Direct Preference Optimization of Video Large Multimodal Models from Language Model Reward

Anonymous ACL submission

Abstract

Preference modeling techniques, such as direct preference optimization (DPO), has shown effective in enhancing the generalization abilities of large language model (LLM). However, in tasks involving video instruction-following, providing informative feedback, especially for open-ended conversations, remains a significant challenge. While previous studies have explored using large multimodal models (LMMs) as reward models for guiding preference modeling, their ability to accurately assess the quality of generated responses and their alignment with video content has not been conclusively demonstrated. This paper introduces a novel framework that utilizes detailed video captions as a proxy of video content, enabling language models to incorporate this information as supporting evidence for scoring video Question Answering (QA) predictions. Our approach demonstrates robust alignment with OpenAI GPT-4V model's reward mechanism, which directly takes video frames as input. Furthermore, we show that applying our reward mechanism to DPO algorithm significantly improves model performance on open-ended video QA tasks.

1 Introduction

This paper addresses the challenge of aligning LMMs, particularly in tasks that involve video instruction following. Despite recent advancements in reinforcement learning (RL) (Ouyang et al., 2022; Bai et al., 2022; Lee et al., 2023; Sun et al., 2023b) and DPO (Rafailov et al., 2024; Chen et al., 2024c; Hosseini et al., 2024), which have been effective in guiding LLMs towards generating more honest, helpful, and harmless content, their effectiveness in video domain remains limited. The critical obstacle lies in developing a robust reward system capable of distinguishing preferred responses from less preferred ones based on video inputs. The challenge is further complicated by the coverage and potential inaccuracies in generated content, stemming from the scarcity of alignment data across different modalities (Liu et al., 2023b; Sun et al., 2023a).

While human preference data is valuable, it is challenging to scale due to its cost and labor-intensive nature, as highlighted by the LLaVA-RLHF (Sun et al., 2023a) paper, which collected 10k human-evaluated instances at a considerable cost of $3000. Existing approaches for distilling preferences, such as those for image data using GPT-4V (Li et al., 2023d), encounter scalability issues, especially for video inputs that require analyzing multiple frames. While (Ahn et al., 2024) leverage a supervised finetuning (SFT) model for self-evaluation, the efficacy of the SFT model remains uncertain, particularly in accurately assessing the factuality of responses in relation to their corresponding videos.

To tackle the aforementioned challenges, we introduce a cost-effective reward mechanism that is both computationally and financially efficient for evaluating the quality of responses generated by video LLMs, serving as a basis for further on-policy preference optimization. We propose the use of detailed video captions as a proxy for video content, enabling a language model analyze the content and assess the quality of an LMM's response to related questions. The language model generates natural language feedback as a chain-of-thought step, and produces a numerical score as the reward, thereby creating an efficient feedback system.

However, high-quality video captions are essential for this process. To mitigate the shortage of high-quality video captions, we have developed a comprehensive video caption dataset, SHAREGPTVIDEO, using a simple prompting technique with the GPT-4V model, comprising 900k captions that encompass a wide range of video content, including temporal dynamics, world knowledge, object attributes, and spatial relationships. With this video caption dataset available, we verify that

our reward mechanism, which utilizes video captions as a proxy, is well-aligned with evaluations derived from the more powerful, albeit costlier, GPT-4V model-generated rewards. Employing this reward mechanism as the basis for DPO algorithm, we train LLAVA-HOUND-DPO that achieves an 8.1% accuracy improvement over the SFT counterpart. This marks a significant advancement in video LMM alignment and represents the first successful application of a DPO method in this domain.

Our contributions are outlined as follows:

1. We release a large-scale detailed video caption (900k) and instruction-following (900k) dataset covering a wide range of video content, which facilitates video LMM model training and research.

2. We demonstrate the effective application of DPO to improve model performance by leveraging the language model feedback as reward, which substantially improves model performance on open-ended video QA tasks.

3. We propose an automated *development* benchmark for evaluating video instruction-following capability, serving as a cost-effective way to validate model performance.

2 Related Work

2.1 Large Multi-Modal Models

LMMs (Liu et al., 2023b,a; Bai et al., 2023; Chen et al., 2023; Li et al., 2023a) have enabled instruction following across modalities by utilizing LLM as backbones. In the context of video understanding, LLMs have been adapted to process video content (Zhang et al., 2023a; Maaz et al., 2023; Li et al., 2023b; Luo et al., 2023; Liu et al., 2023c; Jin et al., 2024; Ahn et al., 2024). Our work adopts Video-LLaVA (Lin et al., 2023a) backbone, focusing on model enhancement through preference modeling with the DPO technique.

2.2 Video-text Datasets

Existing video-text datasets typically provide brief sentences or mere keywords as captions, as indicated by (Bain et al., 2021a; Wang et al., 2023; Yu et al., 2019; Jang et al., 2017; Xu et al., 2016). (Shvetsova et al., 2023). Video-ChatGPT (Li et al., 2023b) employs human effort to create high-quality video instructions, albeit limited to the ActivityNet domain with only 100k instruction pairs. Concurrent work (Chen et al., 2024b) leverages GPT-4V to label video captions. Our work also leverages the GPT-4V model to produce detailed video captions, which we release as community resource for LMM training.

2.3 Preference Modeling for LMMs

Preference modeling techniques are DPO (Deng et al., 2024; Yu et al., 2024; Li et al., 2023d; Gunjal et al., 2023; Sun et al., 2023a) or PPO (Sun et al., 2023a) are applied to LMM alignment. More recently, (Ahn et al., 2024) used RL on AI feedback to improve video LMM performance. Our contribution extends DPO to the video LMM alignment, with the use of detailed captions as factual evidence for reward modeling.

3 Method

As shown in fig. 1, our methodology enhances video LMM alignment through DPO method using rewards from a language model. We elaborate on constructing a video caption dataset in section 3.1. Subsequently, in section 3.2, we discuss the generation of video instruction data and the fine-tuning process of our model. Lastly, section 3.3 details the incorporation of generated captions as a feedback mechanism for DPO method to refine our model's factual alignment in video instruction-following tasks.

3.1 Prompting GPT-4V Model for Detailed Video Caption Distillation

The selection of dataset includes videos from three sources: WebVid (400k) and VIDAL (450k) ActivityNet (50k) datasets. WebVid and VIDAL videos are in the general domain sourced from YouTube, and ActivityNet videos focus on human activities. The three datasets together result in a comprehensive collection of 900k videos. To accommodate the requirement that GPT-4V only takes images as input, we preprocess videos by uniformly extracting ten frames per video content. These frames are then concatenated into a sequence to serve as a proxy for the video. We use GPT-4V to generate a coherent caption for the represented video based on the frame sequence. The prompt (fig. 18) adheres to guidelines covering temporal dynamics, world knowledge, object attributes, spatial relationships, aesthetic assessments, etc., with the goal of comprehensively understanding the video contents (examples in fig. 8).

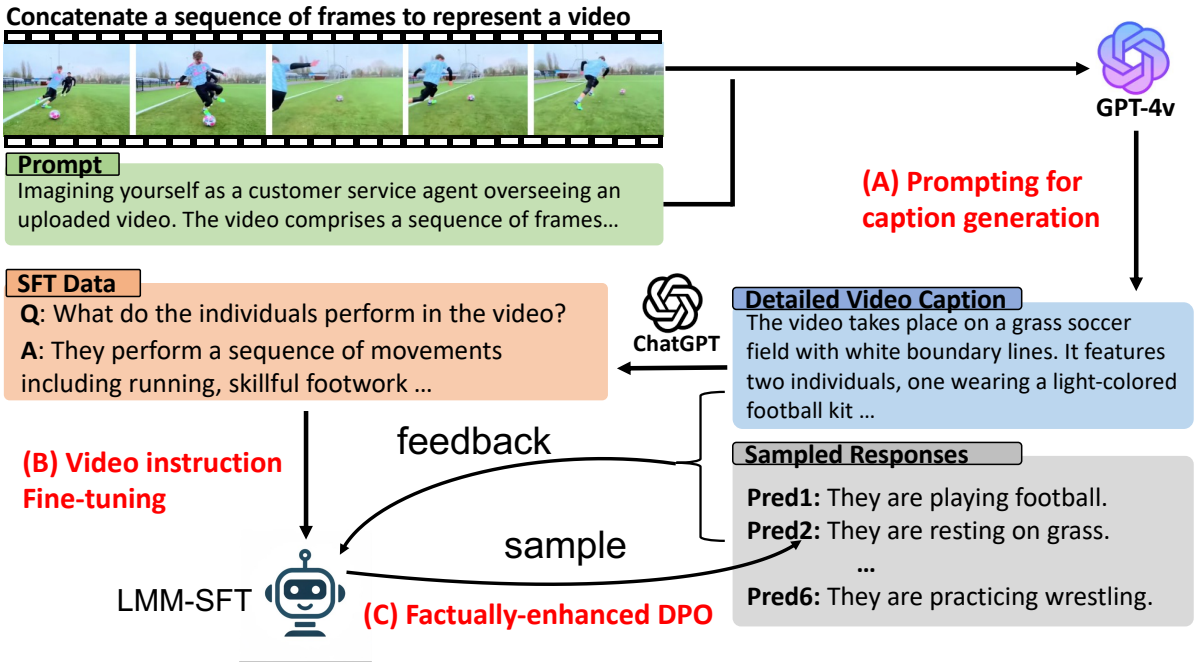

Figure 1: Workflow diagram showing: a) the use of GPT-4V for creating a detailed caption dataset for videos; b) generating video instruction data for SFT; c) integrating captions into a feedback loop for DPO, improving the model's performance on video instruction-following tasks.

3.2 SFT with Generated Video Instruction Data from Detailed Caption

To generate video instruction-following data for SFT, we adopt a similar methodology outlined in Video-ChatGPT (Li et al., 2023b). Specifically, we first randomly sample 300k video captions and then employ ChatGPT to generate 3 question-answer pairs conditioned on each caption (prompt in fig. 19). We release the 900k instruction-following data to public, but we only use a random subset of 240k for our training. This approach ensures that the instructional data remains factually consistent with the content of the detailed captions.

3.3 DPO with Language Model Reward

Acquiring high-quality on-policy preference data can be costly and labor-intensive. Although GPT-4V can be used for reward distillation, for video data, its high computation cost[1], slow response, and limited accessibility hinder scalability. We propose a cost-efficient method to generate reward data for DPO using detailed video captions as supporting evidence, as shown in fig. 2.

Initially, we randomly select a subset of 20k instruction pairs from the dataset described in section 3.2. The SFT model generates six responses per input at a temperature of 1.0. This procedure results in 120k question-answer pairs. Subsequently, we employ ChatGPT to evaluate the model responses based on the ground truth answer and detailed description (prompt in fig. 21). ChatGPT generates an output that includes a natural language explanation as chain-of-thought step, followed by a numerical reward score on a scale from 1 to 5, indicating the overall quality.

For each video and question pair, we randomly select an answer with a score ≥ 3 as positive example, and an answer with a score below 3 as negative. Cases where all responses are uniformly scored above or below 3 are excluded from the dataset. After the selection process, approximately 17k training instances are compiled for DPO training. Formally, the dataset is denoted as $\mathcal{D}_{DPO} = \{(\mathcal{V}, x, y_w, y_l)\}$, where $\mathcal{V}$ is the video, x is the question, y_w and y_l are the positive and negative responses. The DPO objective is defined as below:

$$\mathcal{L}_{\text{DPO}}\left(\pi_\theta; \pi_{\text{ref}}\right) = -\mathbb{E}_{(\mathcal{V},x,y_w,y_l)\sim\mathcal{D}_{DPO}}\Bigg[\log\sigma\left(\beta\log\frac{\pi_\theta\left(y_w \mid x,\mathcal{V}\right)}{\pi_{\text{ref}}\left(y_w \mid x,\mathcal{V}\right)} - \beta\log\frac{\pi_\theta\left(y_l \mid x,\mathcal{V}\right)}{\pi_{\text{ref}}\left(y_l \mid x,\mathcal{V}\right)}\right)\Bigg],$$

where π_θ is the policy model to be optimized and π_{ref} is the base reference model, both models are

[1]Video representation is typically encoded with 2048 tokens, while our captions only uses roughly 140 tokens.

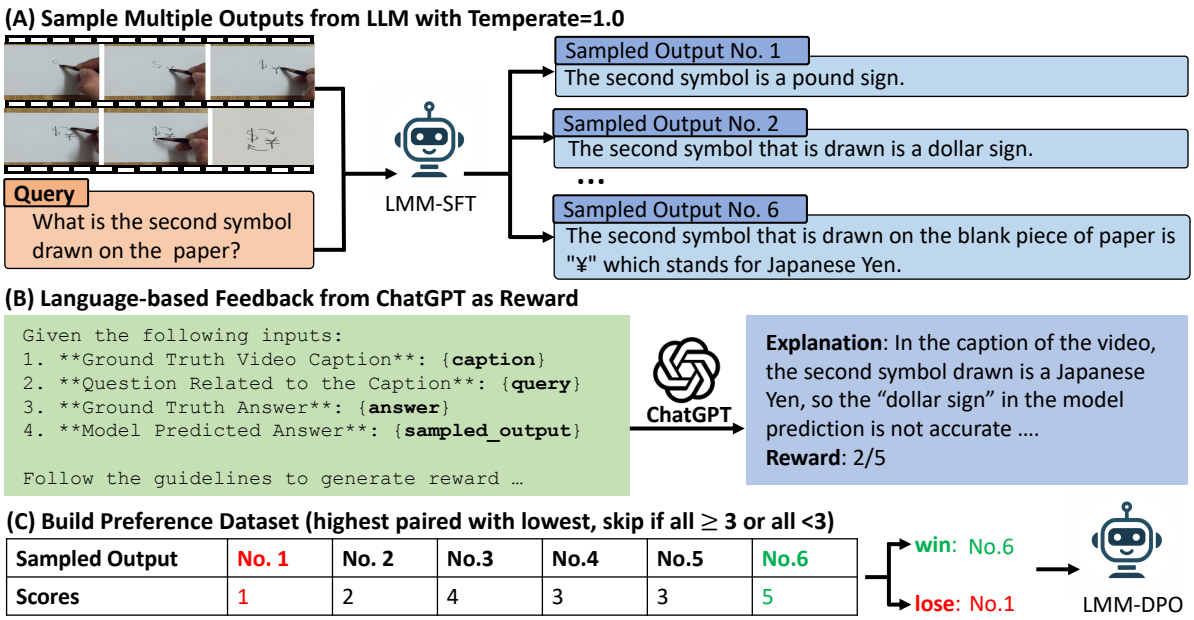

Figure 2: Detailed illustration of the proposed factually-enhanced DPO method.

initialized with SFT weights. σ is the logistic function and β is set to 0.1.

For on-policy reward generation, our method incurs a cost of less than \$20, under a pricing model of \$1.5 per million tokens. In comparison, previous methods of preference data collection, such as in (Sun et al., 2023a), required an expenditure of \$3,000 to gather 10k human preference data points. Additionally, the method proposed by (Li et al., 2023d), which employs GPT-4V for reward data labeling, incurs a significantly higher cost—\$30 per million tokens—and demonstrates considerably slower inference speeds.

4 Assessment of Evaluator with GPT-4V Caption as Video Content

To assess the effectiveness of our proposed reward assignment method, we conducted a comparative analysis the GPT-4V used as a video QA evaluator. Our method utilizes detailed captions as a proxy of actual video frames, while GPT-4V directly takes in video frames as inputs. Both reward systems follow the same set of guidelines for scoring reward (prompt in fig. 22).

To compare the two methods, we sample 200 videos from each of the WebVid, VIDAL, and ActivityNet datasets, each associated with one question and two model predictions from our SFT model, with one preferred and one dispreferred by ChatGPT. This results in $1,200$ examples, for which we used GPT-4V to assign scores. Filtering through the Azure API backend resulted in 196, 151, and 143 videos from each dataset, respectively, having both answers evaluated. The average scores of all examples from ChatGPT and GPT-4V evaluations were 2.9 and 3.5 respectively, indicating a tendency of GPT-4V to yield slightly positive evaluations. The Pearson Correlation Coefficient (PCC) of 0.47 ($p < 0.01$) suggests a moderate positive correlation. In fig. 3 (left), the distribution of the difference between ChatGPT and GPT-4V scores reveals that majority ($> 75\%$) of ChatGPT scores fall within one standard deviation ($\sigma = 1.31$) of GPT-4V scores. Additionally, in fig. 3 (right), the agreement on preference between ChatGPT and GPT-4V, excluding ties, exceeded 70%. These findings cautiously support our benchmark's applicability in video QA evaluation. Further refinements for better alignment—such as incorporating Likert scales (Zhou et al., 2023) or GPT-4 evaluation—are areas for future research.

Human Annotation of Captions: To evaluate the quality of the distilled captions, we conducted human annotations focusing on two aspects: coverage and accuracy (hallucination). Annotators were asked to assess each caption by identifying the number of missing items and the number of incorrect facts. The assessment was performed on a sample of 75 videos, with 25 from each domain. The results showed that annotators identified a total of 21 inaccurate items across 14 videos (accuracy: 81%) and 12 missing items across 8 videos (accu-

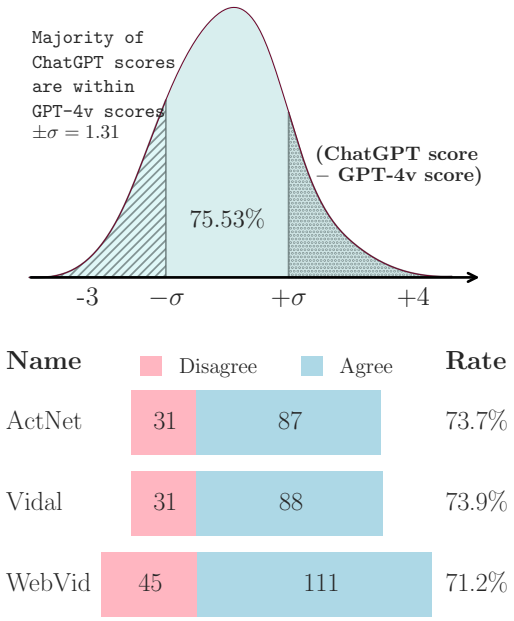

Figure 3: Assessing Evaluator Quality Using Captions in Place of Frames. The left figure shows the distribution of evaluation score differences between ChatGPT (with caption as proxy) and GPT-4V (directly on frames) evaluations. The right figure shows the rate of preference agreement between ChatGPT and GPT-4V as evaluators.

racy: 89%). Annotated examples are provided in appendix D.

5 Experiments

We adopt Video-LLaVA (Lin et al., 2023a) as the backbone of our video LMM, but our method can be applied to any other architectures as well.

Caption Pre-training Stage (LLaVA-Hound-PT): We use captioning data including 650k image caption data from ALLaVA (Chen et al., 2024a) and our distilled 900k video caption. We freeze the visual encoder and fine-tune the MLP projector and LLM, with learning rate 2e-5 and batch size 128.

SFT Stage (LLaVA-Hound-SFT): We use 600k image instruction data from ALLaVA and our generated 240k video instruction data, with learning rate 5e-6 and batch size 128.

DPO training Stage (LLaVA-Hound-DPO): We use the 17k preference data introduced in section 3.3 for DPO training. Following (Ivison et al., 2023), we train our policy model with full model training for 3 epochs with learning rate 5e-7, and a batch size of 128. All the experiments are performed on 8 A100 gpus.

5.1 Benchmark Evaluation

Dataset and Testing Environment We evaluate model performance on four benchmark datasets: MSVD-QA (Chen and Dolan, 2011), MSRVTT-QA (Xu et al., 2016), TGIF-QA (Jang et al., 2017), and Next-QA (Xiao et al., 2021) using ChatGPT with version gpt-3.5-turbo-0611 to assess model predictions. The evaluation prompts follow (Maaz et al., 2023). In our experiment, we found that different ChatGPT versions have high impact on absolute score of metric, but the overall ranking of models is relatively stable. We select gpt-3.5-turbo-0613 due to its closeness to the reported score in Video-LLaVA paper. Further details on the selection rationale and evaluation pitfalls are discussed in Appendix A.

Baseline Selection We select video LMM models that have demonstrated SOTA performance with with accessible code and checkpoints at the time of paper writing, specifically including Video-LLaVA, which is also our choice of architecture. We replicate results including Video-ChatGPT (Maaz et al., 2023), LLaMA-VID (Li et al., 2023e) (7B and 13B), Chat-UniVi (Jin et al., 2023), and Video-LLaVA (Lin et al., 2023b). We copy the results from additional baselines including Frozen-BiLM (Yang et al., 2022), VideoChat (Li et al., 2023b) and VideoLLaMA (Zhang et al., 2023a), sourced from their original publication.

Results In table 1, our analysis shows that within the SFT models, LLaMA-VID-7B and Video-LLaVA exhibit comparable performance, with LLaMA-VID-13B performing the best. Our LLaVA-Hound-SFT model achieves comparable performance to LLaMA-VID-13B. Incorporating preference modeling, LLaVA-Hound-DPO achieves an average accuracy of 70.75%, surpassing LLaVA-Hound-SFT, which has an average accuracy of 62.65%, by 8.1%. Furthermore, LLaVA-Hound-DPO exhibits superior accuracy compared to other RL methods such as VLM-RLAIF. In table 2, our model demonstrated consistent result on a relative new benchmark Next-QA.

Error Analysis Figure 4 illustrates two examples. In the left example, LLaVA-Hound-SFT provides an accurate description of the video's first half but introduces a hallucination with the phrase "I'm not scared of space," absent in the video content. LLaVA-Hound-DPO yields a more accurate inference. In the right example, both LLaVA-

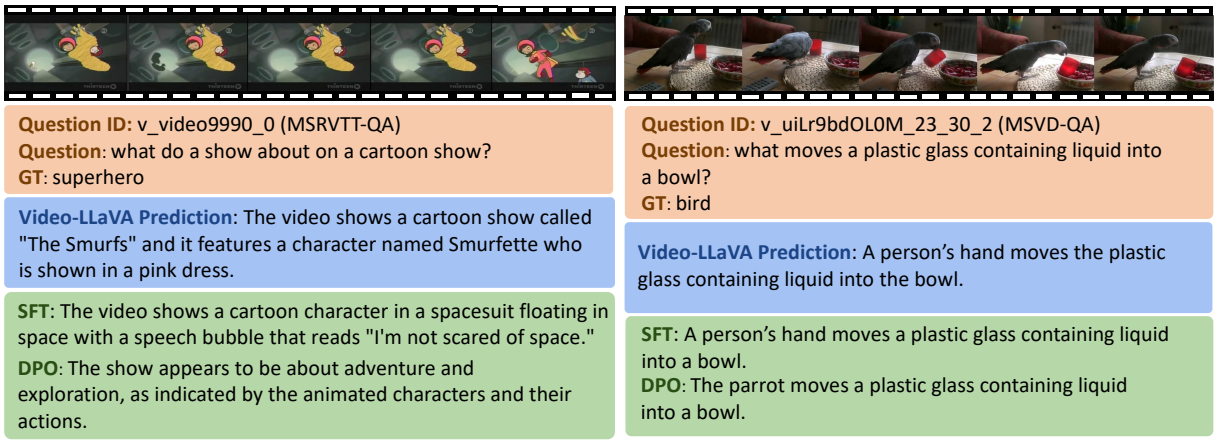

Figure 4: Examples from MSRVTT-QA and MSVD-QA showcase that our LLaVA-HOUND-DPO generates better responses, and reveal key limitations of the existing benchmark evaluation.

Methods	LLM Size	Existing Video QA Benchmark from (Maaz et al., 2023)					
		MSVD-QA		MSRVTT-QA		TGIF-QA	
		Acc.	Score	Acc.	Score	Acc.	Score
FrozenBiLM (Yang et al., 2022)∗	1B	32.2	-	16.8	-	41.0	-
VideoLLaMA (Zhang et al., 2023a)∗	7B	51.6	2.5	29.6	1.8	-	-
LLaMA-Adapter (Zhang et al., 2023b)∗	7B	54.9	3.1	43.8	2.7	-	-
VideoChat (Li et al., 2023b)∗	7B	56.3	2.8	45.0	2.5	34.4	2.3
BT-Adapter (Liu et al., 2023c)∗	7B	67.5	3.7	57.0	3.2	-	-
Video-ChatGPT (Maaz et al., 2023)	7B	68.6	3.8	58.9	3.4	47.8	3.2
Chat-UniVi (Jin et al., 2023)	7B	70.0	3.8	53.1	3.1	46.1	3.1
VideoChat2 (Li et al., 2023c)	7B	70.0	3.9	54.1	3.3	-	-
Video-LLaVA (Lin et al., 2023b)	7B	71.8	3.9	59.0	3.4	48.4	3.2
LLaMA-VID (Li et al., 2023e)	7B	72.6	3.9	58.7	3.4	49.2	3.3
LLaMA-VID (Li et al., 2023e)	13B	74.3	4.0	59.8	3.4	50.8	3.3
VLM-RLAIF (Ahn et al., 2024)∗	7B	76.4	4.0	63.0	3.4	-	-
LLaVA-HOUND-SFT	7B	75.7	3.9	58.7	3.3	53.5	3.3
LLaVA-HOUND-DPO	7B	**80.7**	**4.1**	**70.2**	**3.7**	**61.4**	**3.5**

Table 1: **Evaluation of Model Performance on Zero-Shot Video Question Answering Benchmarks Using gpt-3.5-turbo-0613.** Models denoted with ∗ have their results directly sourced from their original publications. Caution is advised when interpreting these results; see Appendix A for an in-depth analysis of evaluation challenges. All other baseline models were reproduced by our team.

No.	Methods	Next-QA	
		Acc.	Score
[1]	Video-ChatGPT (Maaz et al., 2023)	45.23	2.09
[2]	LLaMA-VID-7B (Li et al., 2023e)	49.43	3.24
[4]	Chat-UniVi (Jin et al., 2023)	47.62	3.14
[5]	Video-LLaVA (Lin et al., 2023b)	48.97	3.25
[6]	LLaVA-HOUND-SFT	60.60	3.51
[7]	LLaVA-HOUND-DPO	**74.27**	**3.74**

Table 2: Evaluation on Next-QA benchmark using gpt-3.5-turbo-0611 on official test set.

HOUND-SFT and Video-LLaVA models produce incorrect inferences, whereas LLaVA-HOUND-DPO successfully correctly identifies the subject in the video.

5.2 Open-ended QA Analysis

In this section, we conduct analysis on open-ended long-form QA with a proposed development benchmark. Specifically, we select 2,000 videos from each source: WebVid (Bain et al., 2021b), VIDAL (Zhu et al., 2023), ActivityNet (Fabian Caba Heilbron and Niebles, 2015), MSRVTT (Xu et al., 2016), MSVD (Chen and Dolan, 2011), TGIF (Jang et al., 2017), and Something-something V2 (SSV2) (Goyal et al., 2017). For each video, ChatGPT was utilized to generate three QA pairs

based on the detailed captions, and we evaluate model predictions with our reward mechanism. WebVid, VIDAL, ActivityNet are classified as in-domain, which are involved in the model's training pipeline. MSRVTT, MSVD, TGIF, SSV2 are classified as out-of-domain.

The evaluation reveals insights into (1) the quality of long-form open-ended QA, (2) in-domain and out-of-domain generalization, and (3) Ablations on SFT and DPO experiments. Additionally, we select our best performing model on the development bench before evaluating on public benchmarks, which avoids tuning hyperparameters on test data. Comparisons are shown in appendix E.

Domain Generalization: Table 3 and table 4 shows the in-domain and out-of-domain evaluation. SFT with our data tends to perform better both in- and out-of-domain, and DPO further enhances the model performance, showing the effectiveness of preference modeling.

Video LMM without Video Instruction: [8] in table 3 is baseline trained with only image instruction fine-tuned on LLaVA-Hound-PT, which achieves an average accuracy of 65.97%, comparable to the LLaVA-Hound-SFT model's 66.06% in in-domain QA scenarios. However, its performance significantly drops in out-of-domain QA contexts (49.32% vs. 56.50%), suggesting that Video QA training could potentially enhance generalization capabilities.

Quality of Generated SFT: [9] substitutes our generated video QA with the Video-ChatGPT dataset for Video-LLaVA fine-tuning. A comparison between the findings of [9] and [6] reveals a marginal performance disparity of 0.2% in average accuracy, indicating that the quality of our generated QA closely parallels that of the existing video QA datasets. Given the similar quality in SFT data, the large gain of [6] over [5] can be reasonably concluded from large-scale pre-training on video captions.

Unfreeze MLP: The comparison between [10] and [7] reveals a significant decrease in performance when the MLP is unfrozen during DPO training. Despite this drop, however, the performance remains superior to that of the SFT baseline.

Smaller Learning Rate: The comparison between [12] and [7] reveals that using a smaller learning rate of 3e-7 (vs. 5e-7) results in a decreasing of model performance. This highlights the future improvements by finding better hyperparameters.

Self-Play vs. DPO: (Chen et al., 2024c) introduced a self-play methodology for DPO training, which designates ground truth answers as preferred and model-generated responses as dispreferred. When comparing the results of [11] with those in [6], a notable decrease in accuracy by 3% from the SFT model is observed, suggesting that self-play may be less effective for video LMM alignment, and introducing reward model is helpful.

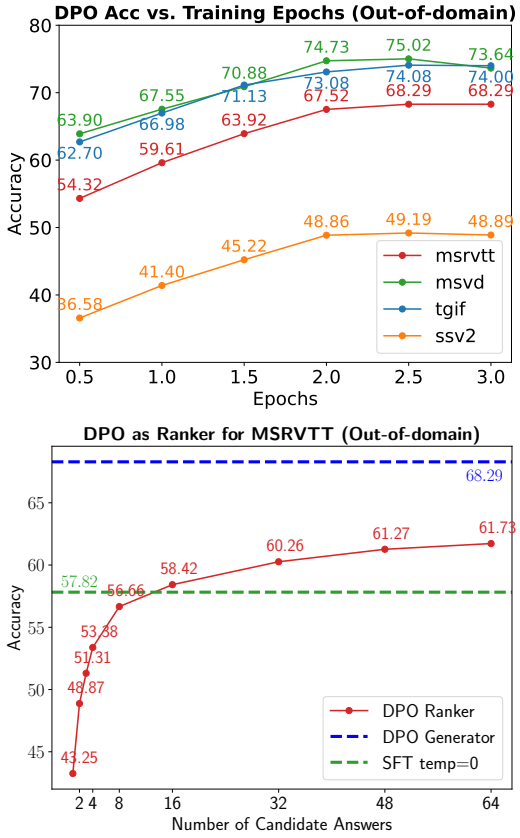

Figure 5: The left figure shows the test set accuracy of the DPO model w.r.t the number of training epochs. The right figure shows a comparison of DPO model performance as generator vs. ranker.

DPO Accuracy vs. Training Epochs. The left of fig. 5 depicts the generalization performance of the model on out-of-domain video QA tasks with respect to the number of training epochs. We observe a consistent enhancement in model performance among datasets during the initial 0 to 2 epochs, with peak performance materializing at around 2.5 epochs, which corresponds to 350 training steps.

DPO as Ranker vs. Generator. Following (Hosseini et al., 2024), we compare the performance of employing the DPO model as a ranker for candidate answers produced by the SFT model, operating at a temperature setting of 1.0. As depicted on the right in fig. 5, we illustrate the test accuracy pro-

No.	Methods	Proposed Video QA Benchmark (In-domain)					
		ActivityNet-QA		VIDAL-QA		WebVid-QA	
		Acc.	Score	Acc.	Score	Acc.	Score
[1]	Video-ChatGPT (Maaz et al., 2023)	34.17	2.19	29.35	2.10	38.88	2.27
[2]	LLaMA-VID-7B (Li et al., 2023e)	36.54	2.27	30.58	2.15	36.99	2.24
[3]	LLaMA-VID-13B (Li et al., 2023e)	37.33	2.29	32.50	2.18	39.73	2.30
[4]	Chat-UniVi (Jin et al., 2023)	39.35	2.32	31.40	2.16	40.05	2.31
[5]	Video-LLaVA (Lin et al., 2023b)	41.35	2.38	34.30	2.24	42.47	2.39
[6]	LLaVA-HOUND-SFT	66.62	3.05	60.50	2.88	71.07	3.17
[7]	LLaVA-HOUND-DPO	**76.62**	**3.18**	**70.06**	**3.04**	**79.82**	**3.29**
[8]	LLaVA-HOUND-PT + Image Inst.	69.31	3.09	60.57	2.85	68.03	3.02
[9]	LLaVA-HOUND-PT + VChat	67.34	3.02	62.33	2.89	68.98	3.00
[10]	LLaVA-HOUND-DPO + training MLP	71.89	3.10	65.57	2.95	75.37	3.21
[11]	LLaVA-HOUND-SFT + Self-play	64.11	2.85	56.28	2.68	67.89	2.95
[12]	LLaVA-HOUND-DPO w/ lr3e-7	71.13	3.08	64.90	2.92	73.25	3.17

Table 3: Our proposed video QA benchmark evaluation on in-domain dataset using gpt-3.5-turbo-0301, with detailed captions as supporting evidence.

Methods	Proposed Video QA Benchmark (Out-of-domain)							
	MSVD-QA		MSRVTT-QA		TGIF-QA		SSV2-QA	
	Acc.	Score	Acc.	Score	Acc.	Score	Acc.	Score
Video-ChatGPT (Maaz et al., 2023)	34.06	2.20	25.65	1.98	31.35	2.09	19.36	1.75
LLaMA-VID-7B (Li et al., 2023e)	34.14	2.21	25.02	1.99	27.18	2.00	22.16	1.84
LLaMA-VID-13B (Li et al., 2023e)	35.81	2.25	26.34	2.02	27.58	2.01	21.98	1.83
Chat-UniVi (Jin et al., 2023)	35.61	2.23	25.89	2.01	33.23	2.13	20.59	1.79
Video-LLaVA (Lin et al., 2023b)	39.46	2.37	30.78	2.15	32.95	2.18	24.31	1.90
LLaVA-HOUND-SFT	66.99	3.09	57.82	2.85	66.13	3.07	35.07	2.23
LLaVA-HOUND-DPO	**73.64**	**3.12**	**68.29**	**2.98**	**74.00**	**3.12**	**48.89**	**2.53**
LLaVA-HOUND-PT + Image Inst.	65.19	2.96	48.66	2.52	53.83	2.62	29.60	2.04

Table 4: Our proposed video QA benchmark evaluation on out-of-domain dataset using gpt-3.5-turbo-0301, with detailed captions as supporting evidence.

gression through the selection of the best among N candidates by the DPO ranker. Initial observations indicate that the SFT model, when set to a temperature of 1.0, demonstrates a reduced accuracy (43.3%) compared to that achieved through greedy decoding (57.8%). A steady enhancement in performance is noted as the number of candidates increases, plateauing at an accuracy of approximately 62% with 64 candidates. This performance, however, falls short when compared with the direct application of the DPO model for answer generation, which yields an accuracy of 68.29%. This difference suggests the stronger generalization of DPO model in answer generation, despite it is trained on a reward classification loss. The contradictory results to (Hosseini et al., 2024) may be due to the difference of tasks, i.e. Math vs. Video QA. Refer to appendix F for more results.

6 Conclusion

We study the techniques for effective video LMM alignment. Specifically, we propose an cost-effective reward system that utilizes detailed captions as proxies for video content. We have shown the reward scores is well-aligned with the evaluation metrics of GPT-4V, and DPO training greatly enhances model performance. In addition, we have released 900k detailed video caption, 900k video instruction-following data, and 17k preference data pairs, with a complete code pipeline including pre-training for video captioning, fine-tuning for video instruction following and reinforcement learning with DPO for better LMM alignment.

7 Limitations

Firstly, several evaluation datasets, such as Video-MME (Fu et al., 2024) featuring multiple-choice questions, were not included in our study. These datasets were available at or before the completion of our manuscript. Given our focus on enhancing open-ended question answering, multiple-choice datasets were not incorporated into our training process. Consequently, we did not retrain the model to include this data.

Secondly, the benchmark we developed is fully automated and does not incorporate human corrections for captions and QA. Human annotations indicate that caption accuracy ranges from 80% to 90%, inherently introducing errors. Therefore, we recommend using this benchmark solely for model development and hyperparameter tuning, treating performance metrics as indicative rather than definitive.

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A Effect of ChatGPT Version on Official Benchmark Evaluation

Methods	LLM Size	MSVD-QA		MSRVTT-QA		TGIF-QA		Summary	
		Acc.	Score	Acc.	Score	Acc.	Score	Avg Acc.	Rank
gpt-3.5-turbo-0301 evaluation									
Video-ChatGPT (Maaz et al., 2023)	7B	78.62	4.00	71.67	3.63	56.31	3.45	68.87	6
LLaMA-VID (Li et al., 2023e)	7B	82.57	4.12	71.94	3.65	59.00	3.63	71.17	4
LLaMA-VID (Li et al., 2023e)	13B	83.72	4.16	73.63	3.68	59.72	3.66	72.36	3
Chat-UniVi (Jin et al., 2023)	7B	80.52	4.02	66.92	3.41	57.73	3.49	68.39	7
Video-LLaVA (Lin et al., 2023b)	7B	81.44	4.08	73.29	3.65	58.34	3.61	71.02	5
LLaVA-HOUND-SFT	7B	85.65	4.10	73.85	3.62	64.98	3.65	74.83	2
LLaVA-HOUND-DPO	7B	**88.50**	**4.20**	**82.10**	**3.84**	**75.48**	**3.81**	**82.03**	1
gpt-3.5-turbo-0613 evaluation									
Video-ChatGPT (Maaz et al., 2023)	7B	68.55	3.80	58.90	3.36	47.83	3.21	58.43	6
LLaMA-VID (Li et al., 2023e)	7B	72.62	3.92	58.73	3.38	49.21	3.28	60.19	4
LLaMA-VID (Li et al., 2023e)	13B	74.29	3.96	59.82	3.41	50.83	3.33	61.65	3
Chat-UniVi (Jin et al., 2023)	7B	70.01	3.79	53.08	3.14	46.09	3.12	56.39	7
Video-LLaVA (Lin et al., 2023b)	7B	71.75	3.88	58.97	3.39	48.39	3.24	59.70	5
LLaVA-HOUND-SFT	7B	75.70	3.86	58.73	3.31	53.51	3.30	62.65	2
LLaVA-HOUND-DPO	7B	**80.73**	**4.07**	**70.15**	**3.66**	**61.38**	**3.46**	**70.75**	1
gpt-3.5-turbo-1106 evaluation									
Video-ChatGPT (Maaz et al., 2023)	7B	73.02	4.01	62.09	3.61	47.76	3.36	60.96	6
LLaMA-VID (Li et al., 2023e)	7B	75.49	4.08	62.09	3.61	51.72	3.47	63.10	4
LLaMA-VID (Li et al., 2023e)	13B	76.97	4.10	63.16	3.61	52.53	3.50	64.22	3
Chat-UniVi (Jin et al., 2023)	7B	72.22	3.92	55.02	3.35	48.16	3.31	58.47	7
Video-LLaVA (Lin et al., 2023b)	7B	74.76	4.04	62.70	3.60	51.21	3.45	62.89	5
LLaVA-HOUND-SFT	7B	81.09	4.08	64.13	3.57	58.05	3.53	67.76	2
LLaVA-HOUND-DPO	7B	**86.05**	**4.23**	**76.75**	**3.85**	**70.02**	**3.71**	**77.61**	1

Table 5: **Performance Evaluation Across ChatGPT Versions on Zero-Shot Video Question Answering Benchmarks.** This table compares the performance of state-of-the-art video LMMs evaluated under different ChatGPT versions. The absolute performance metrics scored by ChatGPT vary by versions. However, the comparative ranking of models under the same ChatGPT version is relatively stable.

In Table 5, we show impact of using different ChatGPT versions on metric scores within zero-shot video question answering benchmarks. Our analysis reveals significant variations in the absolute scores across ChatGPT versions, but based on the average accuracy metric, the relative ranking of models under the same ChatGPT version shows consistency.

This comparison underscores a critical issue: many prior studies neglect to specify the ChatGPT version used, potentially leading to inaccurate conclusions during evaluation. We advocate for the explicit designation of the ChatGPT version in future evaluations. Analysis from Table 5 indicates that the version gpt-3.5-turbo-0613 aligns most closely with the performance of the Video-LLaVA (Lin et al., 2023a) model, serving as the benchmark for model performance comparison in our study.

B Evaluation of Captioning Ability from pre-training

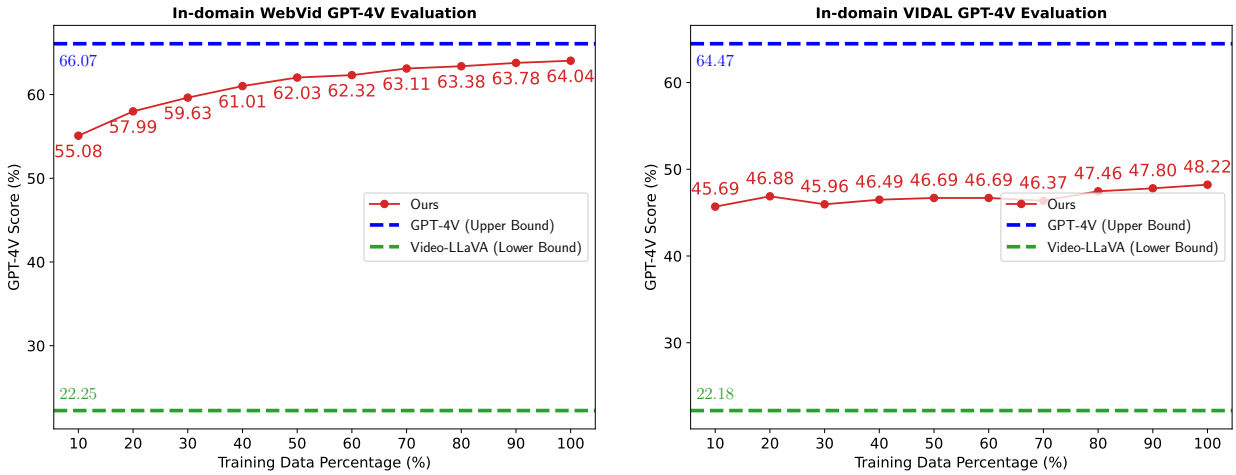


Figure 6: Training subsets exhibit varying levels of generalization difficulty. The WebVid subset (left) requires less data compared to the VIDAL subset (right)

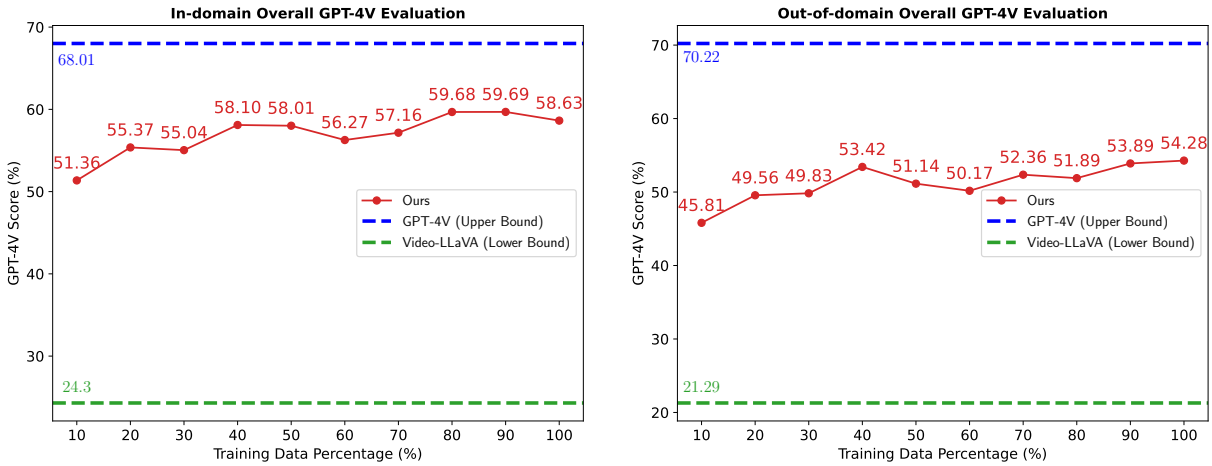


Figure 7: The video caption ability w.r.t number of training data evaluated on both in-domain and out-of-domain test videos using GPT-4V.

In Figure 7, we present the video captioning ability of models across various datasets, with a total of 900k distilled data instances. GPT-4V is employed for self-evaluation (fig. 20), serving as the upper-bound performance, while the Video-LLaVA serves for comparative analysis, establishing a baseline. Notably, Video-LLaVA is trained on 54k video QA data instances. However, our first checkpoint, utilizing only 10% of the data, is trained on 90k high-quality caption data instances, likely accounting for the observed performance disparity in the video captioning task. Our results demonstrate that incorporating more distilled data contributes to improved model performance across both in-domain and out-of-domain datasets. Despite these improvements, a performance discrepancy with the GPT-4V model remains. Further, we evaluate the generalization potential in specific data subsets, as shown in fig. 6 in the Appendix. These subsets reveal varying degrees of generalization challenges for different types of dataset. For example, the WebVid subset, which concentrates on relatively static scenes, necessitates less data for effective training compared to the VIDAL subset, which is marked by dynamic scene transitions and a diversity of video themes.

C GPT-4V Caption Distillation

Original Caption: Time-lapse of purple iris flowers blooming.

GPT-4V Annotation: The video captures a close-up time-lapse of purple irises with bright yellow accents against a black background. Initially, the buds are tightly closed, with green sepals protecting the petals. As the frames advance, the buds begin to open slowly, revealing the velvety texture and deep purple hue of the petals. The blooming is sequential, with some buds opening earlier than others, offering a dynamic contrast between the stages of bloom. At final bloom, the yellow stamen stands out against the purple petals. Throughout the sequence, the number of visible flowers changes.

Original Caption: When you flip a pancake (pt.26) #shorts

GPT-4V Annotation: The video begins with a close-up view of a pancake on a griddle or pan, which has not been flipped yet, showing its uncooked, batter side. The pancake is pale in color with bubbles forming on the surface, typical of a pancake as it cooks. There is a spatula with a novelty design. It resembles a Stormtrooper helmet from the Star Wars franchise placed beside the pancake. Text urging the viewer to "Send this to your bestie!" along with a Snapchat handle are overlaid on top of the video. The spatula is then slid underneath the pancake, which is then flipped over to reveal a cooked side featuring the drawing of a cartoon crab and the phrase "U R CLAWSOME!" written on it. The cooked side of the pancake has a golden-brown color, and the cartoon and text appear to be created with some dark-colored substance, possibly chocolate or some edible ink.

Figure 8: A showcase of our dataset for detailed video caption automatically distilled from GPT-4V via our prompt technique in section 3.

D Human Annotated Examples of Distilled Captions

WebVid Video ID: 2994286

GPT-4V Caption

Initially, the video displays a curved road lined with multiple orange traffic cones and greenery on either side. The focus shifts to a large, dark-colored truck approaching, its engine sound becoming increasingly prominent. The camera angle changes to the rear of the truck, revealing a runner, wearing a blue top with a white number bib marked '108', passing the truck on its left side. The video concludes with the truck's rear-end seen driving away with the traffic cones visible in the background.

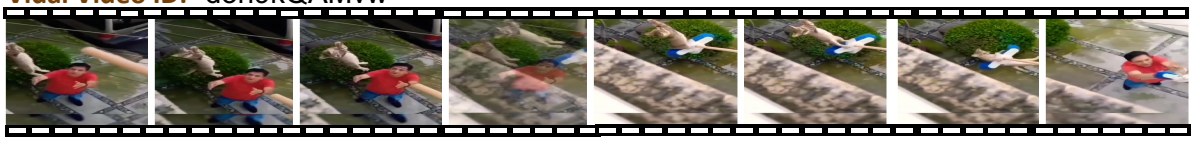
Human Annotation

Inaccuracy (Hallucination):
1. The truck is driving away instead of approaching

Coverage:
1. The runner is holding a cup-like item

Figure 9: Human Annotation Analysis: The video frames depict a truck driving away from the camera, but the distilled caption incorrectly describes the direction, which is identified as a hallucination. Additionally, human annotators noted that the GPT-4V model failed to recognize a man holding a cup.

Vidal Video ID: -d3h9kQAMvw



GPT-4V Caption

The cat is observed suspended by a limb caught in an electrical cable. It is a light-colored feline, possibly tan or cream, with a noticeably fluffy tail. Below, the person stands on what appears to be a blue stool or small ladder, reaching out towards the cat in an attempt to free it. The environment includes a green, neatly trimmed bush directly under the cat, and to the side, there appears a section of a vehicle – likely a car, suggesting the proximity to a driveway or parking spot. The pavement where these activities are occurring has a distinct pattern, likely tiles, surrounded by green grass, which borders a residential building. Above, an electrical pole is partially visible with thick cables extending from it – one of which the cat is caught in.

Human Annotation

Inaccuracy (Hallucination):
1.No blue stool or ladder visible

Coverage:
-

Figure 10: Human Annotation Analysis: GPT-4V incorrectly identified a man wearing blue pants as a man standing on a blue ladder, which is labeled as a hallucination.

ActivityNet Video ID: v__Y4czVoIxvE-Scene-006

GPT-4V Caption

Initially, two people are seen sitting on the floor with crafting materials. They both wear casual clothing: one in a dark blue long-sleeve top with "Johnny's BBQ" written on it and the other in a red and black checkered shirt. They appear to be in a cozy room with a wooden floor and a heater in the background. The next scenes showcase the crafting process in detail, focusing on hands carefully placing square-shaped burgundy materials with patterned textures onto a lighter brown base. The precision of their movements suggests they are experienced in this type of work.

Human Annotation

Inaccuracy (Hallucination):
1. The text on shirt should be "Jimmy's BBQ"

Coverage:
1. Missing text: "Step 3: Adhere Squares Together"

Figure 11: Human Annotation Analysis: The example demonstrates OCR hallucination and a coverage issue. The text on the woman's t-shirt is incorrectly labeled as 'Johnny's BBQ' instead of 'Jimmy's BBQ.' Additionally, the text 'Step 3: Adhere Squares Together' is missing from the description.

ActivityNet Video ID: v__wlTx73-BXw-Scene-003

GPT-4V Caption

The video showcases multiple scenes from a soccer match being played on a field surrounded by an athletic track. It appears to be in the evening, and a scoreboard is visible in the background indicating the game is underway. The players, wearing contrasting uniforms, are seen running, maneuvering the ball, and aiming at the goal. The crowd can be faintly seen on the sidelines watching the game.

Human Annotation

Inaccuracy (Hallucination):
-

Coverage:
1. "Gopher" and "Coca Cola" on the board
2. Score board shows time left

Figure 12: Human Annotation Analysis: The caption does not contain any hallucinations, but some text recognized by human annotators is missing, such as 'Coca Cola' and 'Gopher' on the scoreboard, as well as the time of the score match shown.

ActivityNet Video ID: v__Wag6CT_0j8-Scene-003

GPT-4V Caption

Throughout the video, there are multiple sequences featuring women in athletic attire engaged in a field hockey match. The players are distributed across a well-maintained, green artificial turf field. Two teams are visible: one in dark blue and white striped jerseys, and the other in white jerseys with black numerals. The white-jersey team appears to be on defense, while the dark-jersey team is in an offensive posture, advancing the ball. Some of the key visual elements include the athletic gear, such as shin guards, field hockey sticks, and cleats that the players are wearing. The background includes features like team benches, spectator stands, and a scoreboard that shows "MONMOUTH 0 2nd RIDER 2". Throughout the various frames of the video, players can be seen running, likely maneuvering the ball, and repositioning to either defend or continue their offensive push. Ambient shadows suggest sunny weather conditions during the recording of this match.

Human Annotation

Inaccuracy (Hallucination):
-

Coverage:
1. Score transition from "MONMOUTH 0 2nd RIDER 2" to "MONMOUTH 1 2nd RIDER 2".

Figure 13: Human Annotation Analysis: The figures illustrate a scoring transition that is not recognized by the GPT-4V model, highlighting the challenge of using static frames for accurate captioning.

E Video QA Dataset Demonstration

To build the test dataset, we curated a dataset comprising 2,000 videos from each source: WebVid (Bain et al., 2021b), VIDAL (Zhu et al., 2023), ActivityNet (Fabian Caba Heilbron and Niebles, 2015), MSRVTT (Xu et al., 2016), MSVD (Chen and Dolan, 2011), TGIF (Jang et al., 2017), and Something-something V2 (SSV2) (Goyal et al., 2017). For each video, ChatGPT was utilized to generate three QA pairs based on the detailed captions. The first three datasets (WebVid, VIDAL, ActivityNet) are classified as in-domain, since the captions and QA pairs derived from these sources are used in the model's training pipeline. Conversely, the remaining datasets (MSRVTT, MSVD, TGIF, SSV2) are classified as out-of-domain, evaluating model's zero-shot QA ability.

Appendix E compares our development benchmark with existing benchmark dataset, we identify several issues with the existing evaluation methods: (1) the auto-generated questions from current benchmarks may be grammatically incorrect or nonsensical, and (2) the answers are limited to a *single* word, which is inadequate for evaluating LMMs in the context of long-form QA. We conduct further analysis on open-ended long-form QA with a proposed development benchmark.

We apply our reward system as described in section 4 and report scores from ChatGPT. A score of ≥ 3 is considered correct for accuracy calculations. The development benchmark reveals insights into (1) the quality of long-form open-ended QA, and (2) in-domain and out-of-domain generalization. Additionally, our development benchmark results correlate with existing benchmarks. We recommend that models be evaluated on the development benchmark first, followed by human evaluation.

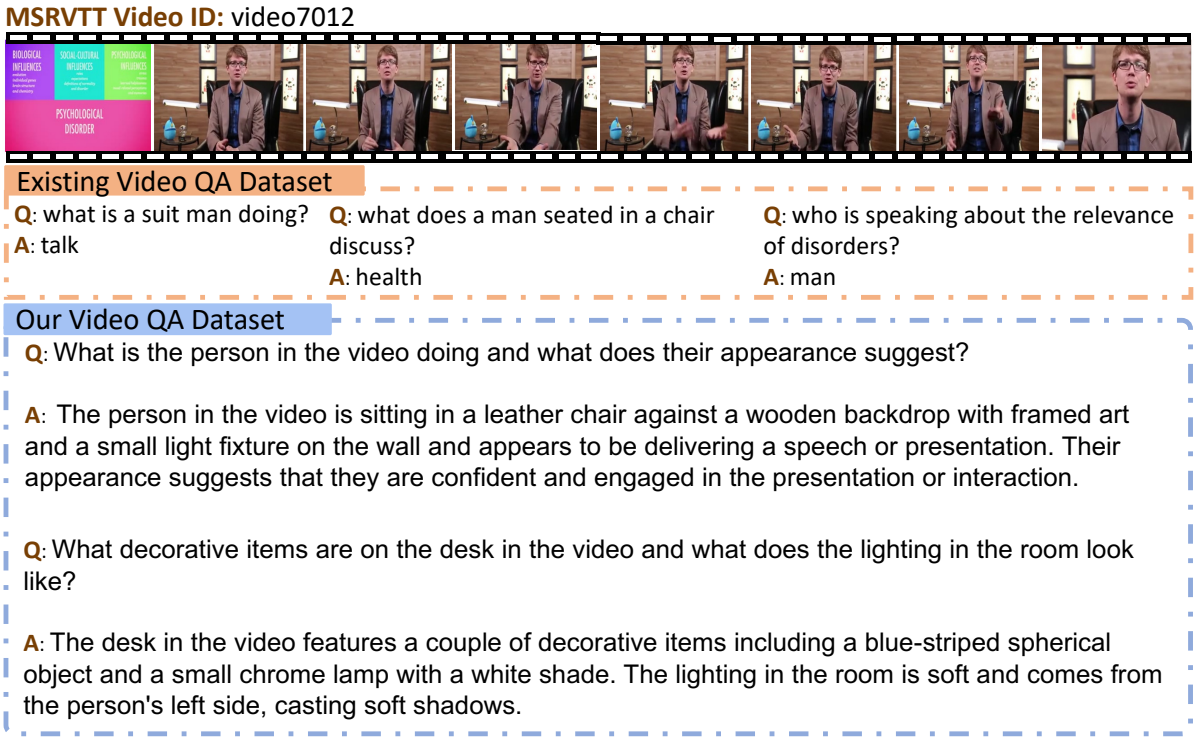


Figure 14: Comparing testing QA in existing benchmark with that in our proposed new benchmark.

MSRVTT Video ID: video7016

Existing Video QA Dataset

Q: what are girls and their mom doing?
A: marble

Q: who does a woman teach how to paint eggs?
A: girl

Q: what is kids doing?
A: color

Our Video QA Dataset

Q: What is the purpose of the video?
A: The purpose of the video is to showcase the process of dyeing Easter eggs.

Q: What are the tools and materials used in the video?
A: The tools used in the video are a wire egg holder, and the materials are a variety of colorful dyes, eggs, and a tablecloth.

Q: What is the significance of the tablecloth in the video?
A: The tablecloth is adorned with whimsical fish designs and protects the workspace where the dyeing process takes place.

Figure 15: Comparing testing QA in existing benchmark with that in our proposed new benchmark, example 2.

F Additional DPO Results

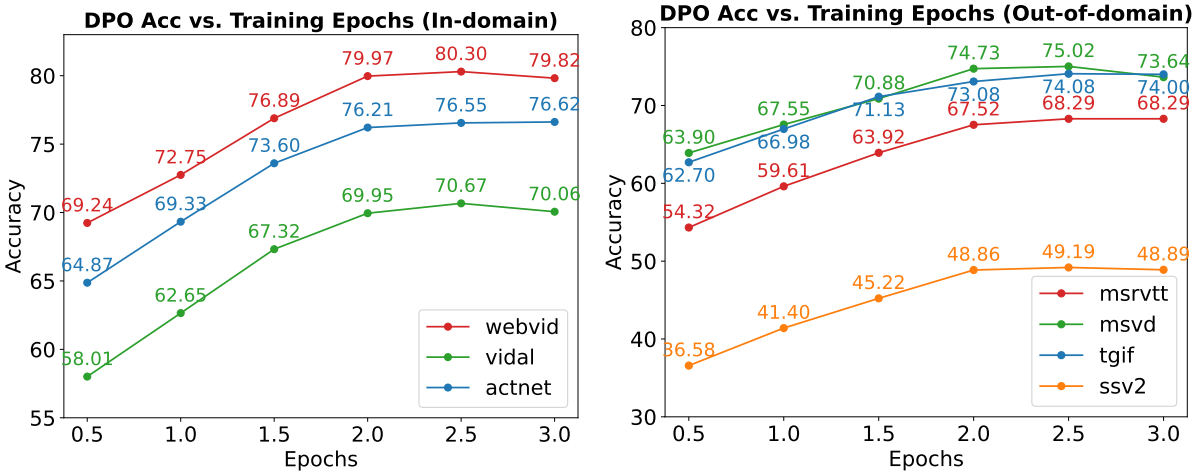


Figure 16: Test Set Accuracy of the DPO Model vs. Training Epochs. The figure illustrates a consistent trend in both in-domain and out-of-domain video QA, with peak performance occurring at approximately epoch 2.5, equivalent to 350 training steps.

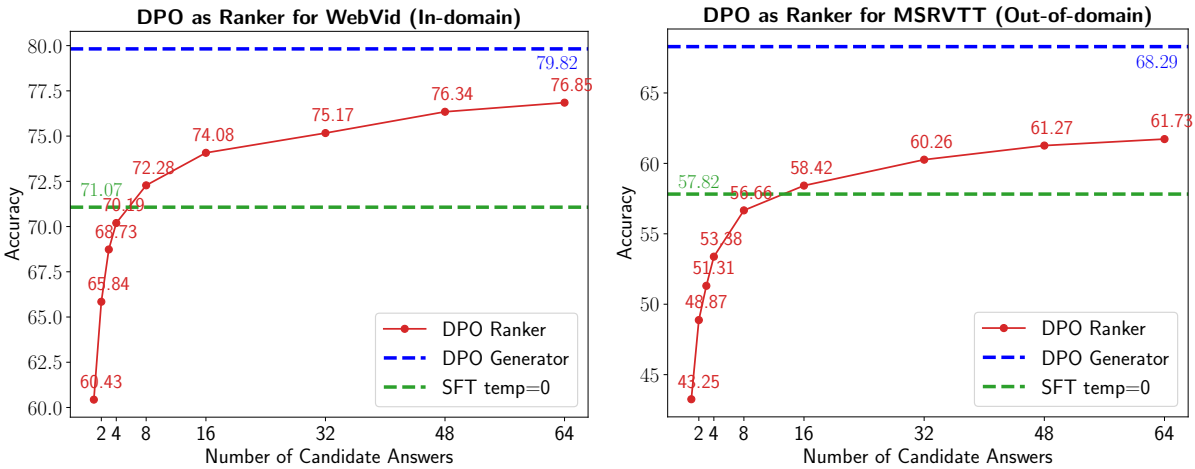


Figure 17: Comparison of DPO Model Performance: Ranker vs. Generator. The DPO model serves as a ranker, assigning reward scores to candidate answers generated by the SFT model with a temperature setting of 1.0. Employing the DPO model directly for answer generation results in superior performance compared to its use as a ranker.

G Prompts for GPT-4V and ChatGPT Queries

```
Picture yourself as a customer service agent managing user-uploaded video. The
uploaded video, captioned with '{}', consists of a seires of images. All the
analysis should be video-level. Your duty is to summarize video content,
highlighting actions and object relationships. Follow this with a detailed
description. The summary briefly covers actions and relationships, while the
detailed description delves into factual, visible details with a logical
structure, considering elements like color, shape, attribute, and count.

Then craft a dialogue between the agent ('A') and the customer ('C') in a manner
suggesting that the agent is actively viewing the video and answering the
customer's questions. Frame questions using 'how many', 'what,' 'how,' 'when,'
'which,' and 'why' to ensure precise and definitive answers, rooted in video
content. Pose varied questions encompassing the visual content, such as object
types, counting objects, object actions, object locations, and relative positions
between objects. Ensure each question has a definite answer, either observed in
the video or confidently determined to be absent. Avoid questions with uncertain
answers.

Ouput format:
Summary: <your summary>
Detail: <your detailed description>
Conversation: <your quesion-answer conversation, clearly labeling the customer
and agent as 'C' and 'A'>
```

Figure 18: GPT-4V prompt for the generation of video summary, detailed caption and conversation generation. We only use detailed caption for experiments.

```
Task Instructions:

Given a caption that summarizes the content of a video, generate three
question-answer pairs that relate directly to the information and context
provided in the caption. The questions should be grounded to the understanding of
the video content.

Guidelines for QA Generation:

1. Helpfulness: Answers should provide sufficient detail and depth to fully
address the question. They should include relevant explanations, or context where
appropriate, to enhance understanding.

2. Faithfulness: The answers must accurately reflect the information presented in
the video caption. Avoid speculation or the inclusion of information not
contained or implied by the caption to maintain the integrity of the content.

3. Diversity: Craft questions that cover different aspects of the video caption
to provide a comprehensive understanding of the content. This includes factual
inquiries, inferential questions, and those that may elicit explanatory
responses.

Input Video Caption:
{caption}

Output format:
Q1: <question1>
A1: <answer1>
Q2: <question2>
A2: <answer2>
Q3: <question3>
A3: <answer3>
```

Figure 19: ChatGPT for instruction generation.

```
Your role is to serve as an impartial and objective evaluator of a video caption
provided by a Large Multimodal Model (LMM). Based on the input frames of a video,
assess primarily on two criteria: the coverage of video elements in the caption
and the absence of hallucinations in the response. In this context,
'hallucination' refers to the model generating content not present or implied in
the video, such as incorrect details about objects, actions, counts, or other
aspects not evidenced in the video frames.

To evaluate the LMM's response:

Start with a brief explanation of your evaluation process.
Then, assign a rating from the following scale:

Rating 6: Very informative with good coverage, no hallucination
Rating 5: Very informative, no hallucination
Rating 4: Somewhat informative with some missing details, no hallucination
Rating 3: Not informative, no hallucination
Rating 2: Very informative, with hallucination
Rating 1: Somewhat informative, with hallucination
Rating 0: Not informative, with hallucination

LMM Response to Evaluate
{LLM_response}

Output format:
Judgment: <your judgment>
Score: <integer value rating>
```

Figure 20: GPT-4V evaluation prompt for video captioning.

```
Given the following inputs:

1. **Ground Truth Video Caption**: {caption}
2. **Question Related to the Caption**: {question}
3. **Ground Truth Answer**: {answer}
4. **Model Predicted Answer**: {prediction}

Your task is to evaluate the model's predicted answer against the ground truth
answer, based on the context provided by the video caption and the question.
Consider the following criteria for evaluation:

- **Relevance**: Does the predicted answer directly address the question posed,
considering the information provided in the video caption?
- **Accuracy**: Compare the predicted answer to the ground truth answer. Does the
prediction accurately reflect the information given in the ground truth answer
without introducing factual inaccuracies?
- **Clarity**: Assess the clarity of the predicted answer. Look for issues such
as repetition, unclear descriptions, or any grammatical errors that could hinder
understanding.
- **Completeness**: Determine if the predicted answer fully covers the scope of
the ground truth answer. Does it leave out critical information or does it
include all necessary details?

**Output Format**:
Explanation: <brief judgement of prediction>
Score: <a integer score of quality from 1-5>
```

Figure 21: ChatGPT-Evaluation Prompt for Video Question Answering. This prompt takes in a detailed caption, question, ground truth answer, and model prediction, subsequently generating an assessment of the prediction's quality alongside a corresponding score based on predefined criteria. A score value ≥ 3 will be considered correct for accuracy calculation.

```
Your task is to act as an impartial and objective assessor of answers generated
by a Large Multimodal Model (LMM) for video-based questions. Utilizing video
frames, a posed question, and the model's provided answer, your evaluation should
focus on the following aspects:

- **Relevance**: Does the predicted answer directly address the question posed,
considering the information provided in the video caption?
- **Accuracy**: Compare the predicted answer to the ground truth answer. Does the
prediction accurately reflect the information given in the ground truth answer
without introducing factual inaccuracies?
- **Clarity**: Assess the clarity of the predicted answer. Look for issues such
as repetition, unclear descriptions, or any grammatical errors that could hinder
understanding.
- **Completeness**: Determine if the predicted answer fully covers the scope of
the ground truth answer. Does it leave out critical information or does it
include all necessary details?

**Input**:
Question: {question}
Model Predicted Answer: {prediction}

**Output Format**:
Explanation: <brief judgement of prediction>
Score: <an integer score of quality from 1-5>
```

Figure 22: GPT-4V Evaluation Prompt for Video Question Answering. Together with video frames input in GPT-4V API, this prompt takes in a question, and model prediction, subsequently generating an assessment of the prediction's quality alongside a corresponding score based on predefined criteria. A score value ≥ 3 will be considered correct for accuracy calculation. This is used to assess the quality of ChatGPT evaluation in fig. 21.