ISR-DPO: Aligning Large Multimodal Models for Videos by Iterative Self-Retrospective DPO

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Abstract

Iterative self-improvement, a concept extending beyond personal growth, has found powerful applications in machine learning, particularly in transforming weak models into strong ones. While recent advances in natural language processing have shown its efficacy through iterative preference optimization, applying this approach to Video Large Multimodal Models (VLMMs) remains challenging due to modality misalignment. VLMMs struggle with this misalignment during iterative preference modeling, as the self-judge model often prioritizes linguistic knowledge over visual information. Additionally, iterative preference optimization can lead to visually hallucinated verbose responses due to length bias within the self-rewarding cycle. To address these issues, we propose Iterative Self-Retrospective Direct Preference Optimization (ISR-DPO), a method that uses self-retrospection to enhance preference modeling. This approach enhances the self-judge's focus on informative video regions, resulting in more visually grounded preferences. In extensive empirical evaluations across diverse video question answering benchmarks, the ISR-DPO significantly outperforms the state of the art. We are committed to open-sourcing our code, models, and datasets to encourage further investigation.

1 Introduction

Progress is not achieved by luck or accident, but by working on yourself daily.

— Epictetus

The human capacity for growth through consistent effort and repetition is a fundamental principle of personal development (Dweck 2006). This concept of iterative self-improvement extends beyond personal growth, finding powerful applications in machine learning to transform weak models into strong ones, without relying on additional human-annotated training data (Schapire 1990; Yuan et al. 2024; Burns et al. 2023). Notably, recent advances in natural language processing (NLP) have demonstrated the efficacy of *iterative* preference optimization in aligning Large Language Models (LLMs) with human intentions (Yuan et al. 2024; Pang et al. 2024; Chen et al. 2024). This approach involves constructing increasingly informative preferences through iterative preference modeling, *i.e.*, LLM-as-a-judge, leading to progressively better-aligned models.

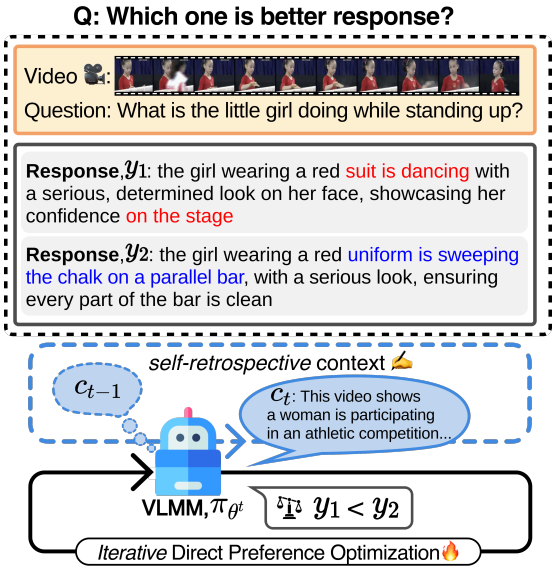

Figure 1: **Illustration of the proposed ISR-DPO.** During iterative direct preference optimization (DPO) in VLMM, we select preferences from responses based on not only video content but also visual context c_t, *i.e.*, detailed video description, to ensure preferences are grounded in video information. Specifically, we enhance the context in the self-retrospective manner by leveraging context c_{t-1} generated in previous iteration, a process we call *self-retrospective* preference modeling. Red indicates irrelevant responses, while blue indicates accurate, visually-grounded responses.

However, this iterative self-improvement principle for LLMs poses specific challenges when applied to large multimodal models, particularly Video Large Multimodal Models (VLMMs). VLMMs suffer from modality misalignment during iterative preference modeling, where the self-judge

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Question: Why does the video suggest using lip gloss instead of lipstick?

Ground-Truth : A text overlay in the video says, “Lipgloss is easier to touch up than lipstick!”, emphasizing the convenience of using lip gloss.

#1st iteration

The video suggests using lip gloss instead of lipstick because it is implied to be easier to apply and less messy.

#9th iteration

The video suggests using lip gloss instead of lipstick because it is implied to be easier to apply and less messy. The text overlays in the video explicitly state that "Lip gloss is easier to touch up than lipstick!" This implies that lip gloss offers a more convenient and accessible beauty option, especially for on-the-go touch-ups. Additionally, the video advises to "Go with a lip balm on a tube so it doesn't get everywhere!" which further emphasizes the practicality and ease of use of lip gloss compared to lipstick. The video seems to be promoting the idea that lip gloss is a practical and user-friendly beauty product.

Figure 2: **Example of verbosity hallucination within iterative preference modeling cycle for VLMM.** At the 1st iteration, the response is concise and visually grounded (in blue). By the $9th$ iteration, the response elaborates further, referencing explicit text overlays in the video. However, it starts to include irrelevant details and assumptions as well, leading to *verbosity hallucination* highlighted in red.

model tends to rely more on their pre-existing linguistic knowledge rather than the given visual information (Ahn et al. 2024; Zhou et al. 2024). This leads to preference data that are linguistically plausible but less grounded in visual content. Moreover, iterative training exacerbates the visually *ungrounded* verbose response in VLMMs due to the length bias within the iterative preference modeling cycle, which favors linguistically *longer* response during preference selection (Prasann Singhal and Durrett 2023; Park et al. 2024). As illustrated in Fig. 2, while somewhat longer responses might enhance the quality of the predicted response, excessively long responses can introduce content irrelevant to the actual video or question, *i.e.*, *verbosity hallucination*, without necessarily improving quality.

To address these challenges, we argue that the self-judge model, *i.e.*, VLMM, should select preferences based on visual content, rather than being merely linguistically plausible at each iteration. We achieve this visually grounded self-judgment by drawing inspiration from cognitive science on human perception (Bransford and Johnson 1972; Kintsch 1988; Anderson 1984), emphasizing the importance of contextual information in interpreting visual data. Specifically, we provide the self-judge with additional video descriptions generated through a self-retrospective manner as an additional visual context. This additional information acts as a focusing mechanism, akin to attention in human cognition (Bransford and Johnson 1972), enabling the VLMM to ground its responses more effectively in the video, reducing the likelihood of generating irrelevant or hallucinated one.

To this end, we propose a simple yet effective iterative self-improvement approach for VLMM: **I**terative **S**elf-**R**etrospective **D**irect **P**reference **O**ptimization (ISR-DPO) as shown in Fig. 1. This approach helps the self-judge focus on more informative regions in the video when comparing responses, producing more visually grounded preferences at each iteration. Our empirical studies demonstrate that our ISR-DPO exhibits superior performance compared to state-of-the-art VLMMs on various video question answering benchmarks.

We summarize our contributions as follows:

- We propose a novel modality alignment method for video large multimodal models (VLMMs), utilizing iterative direct preference optimization (DPO) to align video-text modalities effectively.
- We enhance AI’s feedback by proposing self-retrospective preference modeling, which improves clarity and comprehension in video through the use of iteratively refined visual context for preference selection.
- We demonstrate the effectiveness of our proposed ISR-DPO on various video question answering benchmarks by a noticeable margin.

2 Related Work

Aligning large multimodal models for videos. VLMMs have achieved notable success in various video comprehension tasks, such as video temporal understanding (Liu et al. 2023), question answering (Lin et al. 2023), and instruction-following (Maaz et al. 2024). These models integrate publicly available LLMs (Touvron et al. 2023a,b) with visual encoders (Radford et al. 2021) and additional learnable parameters (Hu et al. 2022), undergoing Supervised Fine-Tuning (SFT) (Maaz et al. 2024; Lin et al. 2023; Li, Wang, and Jia 2023) and, more recently, preference optimization (Rafailov et al. 2023; Zhang et al. 2024a; Ahn et al. 2024). Our work builds upon these efforts by exploring the application of iterative preference optimization to VLMMs and addressing the unique challenges related to length bias and visual grounding during preference modeling process.

Iterative preference optimization. Training LLMs with preference optimization has proven to be an effective approach to align language models with human intention, improving model performance and reliability. Build upon this preference optimization, recent efforts have focused on iterative preference optimization techniques, which typically involve iteratively generating feedback data with AI models themselves, *i.e.*, *self-rewarding*. Many recent work in the NLP domain concurrently propose this, where the aligned model iteratively generates responses and judges its own outputs to build feedback data and learn from this data with DPO (Yuan et al. 2024; Pang et al. 2024; Chen et al. 2024). While these iterative optimization techniques have shown their effectiveness in LLMs, their application in the multimodal domain, particularly for video understanding tasks, remains largely unexplored. Our work proposes an effective iterative preference optimization method for VLMMs.

Verbosity bias in preference optimization. Preference fine-tuning methods such as RLHF, RLAIF, and DPO are

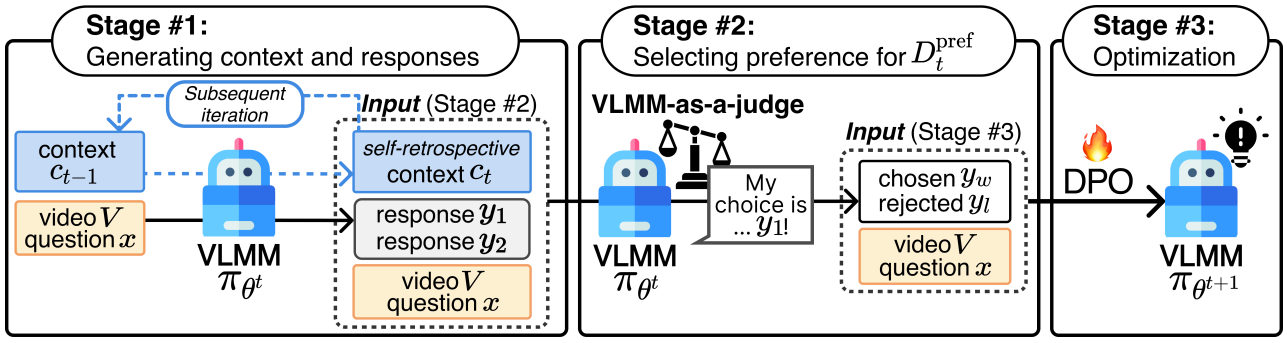


Figure 3: **Overview of self-retrospective Direct Preference Optimization (DPO).** Each iteration of ISR-DPO involves three stages: 1) After training iteration t, the latest updated VLMM (π_{θ^t}) generates two different responses y_1 and y_2 for the given video V and instruction x. In addition, a visual description, *i.e.*, visual context, is generated through self-retrospection, providing the necessary input for the next stage, as indicated by the black dotted line. 2) Using the information generated in the previous stage, the model (π_{θ^t}) compares its responses(y_1 and y_2) and classifies the preferred response y_w and the rejected response y_l. 3) Then, the VLMM (π_{θ^t}) is optimized using DPO to update the parameters to $\pi_{\theta^{t+1}}$.

known to produce responses that are longer than those generated prior to preference optimization, known as length bias. This phenomenon stems from a verbosity bias in preference data, where both human and AI judges tend to favor longer responses (Prasann Singhal and Durrett 2023; Park et al. 2024; Saito et al. 2023). Despite minimal differences in length between preferred and rejected responses, the increase in verbosity is statistically significant (Park et al. 2024). In VLMMs, this length bias can be particularly problematic. It may result in verbose responses that are linguistically comprehensible but not well-grounded in the visual content. Addressing length bias in the multimodal setting of VLMMs remains an open challenge.

3 Iterative Self-Retrospective DPO

To effectively align the multimodalities between video and text, we propose to use an iterative self-improvement approach for VLMM. Figure 3 illustrates the overall training pipeline of our proposed ISR-DPO for one cycle, which executes three stages: 1) generating self-retrospective context and responses, 2) selecting preferences, and 3) optimization.

During iterative execution, we enhance our model's ability to select preferences by conditioning not only the video content, but also on the visual context generated through self-retrospection. This additional visual context generates preferences grounded in the video, improving the alignment between visual and textual modalities.

3.1 Iterative DPO in VLMM

We denote the current VLMM at the t-th iteration as π_{θ^t}. This model generates responses and selects preferences by itself, thereby constructing the preference data, D_t^{pref}. With D_t^{pref}, we train the subsequent VLMM, denoted as $\pi_{\theta^{t+1}}$, at the $t+1$-th iteration.

Initial model. Given a seed preference data annotated in Zhang et al. (2024a), we conduct preference fine-tuning using DPO, starting from the SFT model provided from previous work (Zhang et al. 2024a). This preference fine-tuned model is referred to as the initial model π_{θ^1}.

Preference modeling. Given the current VLMM π_{θ^t}, we generate two different responses for the input video V and question x using a high temperature hyper-parameter (*e.g.*, 0.7). This high temperature flattens the token sampling probability distribution, producing varied responses from the same input in the current VLMM π_{θ^t}:

$$y_1 \sim \pi_{\theta^t}(V, x), \; y_2 \sim \pi_{\theta^t}(V, x).$$

We then select a better response between two responses by leveraging the current VLMM to evaluate its own responses, *i.e.*, VLMM-as-a-judge. In particular, we provide the VLMM with the visual context c_t for enhanced visual clarity (more detailed in Sec. 3.2). We can present this preference selection procedure as follows:

$$(y_w, y_l) \sim \pi_{\theta^t}(V, x, c_t, y_1, y_2),$$

where y_1 and y_2 are two sampled responses, y_w is the chosen response, and y_l is the rejected response.

After constructing the preference data at t-th iteration as $D_t^{\text{pref}} = \{V, x, y_w, y_l\}$, we use this dataset to perform preference optimization on the current VLMM π_{θ^t} using DPO. The DPO objective for the current VLMM π_{θ^t} is represented as follows:

$$\mathcal{L}_{\text{DPO}}(\pi_{\theta^t}; \pi_{\text{ref},t}) = -\mathbb{E}_{(V,x,y_w,y_l)\sim\mathcal{D}_{t-1}^{\text{pref}}}\left[\log\sigma\left(\beta\log\frac{\pi_{\theta^t}(y_w \mid V, x)}{\pi_{\text{ref},t}(y_w \mid V, x)} - \beta\log\frac{\pi_{\theta^t}(y_l \mid V, x)}{\pi_{\text{ref},t}(y_l \mid V, x)}\right)\right],$$

where $\pi_{ref,t}$ is the current base reference model, β is a hyper-parameter controlling the deviation from the current base reference model and σ is the sigmoid function.

Iterative training. Our overall iterative training procedure follows previous work (Yuan et al. 2024), where a series of

models $\pi_{\theta^1}, \ldots, \pi_{\theta^T}$ is trained sequentially. Each successive model at iteration of $t+1$ uses preference data D_t^{pref} generated by the VLMM at iteration t, defined as follows:

$$\pi_{\theta^{t+1}} : \text{Training with } D_t^{\text{pref}} \text{ initialized from } \pi_{\theta^t},$$

where the t-th model π_{θ^t} generates preference data D_t^{pref} through self-judgment.

3.2 Self-Retrospective Preference Modeling

A key aspect of iterative DPO in VLMM involves using a VLMM as a judge to iteratively select preferences that accurately answer posed questions (Ahn et al. 2024). Specifically, we provide the VLMM with detailed visual descriptions as visual context, generated by the VLMM itself in addition to the video content for improved visual clarity. Moreover, inspired by humans learning process, we enhance the visual context in a *self-retrospective* manner. Just as retrospection allows humans to make better decisions by reflecting on the past (Simon 1962; Madaan et al. 2023), we leverage previously generated visual context to generate better context, enhancing the accuracy and relevance of the preference selection process, defined as follows:

$$c_t \sim \pi_{\theta^t}(V, c_{t-1}),$$

where c_{t-1} is the previous visual context at time $t-1$.

Using the generated context c_t, question x, video V, and responses $\{y_1, y_2\}$, we classify the chosen y_w and rejected data y_l from responses using the current aligned VLMM π_{θ^t}, a process we call *self-retrospective* preference modeling, thereby constructing preference data D_t^{pref} at time t.

4 Experiments

4.1 Experimental Setup

Dataset details. Our training dataset utilizes a fixed set of 17k video-instruction ($\{V, x\}$) pairs from (Zhang et al. 2024a), in contrast to previous works (Yuan et al. 2024; Chen et al. 2024) that incremented their dataset across iterations. For all iterations beyond the initial VLMM π_{θ^1}, we generate preference dataset D_t^{pref} at each iteration by generating new responses and preferences. Following (Maaz et al. 2024; Zhang et al. 2024a), we evaluate our method on two types of video question answering datasets: one that requires concise responses, and the other that demands comprehensive answers, across 7 video collections.

Training details. We perform full-parameter fine-tuning using DPO with 9 total iterations, tripling the previous iterative preference optimization approach for LLMs alignment (Yuan et al. 2024). All generative processes use specific prompts. Training is conducted on 8×NVIDIA A100 GPUs (80G). We employ a 7B-sized model for fair comparison with others.

4.2 Quantitative Analysis

In-domain video question answering. As shown in Tab. 1, ISR-DPO demonstrates consistent performance gains at each iteration up to the $9th$ iteration. Moreover, final iterated model (π_{θ^9}), outperforms all previous work across all video benchmarks in both accuracy and score by a noticeable margin. We attribute this performance improvement to the better alignment of video modality provided by the proposed iterative retrospective judgment for VLMMs.

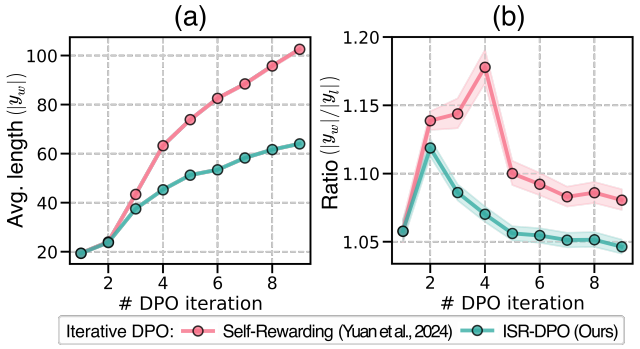


Figure 4: **Length analysis of preference dataset during iterative DPO.** (a) Average (Avg.) word length of chosen response $|y_w|$ in preference dataset D_t^{pref} across DPO iterations. Self-rewarding results in longer responses compared to the ISR-DPO. (b) Ratio of the word lengths of chosen responses ($|y_w|$) to rejected responses ($|y_l|$). ISR-DPO consistently maintains a lowered ratio compared to the self-rewarding, indicating reduced response length after optimized. '# DPO iteration' means the number of DPO iterations.

Out-domain video question answering. For evaluating out-domain video question answering, we use two types of datasets. Tables 2 and 3 show the comparative results for datasets that require complex answers and concise keyword answers, respectively. The final iterated model of ISR-DPO (π_{θ^9}) outperforms the previous work by a large margin in both cases, demonstrating its effectiveness in generating both detailed and precise responses. This model also shows consistent performance improvements at each iteration, as shown in Tables 2 and 3.

4.3 Detailed Analysis

To evaluate the effectiveness of ISR-DPO, we address the following research questions, specifically exploring the effect and design of visual context:

- **RQ1**: What are the effects and benefits of visual context during iterative DPO?
- **RQ2**: How should the visual context be designed?

In particular, we compare ISR-DPO with self-rewarding (Yuan et al. 2024), which serves as our baseline for adopting iterative DPO in VLMMs without self-retrospective context.

Effect of visual context during iterative process Figure 4 demonstrates the effect of including visual context during preference selection. As shown in Fig. 4-(a), ISR-DPO generates shorter chosen responses compared to self-rewarding as training iterations progress. Similarly, Fig. 4-(b) shows a lower ratio of chosen to rejected response

Methods	ActivityNet-QA		VIDAL-QA		WebVid-QA	
	Acc.	Score	Acc.	Score	Acc.	Score
Video-ChatGPT (Maaz et al. 2024)	34.17	2.19	29.35	2.10	38.88	2.27
LLaMA-VID (Li, Wang, and Jia 2023)	36.54	2.27	30.58	2.15	36.99	2.24
Chat-UniVi (Jin et al. 2023)	39.35	2.32	31.40	2.16	40.05	2.31
Video-LLaVA (Lin et al. 2023)	41.35	2.38	34.30	2.24	42.47	2.39
VLM-RLAIF† (Ahn et al. 2024)	53.27	2.56	44.82	2.40	53.69	2.62
PLLaVA† (Xu et al. 2024)	48.44	2.50	42.45	2.39	53.55	2.59
LLaVA-NeXT-DPO† (Zhang et al. 2024b)	68.05	2.88	61.52	2.72	73.35	3.00
LLaVA-Hound-DPO (Zhang et al. 2024a)	<u>76.62</u>	<u>3.18</u>	<u>70.06</u>	<u>3.04</u>	<u>79.82</u>	<u>3.29</u>
ISR-DPO (π_{θ^1})	75.58	3.14	70.07	3.02	80.74	3.28
ISR-DPO (π_{θ^5})	81.62	3.25	77.33	3.10	86.92	3.39
ISR-DPO (π_{θ^9})	**82.99**	**3.26**	**79.00**	**3.13**	**88.11**	**3.40**

Table 1: **Quantitative comparison between different VLMMs on *in-domain* video question answering with detailed captions as supporting evidence proposed in Zhang et al. (2024a).** Our final iterated model of ISR-DPO (π_{θ^9}) consistently outperforms all other models in both accuracy and score across these benchmarks, demonstrating superior performance in in-domain video question answering tasks. The best results are **bold** and the second-best results are <u>underlined</u>. †: reproduced by the authors' implementation. All results except † are directly sourced from Zhang et al. (2024a).

Methods	MSVD-QA		MSRVTT-QA		TGIF-QA		SSV2-QA	
	Acc.	Score	Acc.	Score	Acc.	Score	Acc.	Score
Video-ChatGPT (Maaz et al. 2024)	34.06	2.20	25.65	1.98	31.35	2.09	19.36	1.75
LLaMA-VID (Li, Wang, and Jia 2023)	34.14	2.21	25.02	1.99	27.18	2.00	22.16	1.84
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. 2023)	39.46	2.37	30.78	2.15	32.95	2.18	24.31	1.90
VLM-RLAIF† (Ahn et al. 2024)	51.16	2.55	41.44	2.30	46.52	2.41	29.78	1.94
PLLaVA† (Xu et al. 2024)	48.92	2.53	38.26	2.28	43.83	2.40	30.92	2.07
LLaVA-NeXT-DPO† (Zhang et al. 2024b)	65.08	2.82	59.12	2.65	60.80	<u>2.70</u>	40.14	2.24
LLaVA-Hound-DPO (Zhang et al. 2024a)	<u>73.64</u>	<u>3.12</u>	<u>68.29</u>	<u>2.98</u>	<u>74.00</u>	**3.12**	<u>48.89</u>	<u>2.53</u>
ISR-DPO (π_{θ^1})	74.33	3.12	68.18	2.96	73.57	3.10	48.91	2.52
ISR-DPO (π_{θ^5})	79.63	3.19	74.07	3.05	77.52	3.12	53.13	2.57
ISR-DPO (π_{θ^9})	**80.36**	**3.20**	**75.42**	**3.05**	**78.58**	**3.12**	**54.66**	**2.59**

Table 2: **Quantitative comparison between different VLMMs on *out-domain* video question answering with detailed captions as supporting evidence proposed in Zhang et al. (2024a).** Our final iterated model of ISR-DPO (π_{θ^9}) consistently outperforms all other models in both accuracy and score across these benchmarks, demonstrating superior performance in out-domain video question answering tasks. The best results are **bold** and the second-best results are <u>underlined</u>. †: reproduced by the authors' implementation. All results except † are directly sourced from Zhang et al. (2024a).

lengths in ISR-DPO. We posit that dual conditioning on video content and visual context during preference selection enables the VLMM to select preferences based on video information rather than length bias. This results in a lower chosen-to-rejected preference ratio and shorter, more concise responses from the VLMM, as illustrated in Fig. 5.

Moreover, we compare the $9th$ iteration model's responses between self-rewarding and ISR-DPO to validate the effectiveness of visual context, as in Yuan et al. (2024). In particular, we use GPT-4 as the evaluator by selecting the response closest to the ground truth, assessing win-rates. Figure 6 shows the win-rate between self-rewarding and ISR-DPO across all benchmarks, demonstrating the effectiveness of ISR-DPO. Notably, despite generating more concise responses (Fig. 5), ISR-DPO consistently achieved higher winning rates across all benchmarks. This provides evidence of ISR-DPO's effectiveness at conveying more relevant and accurate information within concise responses, mitigating verbosity hallucinations.

Effect of visual context on human alignment. To evaluate the impact of visual context on judgment quality, we assess the correspondence between AI models' preferences and those of human annotators, following Lee et al. (2023). As shown in Tab. 4, ISR-DPO demonstrates a higher human alignment accuracy (75.0 %) compared to self-rewarding (59.0 %), suggesting that the incorporation of visual context enhances the model's ability to make human-like assessments.

Methods	MSVD-QA		MSRVTT-QA		TGIF-QA	
	Acc.	Score	Acc.	Score	Acc.	Score
Video-ChatGPT (Maaz et al. 2024)	68.6	3.8	58.9	3.4	47.8	3.2
Chat-UniVi (Jin et al. 2023)	70.0	3.9	53.1	3.1	46.1	3.1
VideoChat2 (Li et al. 2024)	70.0	3.9	54.1	3.3	-	-
Video-LLaVA (Lin et al. 2023)	71.8	3.9	59.0	3.4	48.4	3.2
LLaMA-VID (Li, Wang, and Jia 2023)	72.6	3.9	58.7	3.4	49.2	3.3
PLLaVA† (Xu et al. 2024)	78.8	4.0	65.6	3.4	57.9	**3.5**
LLaVA-NeXT-DPO† (Zhang et al. 2024b)	78.6	4.0	63.4	3.1	58.2	3.4
VLM-RLAIF† (Ahn et al. 2024)	81.0	4.2	69.2	3.7	62.3	**3.5**
LLaVA-Hound-DPO (Zhang et al. 2024a)	80.7	4.1	70.2	3.7	61.4	**3.5**
ISR-DPO (π_{θ^1})	80.1	4.1	69.8	3.6	61.0	3.4
ISR-DPO (π_{θ^5})	84.8	4.3	76.0	3.8	66.8	3.5
ISR-DPO (π_{θ^9})	**85.8**	**4.3**	**78.7**	**3.9**	**67.8**	**3.5**

Table 3: **Comparison of different VLMMs on *out-domain* video question answering benchmark (Maaz et al. 2024).** ISR-DPO (π_{θ^9}) outperforms previous work across three video question answering datasets. Best results in **bold**, second-best underlined. †: reproduced with the authors' implementation. eOther results are directly sourced from Zhang et al. (2024a).

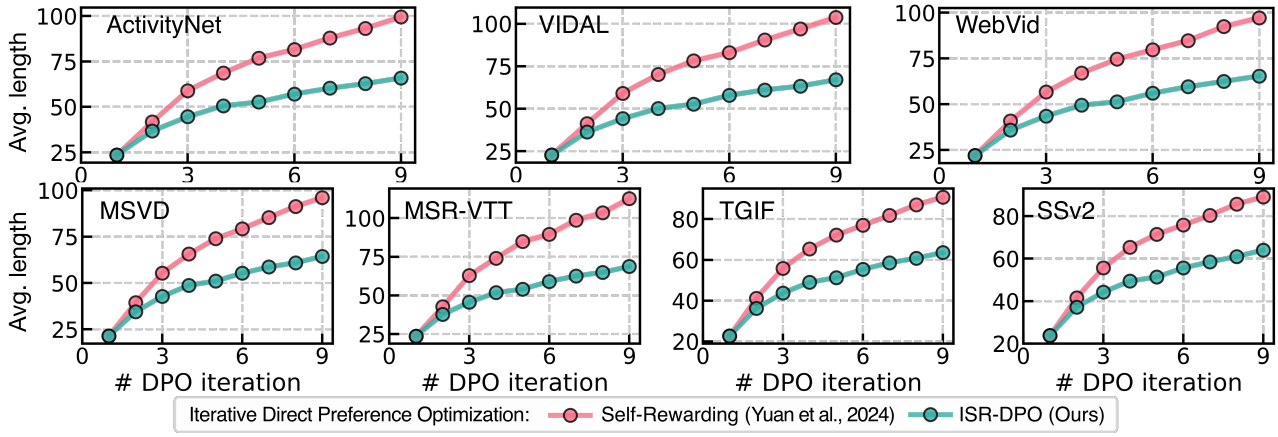


Figure 5: **Average (Avg.) response word length between self-rewarding and ISR-DPO on various video question answering benchmarks.** ISR-DPO yields compact and concise responses at the same iteration compared to self-rewarding.

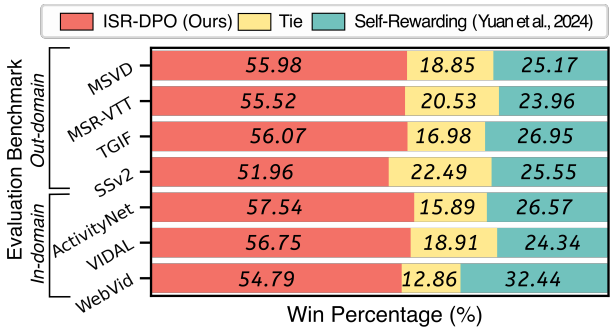


Figure 6: **Head-to-head performance comparison at 9th iteration.** ISR-DPO consistently outperforms the self-rewarding across benchmarks.

Task	Human Alignment Accuracy (%)	
	Self-rewarding	ISR-DPO
Preference selection	59.0	75.0

Table 4: **Human annotator alignment accuracy for preference selection.** We measure human alignment accuracy to evaluate the amount of correlation between human and aligned models, *i.e.*, self-rewarding *vs.* ISR-DPO.

Various design choices for visual context. We examine various design choices for visual context in Tab. 5: (1) without context ('N/A'), (2) Fixed context from the first iteration ('Fixed'), (3) New context at each iteration ('Renew') and (4) Self-retrospective context ('Self-retro.'). The 'Self-retro.' consistently performs the best, leveraging and refining previous context while adding details with improved video understanding (Fig. 7). Interestingly, 'Fixed' outperforms 'Renew' in most benchmarks, except for MSRVTT. For SSv2 and WebVid, 'Renew' even performs worse than 'N/A'. We hypothesize that 'Renew' may introduce incon-

Context Design	Out-of-domain Video QA Benchmark								In-domain Video QA Benchmark					
	MSVD		MSRVTT		TGIF		SSV2		ActivityNet		VIDAL		WebVid	
	Acc.	Score	Acc.	Score	Acc.	Score	Acc.	Score	Acc.	Score	Acc.	Score	Acc.	Score
N/A	78.73	3.14	73.42	3.00	77.10	3.09	54.34	2.56	81.96	3.23	76.71	3.09	87.24	3.39
Fixed	79.17	3.15	74.35	3.02	77.88	3.09	54.29	2.57	82.25	3.24	77.90	3.12	87.49	3.39
Renew	79.49	3.19	74.04	3.04	77.63	3.12	53.03	2.56	82.03	3.26	77.73	3.12	86.68	3.38
Retrospective	**80.36**	**3.20**	**75.42**	**3.05**	**78.58**	**3.12**	**54.66**	**2.59**	**82.99**	**3.26**	**79.00**	**3.13**	**88.11**	**3.40**

Table 5: **Quantitative comparison of various designs for generating visual context.** 'N/A' indicates no use of context, 'Fixed' uses context generated in the first iteration for all subsequent iterations, 'Renew' generates new context each iteration, and 'Retrospective.' employs a self-retrospective context.

#1st iteration

The video presents a series of Betta fish, also known as Siamese fighting fish, displaying their unique color patterns and flowing fins.

#5th iteration

The video is a compilation of clips featuring different goldfish. Each clip shows the fish in various settings, such as against a green aquatic background or on a rocky surface within an aquarium. The goldfish display a range of colors, including shades of black, orange, and combinations there.

#9th iteration

The video is a compilation of clips featuring different fish, each exhibiting unique characteristics and behaviors. The first fish has a rounded body adorned with intricate patterns, indicative of a fancy goldfish, possibly a Ryukin or Oranda variety. The third fish is captured in a natural setting, resting on a rock, hinting at a common freshwater spieces. The fourth fish stands out with its vibrant orange and black coloration and striking finnage. Each fish is shown in motion, either gliding gracefully through the water or interacting with its environment, offering a dynamic view of their species. The focus remains solely on the visual spectacle of the fish and their movements.

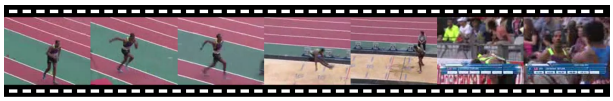
Figure 7: **Visualization of predicted context over iteration.** Generated context becomes increasingly well-grounded over iteration. Red indicates irrelevant responses, while blue indicates accurate, visually-grounded responses.

sistent focus in the video across iterations, potentially causing attention to irrelevant details. These findings suggest that a methodical approach to context renewal, such as our 'Self-retro.', is crucial for maintaining focus on relevant content, thereby improving proper preference modeling.

4.4 Qualitative Analysis

Enhanced visual context over iteration. To show the improving nature of self-retrospective context, we visualize the generated context as shown in Fig. 7. As training iterations progress, the context adds more and more detailed visual information about the video, such as specific species of goldfish. This improved context aids the overall understanding of the video content to improve preference selection process.

Comparison of self-rewarding *vs*. ISR-DPO. Figure 8 compares the responses of self-rewarding, *i.e*., ISR-DPO w/o visual context, and ISR-DPO for $9th$ iterated models. The self-rewarding tends to produce longer responses, but as sentences progress, they become less relevant to the question and visual content. Also, it fails to recognize the athlete's



Question : What is the athlete doing in the video?

Ground-Truth : The athlete is performing the long jump.

Self-Rewarding (Yuan et al., 2024)

The athlete is engaged in a sprinting event, as indicated by their running posture and the athletic attire suitable for such an activity. They are seen running on a track, transitioning from a start position to full sprint, and then crossing the finish line. The athlete's movements are dynamic and focused, demonstrating speed and endurance. The athlete's actions include accelerating, maintaining a high speed, and crossing the finish line, which are all characteristic of a sprinting event. The athlete's expressions and body language convey a sense of determination and exertion, which are typical during competitive athletic endeavors.

ISR-DPO (Ours)

The athlete is engaged in a track and field event, which involves running and jumping. The athlete is seen running on the track, taking off for a jump, and landing in the sand pit. The actions suggest that the athlete is participating in a long jump or a similar track event. The athlete's movements are dynamic and focused, indicative of a competitive sports environment.

Figure 8: **Qualitative comparison of self-rewarding *vs*. ISR-DPO.** The figure contrasts descriptions generated without visual context, *i.e*., self-rewarding (upper), against those with visual context, *i.e*., ISR-DPO (bottom), at the $9th$ iteration. Visual context results in more accurate, concise, and relevant descriptions. Red indicates irrelevant responses, while blue indicates well-grounded responses.

jumping motion accurately. In contrast, ISR-DPO generates more concise and accurate responses that are well-grounded in the video content.

5 Conclusion

We present ISR-DPO, a novel iterative direct preference optimization for VLMMs that enhances the instruction-following ability for videos. In particular, we propose self-retrospective preference modeling to improve VLMM's capability to judge visually grounded preferences. By doing so, ISR-DPO mitigates the model's problematic inclination for visually ungrounded verbosity in judging preferred response, leading to more concise and visually grounded responses. Empirical evaluations across various video question answering benchmarks demonstrate ISR-DPO's superior performance compared to the state of the art VLMMs.

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