ELV-Halluc: Benchmarking Semantic Aggregation Hallucinations in Long Video Understanding

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SenseTime Research

Abstract

Video multimodal large language models (Video-MLLMs) have achieved remarkable progress in video understanding. However, they remain vulnerable to hallucination-producing content inconsistent with or unrelated to video inputs. Previous video hallucination benchmarks primarily focus on short-videos. They attribute hallucinations to factors such as strong language priors, missing frames, or vision-language biases introduced by the visual encoder. While these causes indeed account for most hallucinations in short videos, they still oversimplify the cause of hallucinations. Sometimes, models generate incorrect outputs but with correct frame-level semantics. We refer to this type of hallucination as Semantic Aggregation Hallucination (SAH), which arises during the process of aggregating frame-level semantics into event-level semantic groups. Given that SAH becomes particularly critical in long videos due to increased semantic complexity across multiple events, it is essential to separate and thoroughly investigate the causes of this type of hallucination. To address the above issues, we introduce ELV-Halluc, the first benchmark dedicated to long-video hallucination, enabling a systematic investigation of SAH. Our experiments confirm the existence of SAH and show that it increases with semantic complexity. Additionally, we find that models are more prone to SAH on rapidly changing semantics. Moreover, we discuss potential approaches to mitigate SAH. We demonstrate that positional encoding strategy contributes to alleviating SAH, and further adopt DPO strategy to enhance the model's ability to distinguish semantics within and across events. To support this, we curate a dataset of 8K adversarial data pairs and achieve improvements on both ELV-Halluc and Video-MME, including a substantial 27.7% reduction in SAH ratio. The dataset and evaluation code can be found at https://github.com/hlsv02/ELV-Halluc.

Introduction

Video multimodal large models have demonstrated strong capabilities in visual understanding(Bai et al. 2025; Comanici et al. 2025; Zhu et al. 2025). However, a serious challenge still remains—the hallucination, where models generate content that is inconsistent with or even fabricated beyond the video content, thereby impacting the reliability

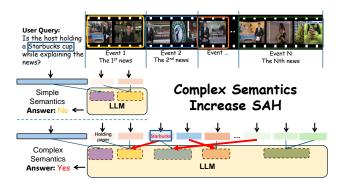


Figure 1: Illustration of how increasing semantic complexity in long-video scenarios amplifies Semantic Aggregation Hallucination (SAH). Red arrows indicate erroneous aggregation into internal semantic groups.

of the models in practical applications. Many works(Rawal et al. 2025; Zhang et al. 2024a; Li, Im, and Fazli 2025; Kong et al. 2025; Wang et al. 2024c) have attempted to measure hallucination in video MLLMs, but they primarily focus on short videos ranging from a few seconds to tens of seconds, leaving hallucination issues in long-video contexts largely unexplored. They attribute hallucinations in Video-MLLMs to factors such as vision—language misalignment, poor frame quality, or suboptimal frame sampling strategies, which cause the model to rely on incomplete or inaccurate visual evidence. Alternatively, model may correctly perceive visual semantics but over-rely on strong language priors, disregarding visual input and producing incorrect content.

While above causes indeed covers large proportion of hallucinations, another cause has been overlooked in prior short video hallucination benchmarks: cases where the model correctly perceives and outputs accurate frame-level semantics but still produces incorrect content by misattributing semantics across event. For example, in Figure 1, the model attributes "Starbucks" to the first event, where the host is holding "some paper" while explaining the news. However, the mention of "Starbucks" actually corresponds to a later event in the video. In this case, while the perception of frame-level visual semantics is correct, the error arises from misaggregating information across temporal segments—incorrectly

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linking visual cues from one event to concepts from another. We refer to this phenomenon as Semantic Aggregation Hallucination (SAH).

In short-video scenarios, the impact of SAH is limited because frame-level semantics usually map directly to a single, self-contained event. As a result, logically consistent event semantics—especially those aligned with language priors—relatively rare (e.g., "person", "horse", "riding"; it is unlikely for the model to hallucinate "horse riding a person,"). In contrast, long videos often contain multiple temporally extended, yet semantically coherent events, increasing the risk of misattributing concepts across events. As illustrated in Figure 1, this richer temporal structure amplifies the likelihood of SAH, where the model confuses when an event occurs, even if all the visual elements are correctly perceived.

To address the aforementioned limitations, we introduce ELV-Halluc, the first long video hallucination benchmark. As SAH is particularly prominent and challenging in long videos yet remains underexplored, ELV-Halluc is designed for studying SAH by quantifying semantic complexity through event-based videos and categorizing hallucination aspects based on semantic granularity, including visual details, action, object, and declarative content. To facilitate focused investigation, it adopts an adversarial triplet question pair design: (1) Ground Truth Question paired with In-Video Hallucinated Question, and (2) Ground Truth Question paired with Out-of-Video Hallucinated Question. We use the accuracy gap between in-video and out-of-video hallucinated question pairs to quantify a model's sensitivity to semantic misalignment across events—a key aspect of SAH. Furthermore, we define the SAH Ratio as the proportion of such cases among all hallucinations, enabling systematic and interpretable analysis.

We conducted extensive experiments on ELV-Halluc, covering 14 open-source MLLMs and 2 closed-source models. Our findings confirm the existence of SAH and reveal that it does not necessarily correlate with overall hallucination rates. Notably, SAH becomes more severe as semantic complexity increases—such as with more events or denser frame sampling—and is more likely to occur in fine-grained, rapidly changing aspects (e.g., visual details rather than declarative content). Since SAH arises from incorrect aggregation of frame-level semantics across events, we show that strengthening the mapping between frames and events-such as through improved positional encodings—can help reduce its occurrence. We further adopt DPO(Rafailov et al. 2023) strategy that explicitly discourages the model's preference for hallucinated semantics. Our contributions are summarized as follows:

- We introduce ELV-Halluc, the first long-video benchmark designed specifically to evaluate SAH.
- We conduct extensive experiments demonstrating that SAH positively correlates with semantic complexity and semantic variation rate(e.g., more SAH on visual details than declarative content). This relationship causes SAH to sometimes exhibit trends opposite to overall hallucination levels (e.g., when more frames are sampled).

 We validate the effectiveness of multimodal positional encoding in mitigating SAH and further adopt DPO strategy to reduce SAH. By curating 8K QA pairs with and without hallucinations, we achieve a maximum 27.7% reduction in SAH ratio while also improving overall performance (+0.9% on VideoMME).

Related Works

Video Understanding Benchmarks

Video Understanding benchmarks such as Video-MME(Fu et al. 2025) and MVBench(Li et al. 2024c) aim to provide a comprehensive evaluation of video understanding capabilities, covering multiple video lengths and diverse aspects of comprehension. Some benchmarks, however, focus on specific abilities of video models; for example, ETBench(Liu et al. 2024) emphasizes temporal localization and time-awareness, while Video-Holmes(Cheng et al. 2025) evaluates complex reasoning capabilities through QA pairs requiring strong reasoning skills.

In long video contexts, LVBench(Wang et al. 2024b) evaluates model comprehension for ultra-long videos exceeding one hour, while MLVU(Zhou et al. 2024) designs tasks with different requirements—such as holistic understanding, single-detail comprehension, and multidetail reasoning—to assess long-video capabilities. Similarly, EgoSchema(Mangalam, Akshulakov, and Malik 2023) emphasizes evaluating model performance in egocentric video scenarios. However, hallucination—an important and relatively independent aspect of model reliability—remains largely underexplored in these general-purpose video understanding benchmarks.

Hallucination Evaluation in Video-MLLMs

Several prior efforts have aimed to construct hallucinationspecific benchmarks. VideoHallucer(Wang et al. 2024c) categorizes hallucinations into two types: intrinsic, where the model outputs content inconsistent with the original video, and extrinsic, where correctness cannot be determined solely from the video. EventHallusion(Zhang et al. 2024a) further identifies two main sources of hallucination in Video-MLLMs: language priors and vision-language bias, and investigates these through QA designs involving rare events and misleading contexts. VidHalluc(Li, Im, and Fazli 2025) focuses on evaluating hallucinations in dynamic video segments and argues that the inductive bias inherent in visual encoders makes hallucinations more likely when processing semantically similar videos. ARGUS(Rawal et al. 2025), on the other hand, emphasizes hallucination evaluation in openended video captioning tasks.

Nevertheless, these existing benchmarks share two major limitations: (1) They primarily target short videos with relatively simple semantics. (2) They lack explicit discussion of Semantic Aggregation Hallucination (SAH), a critical challenge in long-video understanding.

ELV-Halluc

To address above issues, we propose ELV-Halluc, a Event based Long Video Hallucination benchmark and conduct in-

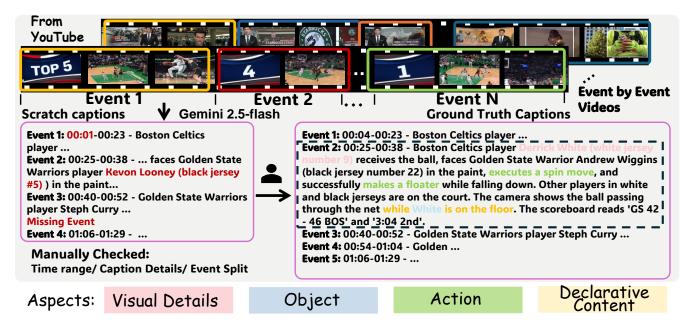


Figure 2: Overview of the data construction pipeline. Scratch captions are first generated using Gemini 2.5 Flash, followed by manual verification to obtain ground-truth captions. Different colors indicate semantic content requiring further modification for hallucination.

depth analysis on SAH. Table 1 shows statistical comparison with other video hallucination benchmarks.

	Videos	QAs per Video	Avg Video Length (s)
Videohallucer	948	1.89	85.6
EventHallusion	397	1.77	11.2
VidHalluc	5002	1.86	24.7
ARGUS	500	19	26.3
Ours	200	24	672.4

Table 1: Statistical comparison with previous video hallucination benchmarks

Event by event Video collection

Our benchmark is composed of **Event-by-Event Videos**. We define event-by-event Videos as videos that consist of multiple clearly separated events sharing the same overall topic. (e.g., a news broadcast with multiple news items).

Event-by-event Videos offer several advantages for establishing a long-video hallucination benchmark:

- Videos with clearly separated events can reduce captioning difficulty by isolating semantic units.
- Increase the likelihood of inducing SAH, as the semantics of event by event videos can be reorganized into multiple plausible yet incorrect descriptions.
- In event by event videos, the number of events can serve as an intuitive indicator of semantic complexity.

Finally, we manually collected 500 videos from YouTube. We removed overlapping samples with datasets such as YouCook2 to prevent potential data leakage.

Semi-automated Caption Pipeline

As shown in Figure 2, we adopt a three stage semiautomated caption pipeline to reduce human effort while ensuring annotation quality.

Video Quality Recheck To reduce annotator disagreement on the Event-by-Event concept, we conducted a quality recheck. Annotators retained videos with 2–10 clearly distinguishable events and provided a keyword summarizing each video's core event (e.g., scoring moments in basketball, news coverage in broadcasts). A total of 348 videos were retained, each reviewed by at least two annotators.

Automated Caption Generation with Gemini We used Gemini-2.5 Flash to generate initial captions. Gemini was prompted to segment videos based on annotated keywords, exclude transitional or non-essential parts, and produce detailed captions for each identified event.

Human Verification and Refinement Annotators are asked to revise the gemini generated captions through the following steps: 1. Correcting inaccurate time ranges; 2. Fixing factual errors in the captions; 3. Removing redundant segments (e.g., introductions, summaries, transition parts); 4. Adding missing events and manually annotating captions.

Following this semi-automated process, we obtained 348 high-quality Event-by-Event videos with human-refined ground truth captions, ensuring accuracy while substantially reducing manual annotation costs.

Hallucinate OAs curation

We design adversarial question pairs for better hallucination evaluating. A model should be able to both chose correct

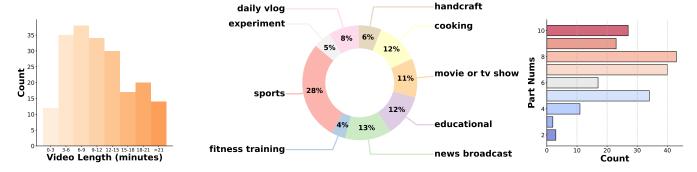


Figure 3: Dataset statistics: duration distribution (left), topic distribution (middle), and number of events per video (right).

caption and reject hallucinated captions. Based on this principle, we use GPT-40 to modify ground truth captions by introducing hallucination elements. Each modified caption is paired with its ground truth to form a Question pair, and the pair is considered correct only if model answers both questions correctly.

Our modifications specifically target the semantics of four aspects: **Visual details**: attributes such as color, shape, size, patterns, spatial relationships, or on-screen text (OCR). **Action**: denotes the key activity or motion being performed. **Object**: refers to humans or physical objects mentioned in the caption. **Declarative content**: descriptive or propositional statements summarizing a situation, asserting an outcome, or conveying a belief or result, rather than concrete actions or events. (e.g., "Team A is leading," "The match seems intense,")



Figure 4: Showcase of in-video and out-video modifications.

GPT-40 is instructed to modify captions by altering one of these aspects. To further investigate SAH, we design two modification strategies:

In-video modification: GPT replaces an object in the ground truth caption with an object drawn from another event within the same video.

Out-video modification: GPT replaces an object in the ground truth caption with a fabricated object that does not appear in any captions from the video.

Captions after modification must remain plausible and reasonable, such that correctness cannot be judged without watching the video. If a model is misled by an in-video hallucinated caption, all hallucination types could be responsible causes. In contrast, if the model is misled by an out-video

hallucinated caption, SAH won't serve as possible cause, since the hallucinated content does not exist in the video. Therefore, subtracting the out-video mislead rate from the in-video mislead rate approximates the contribution of Semantic Aggregation Hallucination. As shown in Figure 4, We use an object as an example to demonstrate the In-video and Out-video modifications.

After applying these modifications, we obtain 20072 hallucinated captions across 348 videos.

Hallucinated Caption Quality Check

We used GPT-40 to automatically recheck all modified captions, ensuring that in-video captions introduce the desired aspect change present in other events' ground truths, while out-video captions introduce changes absent from all ground truths. Captions meeting above criteria were retained, yielding 348 Event-by-Event videos and 8,630 hallucinated caption pairs.

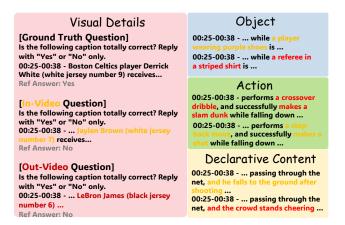


Figure 5: Examples of ELV-Halluc question—answer pairs across different semantic aspects. The left part illustrates the complete QA pair format in ELV-Halluc.

Final Benchmark and Evaluation Metrics

We select 200 videos from the original set of 348, leaving the remaining 148 videos as the training set for DPO. For each selected video, we choose 24 captions to construct binary

QA pairs by appending the question prefix: "Is the following caption totally correct? Reply with 'Yes' or 'No' only."

These QA pairs cover the aforementioned four aspects: visual details, objects, actions, and declarative content. Each aspect includes 6 questions, formed from 2 triplets drawn from different events within the same video. Each triplet consists of three captions: ground truth, in-video hallucinated, and out-of-video hallucinated. Examples of the final QA pairs are shown in Figure 5.

We form adversarial QA pairs by combining a ground-truth question with a hallucinated question, resulting in two pairs per triplet: (GT, In-Video Hallucination) (GT, Out-of-Video Hallucination) A pair is considered correct only if the model predicts "Yes" for the ground-truth question and "No" for the hallucinated question. Overall, the benchmark contains 4,800 binary QA pairs, which can be further grouped into 3,200 adversarial QA pairs. Figure 3 presents detailed statistics of ELV-Halluc, illustrating its diversity in video length, topics, and number of events.

Accuracy We use Accuracy to evaluate the overall hallucination level of models in long-video scenarios. Specifically, we report the following metrics: In-Video Accuracy: Accuracy on QA pairs containing in-video hallucinations. Out-Video Accuracy: Accuracy on QA pairs containing out-of-video hallucinations.

SAH Ratio We further propose the SAH Ratio to quantify the proportion of Semantic Aggregation Hallucination (SAH) among all hallucination errors. If a model achieves high accuracy on out-of-video hallucinations but significantly lower accuracy on in-video ones, it indicates difficulty in resolving semantic misalignment across events—the hallmark of SAH. Therefore, the accuracy gap reflects how prone the model is to confusing correct frame-level content with incorrect event-level attribution, making it a suitable proxy for SAH severity. Therefore, we use the SAH Ratio instead of the absolute difference between Out-Video and In-Video accuracy. This approach enables a more precise measurement of the relative severity of SAH while minimizing the influence of the model's absolute performance level. Consequently, it facilitates targeted solutions specifically addressing SAH. The metric is computed as follows:

$$SAH \ Ratio = \frac{OutAcc - InAcc}{1 - InAcc}$$

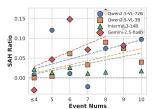
where **OutAcc** and **InAcc** denote the accuracy on out-of-video and in-video hallucination pairs, respectively.

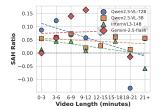
Experiments and discussions

We evaluate 14 open-source models ranging from 1B to 78B parameters, along with two closed-source MLLMs on ELV-Halluc. As shown in Table 2, the results demonstrate that current SOTA LLMs continue to face significant challenges with hallucination in long-video understanding(Note: The results of Gemini-2.5 Flash should not be directly compared with other models, as it was used to generate the initial captions, which may introduce bias). The results also validate the existance of SAH, as most MLLMs exhibit substantially

lower accuracy on in-video hallucinated captions than on out-of-video hallucinated captions. Among the open-source models, Qwen2.5-VL-32B achieves the lowest SAH Ratio, at only 0.2%.

SAH increase as the semantic complexity rises. In Figure 6, we observe that Qwen2.5-VL-3B, Qwen2.5-VL-72B, InternVL3-8B, and Gemini2.5-Flash (representing different model sizes and families) exhibit a positive correlation between the SAH ratio and the number of video events, as a larger number of events typically introduces more complex semantics. Meanwhile, we find that the SAH ratio does not show any consistent relationship with video length, since in our event-by-event dataset, video length does not necessarily correspond to a higher number of events.





(a) SAH Ratio vs. Event Count

(b) SAH Ratio vs. Video Length

Figure 6: Relationship between SAH and video properties: (a) SAH Ratio correlation with the number of events; (b) SAH Ratio correlation with video duration.

SAH Occurs More Frequently at Rapidly Changing Semantic We found that model tend to exhibit SAH more frequently on semantics that change rapidly over time. During modification, we define four aspects—visual details, action, object, and declarative content—each representing a different level of semantic granularity. Among them, visual details vary the fastest, followed by actions, as objects often engage in multiple actions over time. Objects themselves change less frequently, while declarative content represents higher-level semantics that evolve the slowest.

Based on the results of 14 open-source models, we plot the SAH ratio for these four aspects (see Figure 7). Results reveal that Video-MLLMs exhibit the highest SAH ratio on visual details, followed by actions and objects, and the lowest on declarative content, suggesting that models are more prone to SAH on semantics with higher temporal variability.

Hallucination under Varying Frame Numbers and Model Sizes. As shown in Figure 8, We use the Qwen2.5-VL and InternVL3 series models to investigate the relationship between the number of video frames sampled and the occurrence of hallucinations. For Qwen2.5-VL, we disable the dynamic resolution mechanism to ensure that the number of frames serves as the sole varying factor. For accuracy, we observe that for most models, increasing the number of frames generally leads to higher overall hallucination accuracy. For the SAH ratio, most models tend to exhibit higher values as the number of frames increases. We attribute above

Models LLM size		Visual Details		Object		Action		Declarative Content			A AA	A D:66	CATED-41-1			
Models	LLWI SIZE	In.	Out.	Diff.	In.	Out.	Diff.	In.	Out.	Diff.	In.	Out.	Diff.	Avg Acc↑	Avg Diff.↓	SAH Ratio↓
Open Source Models																
InternVL3-1B	0.5B	8	11	3	8.7	11	2.3	8.7	12.5	3.8	11.3	8.3	-3	9.9	1.5	1.6
InternVL3-2B	1.5B	7	15.5	8.5	8.7	17.2	8.5	7.2	10.5	3.3	10	13	3	11.1	5.8	6.3
SmolVLM-2.2B	1.7B	0	0	0	3	5	2	0	0	0	0	0	0	1	0.5	0.5
Qwen2.5VL-3B	3B	2.2	10.5	8.3	7.7	13.8	6.1	5	8	3	6	6	0	7.4	4.3	4.5
LLaVA-Video-7B	7B	3.7	3.7	0	4.5	2.5	-2	3.7	3.2	-0.5	4	4	0	3.6	-0.6	-0.6
Video-chatgpt-7B	7B	2	2.5	0.5	2.5	1.7	-0.7	1.2	1.2	0	2.2	3.2	1	2.0	0.2	0.1
LLaVA-OV-7b	7B	8	13.2	5.2	9.5	13.7	4.2	8.7	10.7	2	7.7	7.5	-0.2	9.9	2.8	3.0
Qwen2.5VL-7b	7B	10.2	26	15.8	17.5	30.7	13.2	13	20.7	7.7	16.8	10.5	-6.3	18.1	7.6	8.8
InternVL3-8B	7B	12.5	19.5	7.0	14.5	19.5	5.0	13.5	20.5	7.0	12.8	17.7	4.9	16.3	5.9	6.8
InternVL3-14B	14B	17.5	24.5	7.0	22.8	24.5	1.7	16.3	17.7	1.4	15.2	15.5	0.3	19.2	2.6	3.1
Qwen2.5VL-32B	32B	16.5	24.5	8.0	21.7	24.5	2.8	17.2	15.0	-2.2	15.2	7.2	-8	17.7	0.1	0.2
InternVL3-38B	32B	25.3	29	3.7	24.2	28	3.8	24	30	6	24.5	24.2	-0.3	26.1	3.3	4.3
Qwen2.5VL-72B	72B	24	35.5	11.5	35.7	41.5	5.8	27.8	32.3	4.5	32.3	27	-5.3	32.0	4.1	5.8
InternVL3-78B	72B	25	31.2	6.2	32	36.5	4.5	28.5	31.2	2.7	24.2	26.5	2.3	29.3	3.9	5.4
Closed Source Models																
GPT-40	/	7.7	8.3	0.6	8	8.7	0.7	8.7	10.2	1.5	8.5	9.5	1	8.7	0.9	1.0
Gemini2.5-Flash	1	47	58	11	56.5	58.8	2.3	50.5	53.2	2.7	48.7	52	3.3	53.1	4.8	9.8

Table 2: Main results on ELV-Halluc. Diff. denotes the gap between in-video and out-video accuracy. Note that the semi-automatic annotation pipeline uses Gemini for initial captioning, which may introduce bias; therefore, metrics for Gemini-2.5 Flash should not be directly compared with other models. All accuracies are shown as percentages.

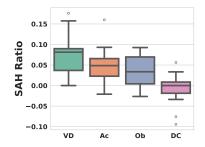


Figure 7: SAH Ratio across different semantic aspects. VD, Ac, Ob, and DC represent Visual Details, Action, Object, and Declarative Content, respectively.

findings to the fact that an increased number of frames provides the model with richer and more complex semantic information. On one hand, this additional information reduces uncertainty about the overall video content, thereby improving the model's robustness against overall hallucinations. On the other hand, the added complexity increases the likelihood of semantic mismatches, leading to more SAH. Interestingly, the Qwen2.5-VL-32B model exhibits a different trend. We hypothesize that this may be due to the reinforcement learning-based post-training of Qwen2.5-VL-32B-Instruct, which likely enhances its ability to aggregate visual semantics effectively.

Furthermore, we observe that larger language models generally achieve higher overall hallucination accuracy, suggesting improved robustness against global hallucinations. However, we do not observe a consistent correlation between model size and the SAH ratio, indicating that increasing model capacity does not necessarily mitigate semantic

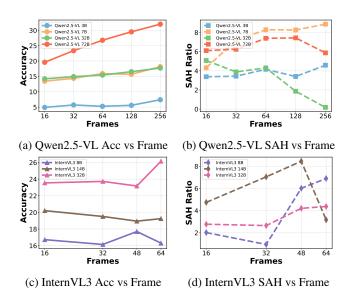


Figure 8: Effect of frame nums and model size on hallucination performance. Each row corresponds to a model family (Qwen2.5-VL and InternVL3), showing (left) overall hallucination accuracy and (right) SAH ratio across varying frame numbers for different model sizes.

aggregation hallucinations.

Strategies for Mitigating SAH

Position Encoding Decease SAH As SAH occur due to errors introduced during the semantic grouping process. We argue that a stronger RoPE mechanism could enhance the model's ability to bind semantic relationships, thereby re-

ducing errors that occur during grouping. Our experiments validate this hypothesis, as shown in Table 3. Specifically, we evaluate checkpoints based on Qwen2-VL, applying different positional encoding strategies: vanilla RoPE(Su et al. 2024), TAD-RoPE(Gao et al. 2024), m-RoPE(Wang et al. 2024a), and VideoRoPE(Wei et al. 2025). The results demonstrate that VideoRoPE achieves the lowest SAH ratio. However, the findings also indicate that stronger RoPE variants do not necessarily mitigate oveall hallucinations.

Method	In.↑	Out.↑	SAH Ratio↓
vanillarope	0.94	2.75	1.82
tad_rope	0.44	2.62	2.18
mrope	1.12	2.06	0.95
videorope	1.19	2.06	0.88

Table 3: Different RoPE Strategies on ELV-Halluc. Bold values indicate the best performance. In. and Out. denote the average in-video and out-video accuracy, respectively.

Mitigate SAH with DPO Considering that SAH mainly arise from incorrect grouping of correct video semantics, applying a method to suppress the model's attention to hallucinatory semantics should reduce SAH possibilities. Therefore, we adopt the Direct Preference Optimization(Rafailov et al. 2023) approach to further optimize the model.

We leverage the remaining 148 videos' ground-truth and hallucinated caption of all events to construct the positive and negative response pairs required for DPO. Specifically, we use the following template to generate data pairs: "Please provide a detailed caption for this segment during mm:ss - mm:ss. Chosen: Ground truth caption Rejected:Hallucinated caption"

Finally, we create two separate datasets of 4k positivenegative pairs each: one using in-video hallucinated captions and the other using out-of-video hallucinated captions.

We use Qwen2.5-VL-7B as the base model and conduct three training settings: 1. In-video pairs, 2. Out-video pairs, 3. Combining above 2 types of pairs.

Model	ELV	-Halluc	VideoMME				
Model	Avg Acc↑	SAH Ratio↓	Short	Medium	Long	Avg↑	
Qwen2.5vl-7B	15.9	8.3	72.7	61.7	51.3	61.9	
+ invideo-4k	16.2	6.0 (-27.7%)	72.4	62.6	51.9	62.3	
+ outvideo-4k	16.0	8.6 (+3.6%)	73.8	62.0	52.6	62.8	
+ together-8k	16.4	8.4 (+1.2%)	73.4	62.1	51.8	62.4	

Table 4: Performance comparison of base model and DPO variants on ELV-Halluc and VideoMME benchmarks.

As shown in Table 4, applying DPO with in-video pairs yields the most notable improvement, reducing the SAH ratio from 8.3 to 6.0. This indicates that aligning the model's preference toward correct event semantics within the same video is highly effective for mitigating semantic aggregation hallucinations. Additionally, the overall average accuracy on ELV-Halluc improves by 0.3 points, while general video understanding performance on VideoMME also improves slightly (+0.4), demonstrating that mitigating hallucination does not compromise general capability.

In contrast, DPO with out-of-video pairs reduces overall hallucination slightly but unexpectedly increases the SAH ratio. This suggests that optimizing the model to reject content entirely irrelevant to the video does not effectively improve SAH and may even bias the model toward overreliance on language priors.

When combining in-video and out-of-video pairs (8k samples together), the model achieves a balanced trade-off: it retains most of the benefits of in-video optimization, while maintaining robustness against out-of-video hallucinations. However, the combined setting does not surpass in-video DPO in reducing SAH.



Figure 9: Attention Gap Heatmap after DPO with In-video pairs, BLUE means lower attention after DPO.

As illustrated in Figure 9, attention visualization reveals that after DPO with in-video pairs, the model significantly reduces its focus on incorrect yet semantically plausible regions, shown in blue areas indicating decreased attention weights. This suggests that DPO effectively reshapes the model's internal preference distribution, promoting stronger grounding of responses in relevant visual semantics. Such alignment at the attention level provides a mechanistic explanation for the observed improvement in SAH mitigation.

Conclusion and Limitations

In this work, we addressed the underexplored challenge of hallucination in long-video understanding by introducing ELV-Halluc, the first benchmark tailored to evaluate Semantic Aggregation Hallucination (SAH). We identified SAH as a distinct and increasingly prominent error type in semantically complex, multi-event videos. To enable comprehensive evaluation, we benchmarked 14 open-source Video-MLLMs (1B–78B) and two closed-source models (GPT-40 and Gemini 2.5 Flash). Our experiments revealed key SAH patterns and overall hallucination trends. To mitigate SAH, we proposed a DPO-based approach and curated an 8K-pair adversarial dataset, achieving a 27.7% reduction in SAH and a 0.9% gain on VideoMME.

Despite its contributions, our work has several limitations. First, although our semi-automated pipeline reduces manual effort, Gemini-generated captions may introduce bias, potentially inflating Gemini 2.5 Flash's performance. Second, while event-based video construction improves control and diversity, it still differs from real-world long videos. Third, the dataset scale is limited due to the high annotation cost.

Nonetheless, we believe our benchmark, analysis, and mitigation strategies lay a solid foundation for advancing reliable long-video understanding.

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ELV-Halluc: Benchmarking Semantic Aggregation Hallucinations in Long Video Understanding

APPENDIX

- A: Experiment Setting
 - A.1: Model Implementation Details
 - A.2: Test Stability Across Multiple Runs
- B: More ELV-Halluc Cases
 - B.1: ELV-Halluc QA Examples
 - B.2: ELV-Halluc SAH Cases
- C: Data Construction Details

Experiment Settings

Model Implementation Details

Model Checkpoints For all evaluated open-source models, we adopt the official weights provided on HuggingFace. For the experiments involving RoPE, we directly utilize the Qwen2-VL-based implementation and weights from VideoRoPE. The specific HuggingFace repository paths, along with the versions of the closed-source models, are listed in Table 1.

Inference Parameters We provide a detailed description of the parameter configurations used during evaluation. For the Qwen2.5-VL series, we set the maximum video resolution to $128 \times 28 \times 28$ pixels and the maximum number of frames to 256, while all other settings follow the official defaults. For the InternVL3 series, we limit the number of frames to 64. For GPT-40, we uniformly sample 50 frames and use the following instruction:

"Here are {nframes} frames sampled from a {video_length}-duration video."

For all remaining models, we adopt the default generation configurations provided in their respective official checkpoints.

DPO Experiment Setting All experiments are conducted on NVIDIA H100 GPUs. During the DPO training process, we train for one epoch with a learning rate of 1×10^{-6} and a batch size of 16. We use Qwen2.5-VL-7B as the base model, with the sequence length set to 32,768 during training. All original parameters (e.g., fps, fps max frames, video max pixels) are preserved. During inference, we fix nframes to 64 for both **ELV-Halluc** and **VideoMME** benchmarks.

Test Stability Across Multiple Runs

As shown in Figure 1, we selected four models from different sizes and series for repeated experiments to evaluate the stability of ELV-Halluc across three separate trials. The results demonstrate that ELV-Halluc achieves relatively stable overall accuracy and SAH ratio.

Model	Checkpoint					
Qwen2.5-VL-3B	Qwen/Qwen2.5-VL-3B-Instruct					
Qwen2.5-VL-7B	Qwen/Qwen2.5-VL-7B-Instruct					
Qwen2.5-VL-32B	Qwen/Qwen2.5-VL-32B-Instruct					
Qwen2.5-VL-72B	Qwen/Qwen2.5-VL-72B-Instruct					
InternVL3-1B	OpenGVLab/InternVL3-1B					
InternVL3-2B	OpenGVLab/InternVL3-2B					
InternVL3-8B	OpenGVLab/InternVL3-8B					
InternVL3-14B	OpenGVLab/InternVL3-14B					
InternVL3-38B	OpenGVLab/InternVL3-38B					
InternVL3-78B	OpenGVLab/InternVL3-78B					
SmolVLM2-2.2B-Instruct	HuggingFaceTB/SmolVLM2-2.2B-Instruct					
LLaVA-Video-7B-Qwen2	lmms-lab/LLaVA-Video-7B-Qwen2					
Video-ChatGPT-7B	MBZUAI/Video-ChatGPT-7B					
LLaVA-OneVision-Qwen2-7B	llava-hf/llava-onevision-qwen2-7b-ov-hf					
GPT-4o(for modification)	gpt-4o-2024-08-06					
GPT-4o(for evaluation)	gpt-4o-2024-11-20					
Gemini2.5-flash	gemini-2.5-flash					
Qwen2-VL-vanilla-rope	Wiselnn/Qwen2-VL-vanilla_rope-128frames-8k-context-330k-llava-video					
Qwen2-VL-tad-rope	Wiselnn/Qwen2-VL-tad_rope-128frames-8k-context-330k-llava-video					
Qwen2-VL-m-rope	Wiselnn/Qwen2-VL-m_rope-128frames-8k-context-330k-llava-video					
Qwen2-VL-video-rope	Wiselnn/Qwen2-VL-videorope-128frames-8k-context-330k-llava-video					

Table 1: Summary of evaluated models and their corresponding official HuggingFace checkpoints.

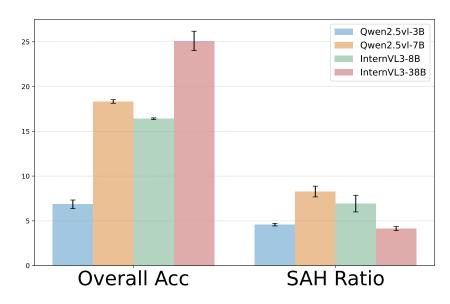


Figure 1: Stability evaluation of ELV-Halluc through repeated experiments. We report overall accuracy and SAH ratio across 3 runs for four representative models of different sizes and series, demonstrating that ELV-Halluc maintains consistent performance.

More ELV-Halluc Cases

ELV-Halluc QA Examples

In the following section, we provide detailed examples of question-answer triplets from ELV-Halluc, covering four aspects: visual details, actions, objects, and declarative content. Each triplet consists of three questions: ground truth, in-video hallucination, and out-video hallucination, respectively. We use green, orange, and red to highlight the GT, in-video, and out-video parts, respectively, and enclose them with boxes of the same colors in the video.



Figure 2: Example of visual details QA triplets from ELV-Halluc.

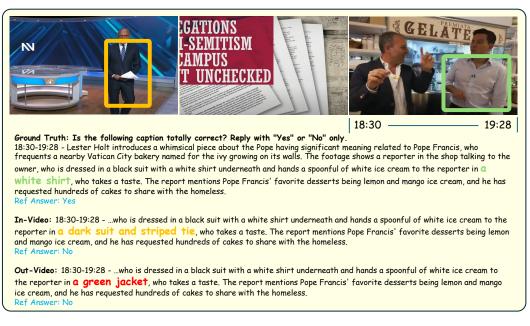


Figure 3: Example of *object* QA triplets from ELV-Halluc.

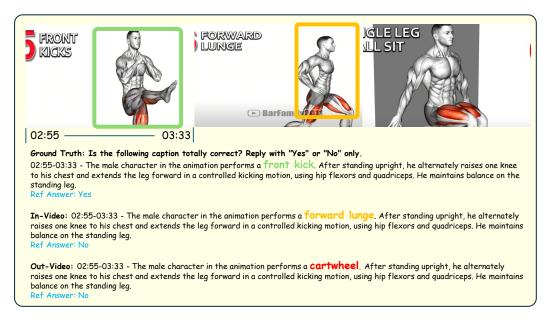


Figure 4: Example of action QA triplets from ELV-Halluc.



Figure 5: Example of declarative content QA triplets from ELV-Halluc.

ELV-Halluc SAH Cases

In the following section, we present specific cases illustrating how SAH happends within ELV-Halluc. The most typical SAH scenario occurs when the ground truth answer is yes, the In-Video response is yes, but the Ou-tVideo response is no. This pattern demonstrates that while the model correctly identifies the hallucination error in the OutVideo scenario, it is misled by the in-video semantic information. These examples clearly show that ELV-Halluc effectively captures and evaluates the presence of SAH. Incorrect answers from the models are highlighted in red.

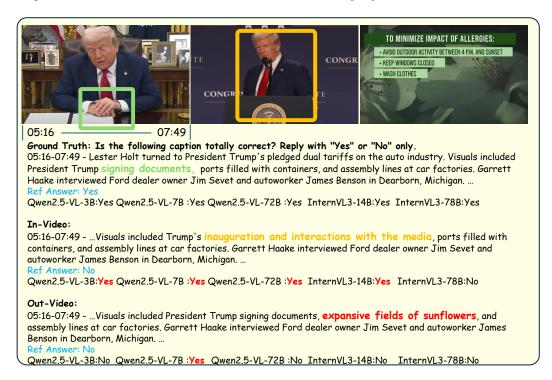


Figure 6: SAH case in ELV-Halluc.



Qwen2.5-VL-3B:Yes Qwen2.5-VL-7B:Yes Qwen2.5-VL-7B:Yes InternVL3-14B:No InternVL3-78B:Yes

Out-Video

02:37-02:59 - River Plate's No. 29 player Marcos Acuña, wearing a white jersey, takes a corner kick from the left side of the field. The ball curves into the crowded penalty area, and River Plate's No. 8 player **Gabriel Batistuta**...

Ref Answer: No.

Qwen2.5-VL-3B:Yes Qwen2.5-VL-7B:Yes Qwen2.5-VL-72B:No InternVL3-14B:Yes InternVL3-78B:No

Figure 7: SAH case in ELV-Halluc.

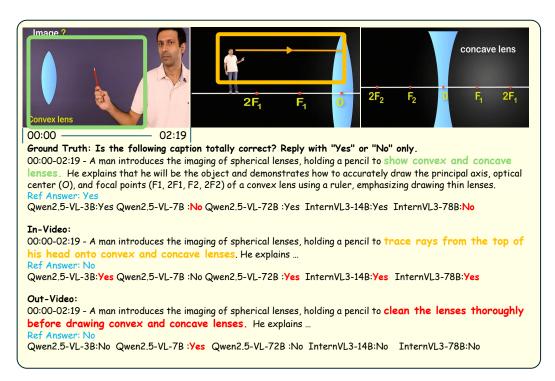


Figure 8: SAH case in ELV-Halluc.

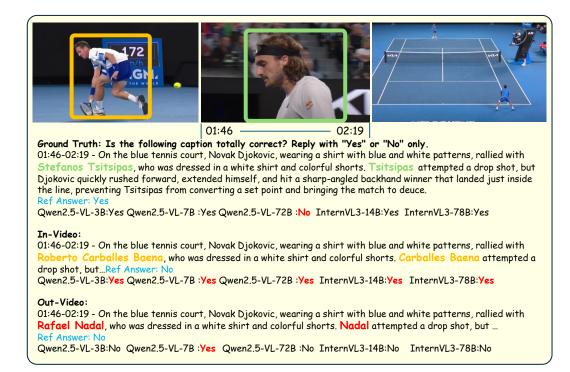


Figure 9: SAH case in ELV-Halluc.

Data Construction Details

In this section, we provide more details on the data construction pipeline, including the prompts used.

As shown in Figure 10, we present the overall word cloud of ELV-Halluc captions to illustrate the diversity of the captions.



Figure 10: Word cloud of all captions in ELV-Halluc.

First, we use the following prompt to instruct Gemini-2.5-Flash to generate scratch captions.

Listing 1: Prompt for gemini-2.5-flash to generate scratch captions.

```
### Task:
You will be provided with a {} video. Your task consists of three main steps:
1. Comprehensively understand the video using both audio and visual information.
2. Segment the video into several parts, while each part contains a isolate and complete **{}**.
3. Generate detailed captions for each part according to the following guidelines.
Note: These parts are parallel, which is **a list of distinct but equally important elements**.
(e.g., several complete news articles, multiple goals, different cooking steps, different movie or TV shows, different parts in vlog, or isolated topics)
```

```
### Guidelines for Video Caption Generation:
Each caption **must include the following aspects**:
1. **Time Range** - Provide the precise time interval of the segment (e.g., "02:15
      02:42").
2. **Visual Details**
                          Describe specific visual elements in the segment with
   fine granularity:
- Objects: Include object shape, color, texture, written text (OCR), logos, jersey
    numbers, etc.
- Scene Layout: Describe background elements.
- Spatial Relationships: Explain relative positions.
3. **Subject**
                  Clearly identify the main subject(s) in the segment.
4. **Action**
                 Describe physical activities with verbs.
5. **Event**
                Describe what happens as a complete narrative.
### Output Instructions:
1. Captions should be coherent and complete sentences.
2. Ignore redundant and uninformative content such as static frames, repetitive
   scenes, intros/outros, idle moments, and summary frames at the beginning or
   end of the video.
3. Ignore transitional or filler content between each major segment.
4. Each video must be conclude into less than 10 parts.
### Output Format:
You must strictly follow the output format below and output nothing beyond the
   specified structure.
'''json
        "part_1": "mm:ss-mm:ss - ...",
        "part_2": "mm:ss-mm:ss - ...",
   } }
. . .
....
```

After manual checking, we prompt GPT-40 to inject in-video and out-of-video hallucinations related to four aspects into the ground truth captions. The prompts are shown below.

Listing 2: Prompt for GPT-40 to inject visual detail hallucinations.

```
You are a professional caption generation assistant.
You will be provided with captions for different parts of the same video. Your
   task is to generate hallucinated captions following the instructions below.
### Current Part Caption (Original Caption):
{current_part}
### Other Parts Captions:
{other_parts}
## Instructions:
1. Break down the current part caption into the following components:
   - **Visual details**: attributes such as color, shape, size, patterns, spatial
      relationships, or on-screen text (OCR).
  - **Objects**: refers to humans or physical objects involved in the caption.
  - **Actions**: refers to the key activity or motion being performed.
  - **Declarative Content**: refers to high-level descriptive or propositional
      statements that summarize a situation, assert an outcome, or convey a
      belief, stance, or result. These are not concrete actions or events.
  - **Time range**: the timestamp segment covered by this caption.
```

```
2. Identify a **visual detail** in the current part caption.
3. Replace that visual detail using:
   - **in_video hallucination**: Replace it with a visual detail that appears in *
      other parts captions \star of the same video.
   - **out_video hallucination**: Replace it with a visual detail that *never
      appears in any part captions* of this video.
4. The hallucinated captions must remain **plausible and reasonable**, so that a
   model cannot reliably judge which is correct (among original, in_video, and
   out_video) without actually seeing the video.
### IMPORTANT:
- You must strictly preserve all the rest of the current part caption (including
   its time range and sentence structure). Only the selected **visual detail** is
    to be replaced.
- The replacement must be logically consistent and naturally integrated, with no
   contradictions or cues that obviously reveal the modification.
- The replacement must change the semantics of the original caption, and cannot
   use synonyms.
### Output Format:
'''json
 "in_video": "in_video caption here",
 "out_video": "out_video caption here"
} }
```

Listing 3: Prompt for GPT-40 to inject object hallucinations.

```
You are a professional caption generation assistant.
You will be provided with captions for different parts of the same video. Your
   task is to generate hallucinated captions following the instructions below.
### Current Part Caption (Original Caption):
{current_part}
### Other Parts Captions:
{other_parts}
## Instructions:
1. Break down the current part caption into the following components:
   - **Visual details**: attributes such as color, shape, size, patterns, spatial
       relationships, or on-screen text (OCR).
   - **Objects**: refers to humans or physical objects involved in the caption.
   - **Actions**: refers to the key activity or motion being performed.
   - **Declarative Content**: refers to high-level descriptive or propositional
       statements that summarize a situation, assert an outcome, or convey a
       belief, stance, or result. These are not concrete actions or events.
   - **Time range**: the timestamp segment covered by this caption.
2. Identify a **object** in the current part caption.
3. Replace that object using:
   - **in_video hallucination**: Replace it with an object that appears in *other
      parts captions* of the same video.
   - **out_video hallucination**: Replace it with an object that *never appears in
       any part captions* of this video.
4. The hallucinated captions must remain **plausible and reasonable**, so that a
  model cannot reliably judge which is correct (among original, in_video, and
```

```
out_video) without actually seeing the video.

### IMPORTANT:
- You must strictly preserve all the rest of the current part caption (including its time range and sentence structure). Only the selected **object** is to be replaced.
- The replacement must be logically consistent and naturally integrated, with no contradictions or cues that obviously reveal the modification.
- The replacement must change the semantics of the original caption, and cannot use synonyms.

### Output Format:
'''json
{{
    "in_video": "in_video caption here",
    "out_video": "out_video caption here"
}}
''''
```

Listing 4: Prompt for GPT-40 to inject action hallucinations.

```
You are a professional caption generation assistant.
You will be provided with captions for different parts of the same video. Your
   task is to generate hallucinated captions following the instructions below.
### Current Part Caption (Original Caption):
{current_part}
### Other Parts Captions:
{other_parts}
## Instructions:
1. Break down the current part caption into the following components:
   - **Visual details**: attributes such as color, shape, size, patterns, spatial
      relationships, or on-screen text (OCR).
   - **Objects**: refers to humans or physical objects involved in the caption.
  - **Actions**: refers to the key activity or motion being performed.
   - **Declarative Content**: refers to high-level descriptive or propositional
       statements that summarize a situation, assert an outcome, or convey a
       belief, stance, or result. These are not concrete actions or events.
   - **Time range**: the timestamp segment covered by this caption.
2. Identify an **action** in the current part caption.
3. Replace that action using:
   - **in_video hallucination**: Replace it with an action that appears in *other
       parts captions* of the same video.
   - **out_video hallucination**: Replace it with an action that *never appears in
       any part captions* of this video.
4. The hallucinated captions must remain **plausible and reasonable**, so that a
   model cannot reliably judge which is correct (among original, in_video, and
    out_video) without actually seeing the video.
### IMPORTANT:
- You must strictly preserve all the rest of the current part caption (including
   its time range and sentence structure). Only the selected **action** is to be
   replaced.
- The replacement must be logically consistent and naturally integrated, with no
   contradictions or cues that obviously reveal the modification.
- The replacement must change the semantics of the original caption, and cannot
   use synonyms.
```

```
### Output Format:
'''json
{{
    "in_video": "in_video caption here",
    "out_video": "out_video caption here"
}}
'''
```

Listing 5: Prompt for GPT-40 to inject declarative content hallucinations.

```
You are a professional caption generation assistant.
You will be provided with captions for different parts of the same video. Your
   task is to generate hallucinated captions following the instructions below.
### Current Part Caption (Original Caption):
{current_part}
### Other Parts Captions:
{other_parts}
## Instructions:
1. Break down the current part caption into the following components:
   - **Visual details**: attributes such as color, shape, size, patterns, spatial
      relationships, or on-screen text (OCR).
  - **Objects**: refers to humans or physical objects involved in the caption.
    **Actions**: refers to the key activity or motion being performed.
  - **Declarative Content**: refers to high-level descriptive or propositional
      statements that summarize a situation, assert an outcome, or convey a
      belief, stance, or result. These are not concrete actions or events.
   - **Time range**: the timestamp segment covered by this caption.
2. Identify a **declarative content** in the current part caption.
3. Replace that declarative content using:
  - **in_video hallucination**: Replace it with a declarative content that
      appears in *other parts captions* of the same video.
   - **out_video hallucination**: Replace it with a declarative content that *
      never appears in any part captions* of this video.
4. The hallucinated captions must remain **plausible and reasonable**, so that a
   model cannot reliably judge which is correct (among original, in_video, and
   out_video) without actually seeing the video.
### IMPORTANT:
- You must strictly preserve all the rest of the current part caption (including
    its time range and sentence structure). Only the selected **declarative
   content ** is to be replaced.
- The replacement must be logically consistent and naturally integrated, with no
   contradictions or cues that obviously reveal the modification.
- The replacement must change the semantics of the original caption, and cannot
   use synonyms.
### Output Format:
'''json
{ {
 "in_video": "in_video caption here",
 "out_video": "out_video caption here"
```

Finally, we prompt GPT-40 to recheck all modified captions, and we retain only the question pairs that are verified as true.

Listing 6: Prompt for GPT-40 to check hallucinated captions.

```
You are a strict video caption checker.
You will be given multiple captions from different parts in a same video.
Each part has a ground-truth caption and two hallucinated captions: 'in_video' (
    containing a modification that should come from another part of the same video
    ) and 'out_video' (containing a plausible but fabricated modification that
   does not appear in any part of the video).
The hallucination aspect of this part is **{aspect}**.
First, identify what information has been added or changed in the hallucinated
   captions compared to the ground_truth.
Second, verify whether:
1. The **in_video** caption introduces a/an **{aspect}** modification that **
   semanticly appears** in at least one **other part's** 'ground_truth' (
   excluding the current part).
2. The **out_video** caption introduces a/an **{aspect}** modification that **
   semanticly does NOT appear** in any of the ground_truth captions.
Focus on the differences between the hallucinated captions and the original
   ground_truth.
Please return your judgment strictly follows the below JSON format, don't provide
   any reasons, explanations, verifications:
···json
 "in_video_valid": true/false,
 "out_video_valid": true/false
} }
, , ,
Ground Truth:
{ground_truth}
In-Video Hallucination:
{in_video}
Out-Video Hallucination:
{out_video}
Other Parts' Ground Truths:
{other_parts_gt}
```