain of the collision. The sphere's appearance is a separate event that occurs after the fact. The other three options are all directly linked: the yellow cube enters the scene (D), is therefore present (B), and then collides with the gray cube (C), causing the gray cube to hit the green one. The sphere is just a distraction. So, the sphere's entrance is not responsible for the collision.

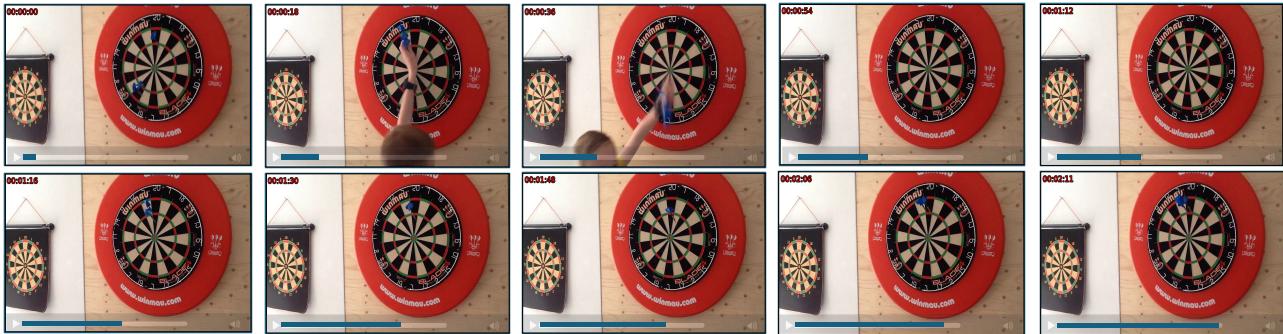
</think>

<answer>

- A. The sphere's entrance

</answer>

Figure A19. Dataset Example 2



Question: What is the sequence of actions repeated throughout the video?

- Options:**
- A. Throwing blue darts, removing them, and resetting the board
 - B. Throwing red darts, removing them, and resetting the board
 - C. Throwing black darts, removing them, and resetting the board
 - D. Throwing green darts, removing them, and resetting the board

Reference Reasoning

<think>

Okay, I need to figure out the repeating sequence of actions in this video. The video shows someone playing darts. Let me watch carefully.

The video starts with a couple of darts already in the board, and a hand pulls them out. The darts look like they have blue flights. Then the person starts throwing. The first dart is thrown around **00:08**, it has a blue flight. The second one at **00:13** is also blue. The third one at **00:16** is blue as well. So, the person throws three blue darts. Immediately after, at **00:17**, a hand comes in and removes all three darts. This seems like one complete cycle: throw three blue darts, then remove them.

Let's see if this pattern repeats. The throwing starts again. At **00:25**, a blue dart is thrown. At **00:28**, another blue dart. At **00:31**, a third blue dart. After these three throws, the hand comes in at **00:34** and removes them. So yes, the pattern is repeating. The person is consistently using blue darts, throwing a set of three, and then clearing the board.

I'll just check another sequence to be absolutely sure. A new round of throws begins. At **00:41**, a blue dart is thrown. At **00:45**, another blue one. At **00:48**, the third blue dart. And then at **00:50**, they are all removed. The sequence is definitely consistent throughout the video. The darts are always blue, and the actions are throwing and then removing.

Now I'll look at the options.

Option A is "Throwing blue darts, removing them, and resetting the board". This matches my observation perfectly.

Option B says "red darts". I haven't seen any red darts being thrown.

Option C says "black darts". The flights are clearly blue, not black.

Option D says "green darts". Again, incorrect color.

So, the correct sequence involves blue darts. The action of removing the darts is what "resets the board" for the next turn. Therefore, option A is the only one that accurately describes the repeated cycle of events shown in the video.

</think>

<answer>

- A. Throwing blue darts, removing them, and resetting the board

</answer>

Figure A20. Dataset Example 3

References

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