Beyond Hallucinations: Enhancing LVLMs through Hallucination-Aware Direct Preference Optimization

Zhiyuan Zhao, Bin Wang, Linke Ouyang, Xiaoyi Dong, Jiaqi Wang, Conghui He[†] Shanghai AI Laboratory

{zhaozhiyuan, wangbin, ouyanglinke, dongxiaoyi, wangjiaqi, heconghui}@pjlab.org.cn

Abstract

Multimodal large language models have made significant advancements in recent years, yet they still suffer from a common issue known as the "hallucination problem", in which the models generate textual descriptions that inaccurately depict or entirely fabricate content from associated images. This paper introduces a novel solution, Hallucination-Aware Direct Preference Optimization (HA-DPO), which reframes the hallucination problem as a preference selection task. The model is trained to favor the non-hallucinating response when presented with two responses of the same image (one accurate and one hallucinatory). Furthermore, this paper proposes an efficient pipeline for constructing positive (non-hallucinatory) and negative (hallucinatory) sample pairs, ensuring a highquality, style-consistent dataset for robust preference learning. When applied to three mainstream multimodal models, HA-DPO significantly reduced hallucination issues and amplified the models' generalization capabilities. Notably, the MiniGPT-4 model, when enhanced with HA-DPO, demonstrated a substantial improvement: POPE accuracy rose from 51.13% to 86.13% (an absolute improvement of 35%), and the MME score surged from 932.00 to 1326.46 (a relative improvement of 42.32%). The codes, models, and datasets are made accessible at https:// opendatalab.github.io/HA-DPO.

1. Introduction

Large Vision-Language Models (LVLMs) have achieved substantial advancements in synchronizing visual and textual features, thanks to extensive unsupervised pre-training on image-text pairs and meticulous fine-tuning on high-quality data. This progress has endowed these models with the ability to follow multimodal instructions [5, 14, 32, 36], resulting in significant advancements in a variety of mul-

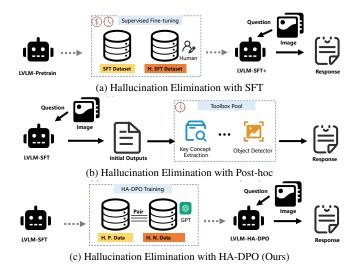


Figure 1. Comparative diagram of strategies for hallucination elimination in LVLMs. 'H.' represents hallucination, 'H.P.' stands for positive samples without hallucination, and 'H.N.' denotes negative samples with hallucination.

timodal tasks. However, even the most advanced LVLMs are not immune to the pervasive issue of "hallucination". This phenomenon, where the model's output includes fictitious information, such as non-existent objects or incorrect categories, attributes, or relationships, is a critical challenge [7, 10, 12, 26, 31, 35]. These hallucinated details not only tarnish the user experience but can also mislead users, potentially triggering severe consequences. For instance, an inaccurate description in medical diagnostics could lead to a misdiagnosis, posing unforeseeable harm to patients.

Researchers have embarked on a series of studies to mitigate the hallucination issue in multimodal models. Current mainstream solutions can be broadly divided into two categories: the first, as shown in Figure 1a, involves constructing abundant hallucination-free data and employing exhaustive Supervised Fine-Tuning (SFT) process to mitigate hallucination phenomenon [5, 12, 32]. Although SFT-based method reduces hallucination to a certain extent, this method demands high-quality data and comes with high

^{*}Equal contribution.

[†]Corresponding author.

annotation and training overheads. The second, as shown in Figure 1b, treats the elimination of hallucination as a post-processing operation on model output and uses existing tools or expert models (such as tokenizers and detection models) to rectify hallucinated content [35]. This approach does not necessitate additional data and training, unless a certain customized model is required [30] for post-hoc hallucination processing. However, its effectiveness is constrained by existing resources, and the time cost increases with additional post-processing tools.

While the SFT method is beneficial, it lacks flexibility for algorithm optimization and custom hallucination handling, and it demands substantial resources for data construction and training. Conversely, the Post-Hoc method's performance wholly depends on the existing toolset. In contrast, this paper perceives hallucination elimination as a model preference, biasing the model towards hallucinationfree output. Following this approach, we decouple the task of multimodal hallucination elimination into a preference optimization problem. Through this preference learning strategy, we anticipate that multimodal models will exhibit a preference constraint during training, leading to a bias toward hallucination-free output. RLHF [1] and DPO [22] are two effective strategies proposed to address the preference issue in large language models. Given the lightweight nature and efficient training of the DPO, this paper extends DPO to propose a multimodal DPO strategy sensitive to hallucinations (Hallucination-Aware Direct Preference Optimization, termed HA-DPO), thereby customizing and enhancing the hallucination elimination capability of multimodal models.

In scrutinizing current methodologies for multimodal hallucination evaluation, we've identified significant short-comings in existing assessment systems [10, 24, 29]. Firstly, these systems limit categories to predefined ones, leading to the erroneous marking of unrecognized content as hallucinations. Additionally, they predominantly focus on specific areas, such as the existence and attributes of objects, neglecting a wider range of hallucinations. To address these issues, we introduce the Sentence-level Hallucination Ratio (SHR), a comprehensive and intuitive benchmark. Unconfined by fixed categories and scopes, the SHR offers a broad, fine-grained, and quantitative measurement for multimodal hallucinations.

In summary, our contributions are as follows:

- We propose the HA-DPO strategy, a novel paradigm specifically designed to overcome hallucinations in large multimodal models, which is demonstrated in Figure 1c. Additionally, we develop a method for constructing style-consistent hallucination sample pairs, ensuring the stability of HA-DPO training.
- 2. We introduce the Sentence-level Hallucination Ratio (SHR), an intuitive and comprehensive metric for assess-

- ing hallucinations in LVLMs.
- 3. Through extensive experiments on prevalent models, we demonstrate the effectiveness of our approach, showing a marked reduction in hallucinations and a notable enhancement in the general performance of the models.

2. Related Work

2.1. Hallucination in LLMs

Hallucinations in Large Language Models (LLMs) refer to a phenomenon where the model generates responses that conflict with known facts [11, 23, 33]. Early research has indicated that hallucinations are often attributed to noise in the pre-training data [16, 20] and a lack of prior knowledge during supervised fine-tuning (SFT) [20]. To address these issues, Falcon [21] has developed a powerful strategy for cleaning internet data. LLaMA2 [27] reduces data noise by increasing the sampling ratio of high-quality data sources. As for hallucination mitigation during SFT, LIMA [34] suggests reducing SFT data volume for enhanced performance. Reinforcement Learning from Human Feedback (RLHF) is another strong method for mitigating hallucinations. For instance, by employing RLHF, GPT4 enhances the accuracy of TruthfulQA from 30% to 60% [18].

2.2. Hallucination in LVLMs

The hallucination issue in LVLMs, exacerbated by language and image modal space misalignment, has recently become the focus of numerous studies. POPE [10] identifies the object existence hallucination issue in LVLM, illustrating its severity. LRV [12] creates abundant questions with rich annotations and GPT4-assisted evaluation. However, existing benchmarks fail to cover a sufficient range of object categories and types of hallucinations.

In terms of mitigating hallucination, most methods have focused on improving the quality of the SFT data. VIGC [28] introduces a module for visual instruction correction to minimize long sequence generation hallucinations. LRV [12] and InstructBLIP [5] mitigate hallucinations by constructing substantial and diverse SFT data. LLaVA-RLHF [26] is the first to apply RLHF in hallucination mitigation of LVLM. Gunjal *et al.* utilize DPO (Direct Preference Optimization) [22] for hallucination reduction, but use only dis-preferred data [22]. However, their approach risked over-exploitation due to lack of preferred data, complicating effective strategy learning [2, 4, 17, 19]. In contrast, our framework integrates high-quality, humanfree, style-consistent data into DPO, enhancing data quality and RL strategy beyond previous methods.

2.3. Human-preference Learning

Human-preference learning is a crucial approach in constructing effective, safe, and trustworthy models. [18, 20,

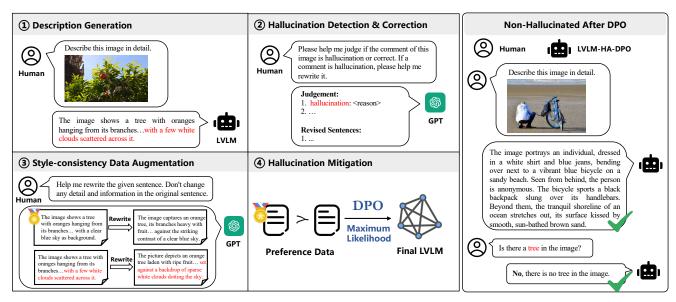


Figure 2. Our proposed hallucination mitigation process involves four steps: (1) **Description Generation**, where the LVLM is tasked with a detailed image description; (2) **Hallucination Detection and Correction**, GPT-4 identifies and corrects hallucinations in model responses using rich annotations; (3) **Style-consistency Data Augmentation**, GPT-4 rewrites samples to maintain style consistency; and (4) **Hallucination Mitigation**, style-consistent data is gathered for DPO training.

27]. RLHF [15, 20, 37] has been the most successful implementation in learning human preference. It constructs a reward model based on human preferences and optimizes the policy model guided by feedback from the reward model. [25]. Similarly, InstructGPT exploits human preference data for RL optimization, building upon GPT3 [3]. Bai *et al.* [1] aim to enhance human-preference learning with updated RL policies. Recently, DPO proposes a method [22] that bypasses learning the reward model and directly learns policies, resulting in a much simpler approach with superior performance compared to PPO. The current state-of-the-art AI agent, GPT4, also utilizes human-preference alignment via extensive data processing during its construction [18].

3. Our Method

In this work, we introduce a novel method, Hallucination-Aware Direct Preference Optimization (HA-DPO), designed to constrain the model's preference toward outputs that are devoid of hallucinations. The primary objective is to promote non-hallucinatory outputs. Considering the inherent complexity in data construction and model training processes when utilizing classical RLHF methods to constrain model preferences, we opt for Direct Preference Optimization (DPO). DPO, being a simpler, more efficient, and RL-free method, serves as our foundational strategy. We extend this strategy to the multimodal domain with the intention of eliminating hallucinations, thereby enhancing the authenticity and precision of multimodal model outputs.

As illustrated in Figure 2, we construct a style-consistent hallucination dataset through three primary steps: ① description generation, ② hallucination detection and correction, and ③ style-consistent data augmentation. This dataset is subsequently utilized for the training of the HADPO model. The models trained using this method demonstrate a significant reduction in hallucination phenomena in tasks involving detailed descriptions and dialogues.

3.1. Multimodal Hallucination-Aware DPO

We formulate the elimination of hallucinations as a preference selection problem, where, in conjunction with a style-consistent dataset, preference learning is conducted. This encourages the model to favor non-hallucinatory positive response y_{pos} and reject hallucinatory negative response y_{neg} . During the human-preference learning stage, a reward model, denoted as \hat{r} , is trained to ensure the model's propensity for outputting non-hallucinated responses y_{pos} and rejecting hallucinated responses y_{neg} . This reward model is capable of assigning scores to different responses y, thereby accurately reflecting human preferences. Once the reward model r is obtained, it is used to provide feedback for guiding an additional fine-tuning phase, which learns a policy model π_{θ} guided by human preference.

Building on the DPO framework, HA-DPO avoids the need for implicit reward model learning, instead directly optimizing the policy model π_{ref} as follows:

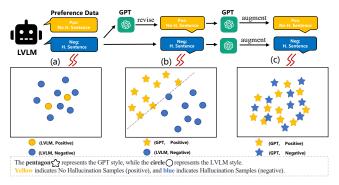


Figure 3. Style Consistency Analysis for Hallucination Dataset.

$$L_{dpo}(\pi_{\theta}; \pi_{ref}) = -E_{(x_T, x_I, y_{pos}, y_{neg}) \sim D}$$

$$\left[\log \sigma(\beta log \frac{\pi_{\theta}(y_{pos}|[x_T, x_I])}{\pi_{ref}(y_{pos}|[x_T, x_I])} - \beta \log \frac{\pi_{\theta}(y_{neg}|[x_T, x_I])}{\pi_{ref}(y_{neg}|[x_T, x_I])})\right]$$

$$(1)$$

where x_T and x_I denote the text and image prompts, respectively, while $[\]$ signifies feature concatenation. We refer to π_{ref} and π_{theta} as the reference and policy models, respectively. D represents the style-consistent dataset, and $\log \sigma$ stands for the log-sigmoid function. This objective function is designed to train the reward and policy models concurrently, skewing the reward model to favor positive responses y_{pos} and reject negative responses y_{neg} . Instead of training the reward model explicitly, Eq. 1 optimizes the policy model π_{ref} directly, with the reward model r represented implicitly as follows:

$$\hat{r}(x_T, x_I, y) = \beta \log \frac{\pi_{\theta}(y_{pos}|[x_T, x_I])}{\pi_{ref}(y_{pos}|[x_T, x_I])}$$
(2)

Building on Eq. 2, we formulate Eq. 1 to maximize the reward margin $\hat{r}(x_T, x_I, y_{pos}) - \hat{r}(x_T, x_I, y_{neg})$. This approach effectively amplifies the log-likelihood of the positive, non-hallucinated sample y_{pos} , while diminishing that of the negative, hallucinated sample y_{neg} . Consequently, the model is steered to favor non-hallucinated over hallucinated samples. To ensure training stability, we incorporate an auxiliary causal language modeling task into the preference learning process, drawing inspiration from Instruct-GPT [20]. The auxiliary task is defined as follows:

$$L_{aux} = -\sum \log P(y|x_P; \pi_\theta), \{x_P, y\} \sim D_{sft}$$
 (3)

where x_P represents the prompt and y corresponds to the associated response. D_{sft} denotes the data utilized during the SFT training phase, and π_{θ} refers to the policy model. Eq. 3 integrates the supervised fine-tuning gradient into the preference learning process, which serves to mitigate potential performance regression and ensure stable training.

During HA-DPO training, we minimize an objective where λ balances preference learning loss and auxiliary language modeling loss:

$$L = L_{dpo} + \lambda L_{aux} \tag{4}$$

3.2. Dataset Construction with Style Consistency

3.2.1 Data Source

This paper uses the Visual Genome (VG) dataset [9] to construct hallucinated samples y_{neg} and non-hallucinated y_{pos} . The VG dataset contains abundant annotated information. Each image includes multiple region bounding boxes, each corresponding to a detailed description. These annotations can adequately cover various detailed information related to the image: diverse objectives, attributes, relationships, etc., unrestricted by specific categories and scopes.

3.2.2 Generation of Hallucination Sample Pairs.

As shown in Figure 2, based on Visual Genome images with detailed annotation information, we propose the following data construction process:

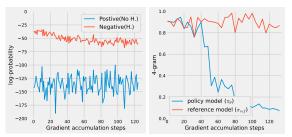
Description Generation. We randomly select images from the VG dataset and use the LVLM to generate corresponding detailed descriptions.

GPT-4 Hallucination Detection and Correction. Next, input the model-generated description and all the annotation information of the original image into GPT-4 and provide a detailed prompt template to enable GPT-4 to check whether there are hallucinations in the generated description. If hallucinations exist, a corrected description without hallucinations needs to be provided. This way, we can obtain the positive and negative responses corresponding to an image. In fact, hallucinations almost always occur when a multimodal model provides a detailed image description.

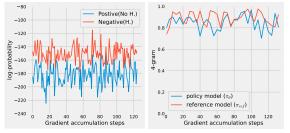
Style-consistent Data Augmentation. To ensure style consistency and amplify our sample pool, we use GPT-4 to rewrite earlier positive and negative samples, preserving their polarity. These data are further augmented into a question-answer format. Specifically, GPT-4 transforms descriptive data into questions coupled with positive-negative answer pairs, which are then fed into LVLM. Responses are sampled based on prior answers. In HA-DPO training, the preference learning data consists of both descriptive and question-answer data. Consequently, high-quality positive (x,y_{pos}) and negative (x,y_{neg}) sample pairs for the HA-DPO training process have been successfully constructed.

3.3. Style Consistency Analysis

High-quality and style-consistent data are crucial for the effective training of HA-DPO, as demonstrated in Figure 3-(a), which illustrates our initial generation of detailed image descriptions using a multimodal model that yields a small



(a) w/o style consistency control. Left: log-likelihood distribution; Right: N-grams comparison between reference and policy model.



(b) w/ style consistency control. Left: log-likelihood distribution; Right: N-grams comparison between reference and policy model.

Figure 4. Quantative analysis on style-consistent control.

proportion of responses free from hallucinations. However, HA-DPO training necessitates a balance of positive and negative samples, (x, y_{pos}) and (x, y_{neq}) , as indicated in Equation 1. To achieve this, we utilize GPT-4 to refine hallucinated responses and produce positive responses without hallucinations, as shown in Figure 3-(b). Despite this, the observed distribution difference between the nonhallucinatory positive samples and hallucinatory negative samples does not result from the presence of hallucination. Instead, it arises from the stylistic variations between the direct outputs of the VLM and the refined outputs from GPT-4. This could potentially mislead the DPO into learning stylistic differences instead of distinguishing between hallucination-free and hallucination-prone responses. In order to address this, we utilize GPT-4 to augment the initial positive and negative samples in Figure 3-(b), as depicted in Figure 3-(c). At this point, both the hallucinatory negative samples and non-hallucinatory positive samples adopt the style of GPT-4, ensuring style consistency. Consequently, this enables the HA-DPO to learn a true preference for nonhallucination, thereby eliminating model hallucinations.

To intuitively understand the impact of style-consistency on HA-DPO training, we analyzed its effects on data distribution and sentence fluency during the training process. Prior to applying style-consistency alignment, as shown on the left side of Figure 4a, there is a significant distribution difference between non-hallucination negative samples and hallucination positive samples. Concurrently, the right side of Figure 4a illustrates a rapid decline in sentence fluency as training progresses, with the model losing its question-

answering capability after a certain training period, manifested as repetitive output of the same word or sentence. However, after style-consistency alignment, as shown on the left side of Figure 4b, the distributions of both types of samples are successfully pulled into the same feature space. Under this condition, sentence fluency is not affected as training progresses, and the model trained ultimately possesses the ability to eliminate hallucinations.

Moreover, we corroborate, from the perspective of gradient optimization of objective 1, that a misalignment in the distribution of positive and negative samples can induce instability during training. By deriving the optimization objective from objective 1, we obtain:

$$\begin{split} \nabla L(\pi_{\theta}; \pi_{ref}) &= -\beta E_{x_T, x_I, y_{pos}, y_{neg}} \\ &\sim \mathcal{D} \underbrace{\left[\underbrace{\sigma(\hat{r}_{\theta}(x_T, x_I, y_{neg}) - \hat{r}_{\theta}(x_T, x_I, y_{pos}))}_{\text{weighting coefficient}} \\ &- \underbrace{\left[\nabla_{\theta} \log \pi(y_{pos} | [x_T, x_I]) - \nabla_{\theta} \log \pi(y_{neg} | [x_T, x_I)] \right]}_{\text{dominate gradient when } y_{pos} \text{ and } y_{neg} \text{ are misaligned} \end{split}}$$

where the optimization gradient consists of two components. The first, represented by the reward model \hat{r} , serves to realign the model when the reward estimates deviate. The second component aims to enhance the log-likelihood of y_{pos} while diminishing that of y_{neg} . As empirically demonstrated by [22], the weight factor of the reward model plays a pivotal role in maintaining the stability of training. As suggested by Eq. 5, once the distribution of positive and negative samples $(y_{pos}$ and $y_{neg})$ becomes misaligned, this misalignment predominates the gradient, thereby destabilizing training despite the presence of the weighting factor. Further analysis can be found in Sec 10.

4. Sentencel-level Hallucination Ratio (SHR)

4.1. Benchmark Details

The currently prevalent LVLM hallucination evaluation benchmark, POPE [10], restricts its evaluation scope to a limited number of target categories, neglecting a broader range of categories, attributes, emotions, and other elements. To overcome the limitations posed by POPE, we introduce a new evaluation metric, the SHR (Sentence-level Hallucination Ratio).

The SHR aims to provide a comprehensive and broad measurement of whether the output of LVLMs contains hallucinations. The hallucination check is not confined to categories or attributes, but encompasses all textual descriptions that do not match the image content, thereby offering a quantifiable metric at the sentence level. The formal definition of the SHR is:

$$SHR = \frac{\sum_{i=1}^{N} h_i}{\sum_{i=1}^{N} s_i}$$
 (6)

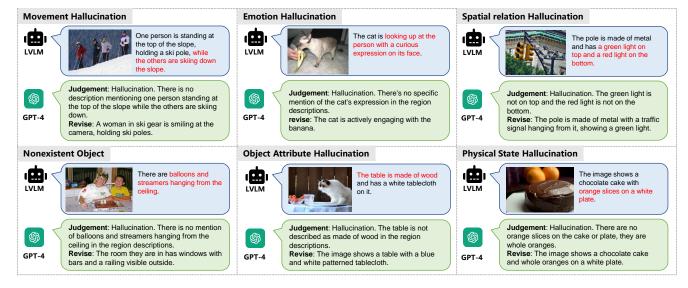


Figure 5. SHR evaluation covers diverse types of hallucinations.

where N is the total number of images, s_i and h_i denote the number of hallucinated sentences and all sentences in the response, respectively. Specifically, we randomly selected 200 images from VG as the validation set. The determination of h_i is made by GPT-4 based on the model's outputs and the corresponding annotations for the current image.

4.2. Benchmark Advantages

Our proposed SHR offers a more compelling evaluation than its counterparts, such as POPE and HaELM. It excels in three key areas: (1) *Reliability*: SHR relies on manually annotated factual information to enhance GPT-4's judgment accuracy, achieving an impressive accuracy rate of approximately 95% (see Section 9 for more details). (2) *Universality*: unlike benchmarks limited to a select few categories (such as COCO's 80), SHR accommodates an unlimited number of object types within VG images. (3) *Comprehensiveness*: SHR can recognize a wide spectrum of hallucinations, tagging any description that contradicts image content as a hallucination. This includes hallucinations involving nonexistent objects, emotions, attributes, movements, and more (see Figure 5 for illustrations).

5. Experiments

5.1. Data and Evaluation

Training Data: Based on the VG dataset [9], we filtered out images that had either too many or too few objects, or those with insufficient annotation information, and randomly selected 2K images. The hallucination dataset was built using GPT-4 in three rewrites, yielding 2K images with 6K non-hallucinatory and 6K hallucinatory responses. With the conversion of descriptive data into a question-answer format, we added about 10K data pairs for training, summing

β	SHR↓	1-gram	2-gram	3-gram	4-gram
0.3	57.2	56.7	82.3	86.4	87.9
0.4	55.8	57.8	84.3	88.4	90.0
0.5	52.3	59.0	85.9	90.3	91.8
0.6	51.4	60.1	87.4	91.7	93.1
0.8	52.3	59.0	85.9	90.3	91.8
1.0	56.7	61.0	88.8	93.1	94.6

Table 1. Ablation studies on β . Too low β can lead to unstable training, and too high β constraint model from learning knowledge about how to distinguish hallucinations.

up to 16K total data used.

Evaluation with POPE. The POPE dataset, a mainstream dataset for hallucination evaluation in multimodal models, contains 9,000 questions of 3 types. POPE targets at object existence of fixed categories (80 COCO) in images, supplying Yes/No responses. The model's accuracy is benchmarked against the ground truth answer.

Evaluation with SHR: The SHR evaluation uses 200 images from the VG dataset. During the evaluation, the model is required to provide detailed descriptions for these 200 images. SHR then measures the ratio of hallucinated sentences in these descriptions. GPT-4 determines if a sentence is hallucinated by comparing the model output with VG annotations and human-annotated factual information.

5.2. Implementation Details

MiniGPT-4. We fine-tune MiniGPT-4 model [36] parameters via LoRA [8], fixing all but q_{proj} , k_{proj} and v_{proj} . The LoRA's dimensionality (rank) is 64 and α is 16. A cosine scheduler adjusts the learning rate at $1e^{-4}$ initially, with a warmup ratio of 0.03 for 100 rounds. The batch size is 1, and HA-DPO's β and λ is set to 0.1 and 0.5. Training is

POPE	Model	HA-DPO	Accuracy	Precision	F1 Score	Yes Ratio (%)
	MiniGPT-4-LLama2-7B [36]	×	51.13	50.57	67.13	98.66
	Williof 1-4-LLallia2-7B [30]	✓	86.13	92.81	84.96	42.20
Random	InstructBLIP-13B [5]	X	88.70	85.03	89.26	55.23
	HISTIUCIDEIT-13D [3]	/	89.83	93.07	89.43	46.23
	LLaVA-1.5-7B [13]	X	89.60	88.77	89.70	51.06
	LLa VA-1.3-7D [13]	/	90.53	92.99	90.25	47.13
	MiniGPT-4-LLama2-7B [36]	X	51.46	50.74	67.72	98.06
	Willior 1-4-LLallia2-7D [30]	✓	79.50	80.20	79.25	48.83
Popular	InstructBLIP-13B [5]	X	81.36	75.06	83.44	62.56
	HISHUCIDEIF-13D [3]	✓	85.76	85.55	85.80	50.03
	LLaVA-1.5-7B [13]	X	86.20	83.23	86.79	54.46
	LLa VA-1.3-7D [13]	✓	87.90	88.07	87.81	49.76
	MiniGPT-4-LLama2-7B [36]	X	51.26	50.64	67.16	98.40
	Willior 1-4-LLamaz-7D [30]	✓	75.66	74.36	76.29	52.66
Adversarial	InstructBLIP-13B [5]	×	74.50	67.64	78.64	69.43
	HISHUCIDEH -13D [3]	✓	80.70	77.72	81.68	55.36
	LLaVA-1.5-7B [13]	X	79.76	74.43	81.75	60.90
	LLa VA-1.3-7D [13]	✓	81.46	77.99	82.54	56.20

Table 2. Results on POPE Benchmark: HA-DPO significantly enhances the model's ability to discern hallucinatory objects in images.

performed on $8\times A100$ GPUs takes 1-2 hours for 1K steps. **InstructBLIP.** We fine-tune the InstructBLIP-13B model [5] parameters with LoRA, setting its rank to 64 and α to 16. $q_{proj}, k_{proj}, v_{proj}$ in the language model are fine-tuned. We use a learning rate of $4e^{-6}$ with a cosine learning rate schedulera a batch size of 1, and set HA-DPO's β as 0.1 with λ being 0. Training runs on $8\times A100$ GPUs for 1 epoch (less than 1 hour).

LLaVA-1.5. Experiments on the LLaVA-1.5-7B model [13] involve fine-tuning all linear layers, using LoRA with a rank of 256 and α of 128, following the original LLaVA-1.5 configuration. The learning rate, batch size, and hyperparameters β and λ is set to $2e^{-6}$, 16, 0.1, and 0 respectively, with learning rate adjusted by a cosine scheduler. Training is conducted using $8\times A100$ GPUs for 1 epoch, which takes less than 1 hour.

5.3. Ablation Studies

5.3.1 Ablation on the Effect of Beta

We conducted experiments on different hyper-parameter β to verify their effects in HA-DPO. We carried out an experiment of MiniGPT4-LLaMA2 on a subset of SHR. Results are shown in Table 1. It can be observed that when β is too small, HA-DPO training is unstable, and what the model mostly learns is noise rather than how to distinguish hallucinations. When β is very large, the loss is more focused on constraining the consistency between the policy model and the reference model, which will also result in the model's

inability to learn how to distinguish non-hallucination from hallucination.

5.4. Main Results

5.4.1 Results on Hallucination Mitigation

The phenomenon of hallucination is significantly reduced in models optimized with HA-DPO. We analyze this from both POPE and SHR perspectives.

POPE. The results of the POPE experiment are shown in Table 2. As can be seen, The phenomenon of hallucination in MiniGPT-4 is significantly reduced after optimization with HA-DPO. The accuracy metrics on the Random, Popular, and Adversarial sets improved by 35.0%, 28.04%, and 24.4\%, respectively, and F1-Score improved by 17.83\%, 11.53%, and 9.13%, respectively. LLaVA-1.5, due to the diversity of data in the supervised fine-tuning phase, has the least hallucination. After fine-tuning with HA-DPO, the performance of this model is further improved, reaching a new SOTA result of 90.25% F1 score. Besides, HA-DPO optimized model achieves better performance on not only random set, but also more challenging set such as popular and adversarial set. Meanwhile, we compare HA-DPO with other hallucination mitigation methods, as shown in Table 7. Results show that HA-DPO outperforms other competitive methods and achieves SOTA (state-of-the-art) in POPE accuracy and F1 score. Notably, LRV and LLaVA-RLHF used 400K and 160K training data, respectively, while HA-DPO only used 2,000 images and corresponding 16K pairs of

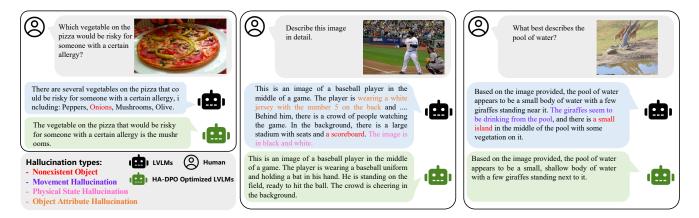


Figure 6. Comparison of model responses before and after our proposed hallucination elimination method.

Model	HA-DPO	SHR ↓
MiniGPT-4-LLama2-7B	×	47.3
MINIGP1-4-LLama2-/B	✓	44.4
In the ADLID 12D	X	51.2
InstructBLIP-13B	✓	49.1
I I "WA 1 5 7D	×	36.7
LLaVA-1.5-7B	/	34.0

Table 3. Hallucination evaluation results on SHR benchmark.

positive and negative reply samples.

SHR. To more intuitively evaluate the model's hallucination at the sentence level, we use the SHR evaluation metric. As shown in Table 3, the original MiniGPT-4's SHR metric is 47.3%, meaning that nearly half of the sentences in its detailed descriptions of images exhibit hallucination, a rather alarming figure. After optimization with HA-DPO, the proportion of hallucinatory sentences decreased by about 3%. An improvement of 2.1% and 2.7% are also achieved in InstructBLIP and LLaVA-1.5. However, we can see that the problem of LVLM hallucination remains severe.

5.4.2 Results on General Performance Enhancement

In order to verify the impact of HA-DPO's elimination of multimodal model hallucination on the model's general capabilities, we evaluated it on MME [6], which aims to evaluate the general ability of LVLMs. The results, shown in Table 4, indicate that the MiniGPT-4 model optimized with HA-DPO significantly improved its MME metrics. The Perception metric increased from 726.72 to 1051.41, and Cognition increased from 169.64 to 233.57. As for Instruct-BLIP, an improvement of 71.32 is also seen in Perception. The general capabilities of the model showed a clear improvement after the elimination of hallucinations, further demonstrating the necessity of eliminating hallucinations.

Model	HA-DPO	Perception	Cognition
MiniGPT-4-LLama2-7B	×	733.79	198.21
MilliGF 1-4-LLallia2-/B	/	1092.18	234.28
InstructBLIP-13B	×	1344.91	232.50
IIISTRUCUBLIP-13B	/	1416.23	233.21
LLaVA-1.5-7B	×	1510.74	355.71
LLa vA-1.J-/B	/	1502.58	313.93

Table 4. Results on MME Benchmark. Recognition and cognition each represent two major capability dimensions in MME, examining recognition and perceptual reasoning ability, respectively.

5.4.3 Hallucination Elimination Examples

In this section, we illustrate extensive hallucination elimination examples to further validate the effectiveness of HA-DPO. As shown in Figure 6, the application of the HA-DPO strategy significantly reduces multiple kinds of hallucinations, including but limited to object existence hallucination, object attribute hallucination, movement hallucination, and physical hallucination, etc.

6. Conclusion

In this work, we present the Hallucination-Aware Direct Perception Optimization strategy and utilize style-consistent hallucination data to enhance the performance of LVLMs. The improved models tend to generate non-hallucinatory outputs, demonstrating enhanced generalization capabilities. Additionally, we introduce the Sentence-level Hallucination Ratio (SHR) as a direct measure of hallucination in model outputs. In future research, we aim to adapt these techniques to real-world scenarios, with the goal of establishing a precise framework for effective hallucination identification and reduction.

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Beyond Hallucinations: Enhancing LVLMs through Hallucination-Aware Direct Preference Optimization

Supplementary Material

7. Dataset

Visual Genome (VG). Visual Genome is a large-scale vision-language dataset that includes dense captions [9]. It contains over 100,000 densely annotated images, each averaging 21 objects, 18 attributes, and 18 object relationships. As the largest and densest dataset of image descriptions, objects, attributes, relationships, and question answers, VG bridges visual concepts with language. In our study, VG images are used to create both the hallucination training dataset and the SHR evaluation set.

SHR Evaluation Set. The SHR evaluation set, dedicated to evaluating the LVLM's hallucination at the sentence level, comprises 200 images from the Visual Genome. To ensure precise hallucination judgment, GPT-4 is provided with detailed annotations from Visual Genome and manually annotated factual information. There's no overlap between the SHR set images and those in the positive-negative data.

8. Details of Hallucination Data Generation

In this section, we delve into the specifics of the hallucination data generation process. This is illustrated through concrete examples at each of its three crucial stages: description generation, hallucination detection and correction, and style-consistency data augmentation.

8.1. Description Generation

We provide the images from Visual Genome dataset to LVLMs with the instruction "Describe the image in detail." (as shown in Figure 8). For both hallucination dataset construction and SHR evaluation, generation parameters are configured as shown in Table 5.

num_beams	temperature	do_sample	
5	1.0	False	

Table 5. Generation parameters.

8.2. Hallucination Detection & Correction

We utilize GPT-4 to detect hallucinations in sentences produced by LVLMs, leveraging the detailed and rich image information provided by the annotations of the VG dataset. GPT-4 is prompted to identify hallucinated sentences and rectify these sentences. Any sentence deemed as a hallucination is preserved as a negative sample, while its cor-

	P	R
H	88.81%	89.43%
C	86.99%	87.70%

		_			
	89.43% 87.70%		H C	97.76% 92.60%	92.25%
_					

(a) w/o factual information.

(b) w factual information.

Table 6. Precision and Recall of GPT-4 judgment. "P" stands for precision and "R" stands for recall. "H" stands for hallucination and "C" stands for correct. The precision and recall of GPT-4 judgment is much improved with human-annotated factual information.

rected version is treated as a positive sample. An example is demonstrated in Figure 9.

8.3. Style-consistency Data Augmentation

Following hallucination detection and correction, we further prompt GPT to rewrite both the positive and negative samples. This ensures style-consistency between positive and negative samples. An instance of negative augmentation is displayed in Figure 10 and an instance of positive augmentation is presented in Figure 11.

9. Details of SHR evaluation

9.1. Evaluation Example

In the SHR evaluation, GPT-4 classifies each sentence in the model response as **hallucination** or **correct**. The SHR is then computed as the proportion of hallucinated sentences to total sentences. Consult Figure 12 for illustration.

9.2. Factual-assisted Evaluation

During the SHR evaluation, some inaccuracies in GPT-4's judgments were observed due to insufficient VG annotations. To improve the judgment accuracy of GPT-4, we manually supplement each image with extra factual information. Therefore, incorrect GPT-4 judgments are corrected with this additional information. Next, to validate the effect of additional factual information, we meticulously check judgments of GPT-4 and responses of three LVLMs (MiniGPT-4, LLaVA-1.5, and InstructBLIP) on 20 images (about 250 sentences), both with and without this factual information. Tables 6 present improved precision and recall with the help of additional factual information. Overall, human-annotated factual annotation enhanced GPT-4's judgment accuracy from 88.30% to 95.84%.

Method	Random		Popular		Adversarial	
Wiethou	Accuracy	F1 score	Accuracy	F1 score	Accuracy	F1 score
LRV [12]	86.00	88.00	73.00	79.00	65.00	73.00
LLaVA-RLHF [26]	84.80	83.30	83.90	81.80	82.30	80.50
LLaVA-1.5-7B	89.60	89.70	86.20	86.79	79.76	<u>81.75</u>
InstructBLIP-13B	88.70	89.26	81.36	83.44	74.50	78.64
MiniGPT4-LLaMA2-7B	51.13	67.13	51.46	67.72	51.26	67.16
LLaVA-1.5-7B w HA-DPO	90.53	90.25	87.90	87.81	81.46	82.54
InstructBLIP-13B w HA-DPO	89.83	<u>89.43</u>	85.76	85.80	80.70	81.68
MiniGPT4-LLaMA2-7B w HA-DPO	86.13	84.96	79.50	79.25	75.66	76.29

Table 7. Results comparisons with other hallucination mitigation methods on POPE Benchmark. HA-DPO outperforms other competitive methods and achieves SOTA (state-of-the-art) in POPE accuracy and F1 score. Bolded denotes the best score and underline denotes the second best score.

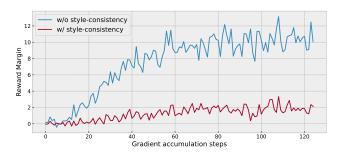


Figure 7. Comparison of gradient value between training with and without style-consistency data. Gradient changing using style-consistent data is much smoother.

10. Additional Style-consistency Analysis

To further demonstrate the effect of style-consistent control, we quantitatively examine the role of data style-consistent control in preventing training instability. Specifically, MiniGPT4-LLaMA2 model is fine-tuned with and without style-consistency control and evaluated on a subset of SHR. Instability is evaluated based on the degree of model degeneration, using n-gram fluency as an indicator, represented by $\frac{set(ngrams(s))}{len(ngram(s))}$, where s stands for the image description generated by the model. High n-gram fluency indicates smoother sentences, whereas low values denote repetition and degeneration, which is the main indicator of failure in preference learning [22]. Table 8 demonstrates that applying style-consistent control can ease training instability and reduce degeneration.

To allow readers to better understand the importance of style-consistency, we further provide some quantitative analysis regarding style consistency here. As shown in Eq 5, we mentioned that the lack of style consistency could lead to a disfunctioning of the weight factor, thereby causing extremely unstable gradients in preference learning. To

β	Style Consistency	1-gram	2-gram	3-gram	4-gram
0.1	×	17.9	23.9	25.2	25.9
0.1	✓	56.8	83.5	88.1	90.0
0.3	×	40.8	58.0	61.1	62.3
0.5	✓	58.7	87.0	91.7	93.4
0.5	×	47.3	69.1	73.0	74.6
0.5	✓	59.4	87.8	92.4	93.9
1.0	×	57.2	85.3	90.1	91.8
1.0	✓	60.1	89.1	93.8	95.4
	MiniGPT-4	60.0	91.7	96.6	98.0

Table 8. Ablation studies on on the effect of style-consistency control in stabilizing training and mitigating degeneration.

further validate this conclusion, we demonstrate the gradient variates with and without style consistency in Figure 7. It can be observed that optimizing gradient on a style-consistent dataset is much more stable.

11. Comparison with other hallucination mitigation methods

In this section, we compare our proposed method with other hallucination mitigation methods, results are shown in Table 7. Results show that HA-DPO outperforms other competitive methods and achieves SOTA (state-of-the-art) in POPE accuracy. Notably, LRV used 400, 000 training data, while our hallucination elimination only used 2,000 images and corresponding 6,000 pairs of positive and negative reply samples.

To clarify, the decrease in HA-DPO's POPE recall is not an indicator of model degradation. POPE Recall merely considers the correctness of "Yes" responses and overlooks "No" answers. For instance, models like MiniGPT-4, favoring "Yes" outputs, can attain near 100% Recall, but with most "No" responses being wrong and accuracy is just 51%.



Describe this image in detail.



The image shows a group of people skiing down a snowy slope. They are all wearing ski gear, including helmets, goggles, and skis. One person is standing at the top of the slope, holding a ski pole, while the others are skiing down the slope. The slope is covered in snow and there are trees in the background. The sky is blue and there are some clouds in the distance. The overall mood of the image is one of excitement and adventure.



Figure 8. Detailed Image Description Generation Using LVLMs.

Therefore, Accuracy and F1 score are holistic measures for model hallucination in POPE.

12. Quality Examples

Figure 13, Figure 14 and Figure 15 present hallucinationeliminated examples generated by the MiniGPT4-LLaMA2-7B, InstructBLIP-13 and LLaVA-1.5, respectively. Models optimized using HA-DPO produce significantly less hallucinated content in both visual question-answering and image description tasks.

12.1. Efficacy and Potential of HA-DPO

According to the POPE and SHR evaluation results, we observe that the HA-DPO method can learn to output without hallucination bias during training, thereby providing more precise results and reducing the phenomenon of hallucination in large vision-language models. Given the effectiveness and simplicity of the HA-DPO method, we envision HA-DPO as a specialized stage following supervised finetuning, capable of rectifying biases in hallucination and potentially other dimensions. This would enable the model to produce outputs that are more realistic and in line with human expectations.

Please help me judge if the comment of this image is hallucination or correct.

I will give you a list of region description of a image. The format is [x1, y1, x2, y2]: region description, where [x1, y1, x2, y2] is the bounding box of the region. Highly overlapping bounding boxes may refer to the same object. This is the ground truth information of the image. Your judgement should base on this information. However, this information only describe the objects in the region of image, so it cannot describe the subjective part of the image, e.g., atmosphere, style, emotion. In that case, you can return "Cannot judge".

Also, I will give you a list of comments of the image for you to judge if it is hallucination. Please give a judgement one by one along with the reason.

If a comment is hallucination, please help me rewrite it. When rewrite the comment, sound like you are looking at the image directly.

Each rewritten comments should compose a description about the image which is correct, detailed, smooth and has strong readability.

If not hallucination (correct or cannot judge), keep the original comment.

Your output should be:

Judgement:

1. hallucination or correct or cannot judge: <reason>

2.

Corrected Sentences:

1. ... 2. ...

Here are the region descriptions of the image:

[0.02, 0.02, 0.98, 0.65]: people are posing for the picture [0.81, 0.0, 0.94, 0.2]: the woman is wearing goggles [0.79, 0.0, 0.94, 0.22]: the woman is wearing a scarf

Here is the comment for you to judge if it is hallucination and revise:

- 1. The image shows a group of people skiing down a snowy slope.
- 2. They are all wearing ski gear, including helmets, goggles, and skis.
- 3. One person is standing at the top of the slope, holding a ski pole, while the others are skiing down the slope.
- 4. The slope is covered in snow and there are trees in the background.
- 5. The sky is blue and there are some clouds in the distance.
- 6. The overall mood of the image is one of excitement and adventure.

GPT-4 Output

Judgement:

- 1. The image shows a group of people skiing down a snowy slope. (correct: The region descriptions mention four skiers on a snowy hill, and objects related to skiing.)
- 2. They are all wearing ski gear, including helmets, goggles, and skis. (correct: The region descriptions include ski gear like helmets, goggles, ski poles and skis.)
- 3. One person is standing at the top of the slope, holding a ski pole, while the others are skiing down the slope. (hallucination: There is no description mentioning one person standing at the top of the slope while the others are skiing down.)
- 4. The slope is covered in snow and there are trees in the background. (hallucination: There is no description involving trees in the background and the slope being covered in snow.)
- 5. The sky is blue and there are some clouds in the distance. (hallucination: There is no description involving the sky or clouds.)
- 6. The overall mood of the image is one of excitement and adventure. (correct: The overall mood is adventurous.)

Corrected Sentences:

- 1. The image shows a group of people skiing down a snowy slope.
- 2. They are all wearing ski gear, including helmets, goggles, and skis.
- 3. A woman in ski gear is smiling at the camera, holding ski poles. (Corrected)
- 4. Four skiers are present on a snowy hill. (Corrected)
- 5. The skiers are equipped with helmets, goggles and ski poles. (Corrected)
- 6. The image portrays a winter sport scenario, with skiers ready for an adventure.

Figure 9. Hallucination Detection and Correction in LVLM-Generated Sentences.

Help me rewrite the given sentence. Don't change any detail and information in the original sentence. Don't add any new information. Give 3 different versions.

The format of your output should be:

- I. ..
- 2. ...
- 3. ...



The sentence you need to rewrite:

The image shows a group of people skiing down a snowy slope. They are all wearing ski gear, including helmets, goggles, and skis. One person is standing at the top of the slope, holding a ski pole, while the others are skiing down the slope. The slope is covered in snow and there are trees in the background. The sky is blue and there are some clouds in the distance. The overall mood of the image is one of excitement and adventure.

GPT-4 Output

- 1. In the image, a snowy slope is depicted with a group of individuals skiing down it. Each person is outfitted in ski gear, complete with helmets, goggles, and skis. Positioned at the top of the slope, one individual stands, clutching a ski pole, while the rest joyfully descend. Snow blankets the slope, accompanied by a backdrop of trees. The sky above is a vibrant blue, adorned with distant clouds. The atmosphere captured in the image exudes enthusiasm and a sense of thrilling exploration.
- 2. A snowy slope takes center stage in the image, featuring a spirited group of skiers descending down its snowy expanse. All members are donned in ski gear, incorporating helmets, goggles, and skis into their attire. One person stands confidently at the peak, gripping a ski pole, while the remaining skiers revel in the thrill of their descent. The snow-covered slope harmonizes with the surrounding lush trees, while the vibrant blue sky is complemented by distant clouds. The overall ambiance of the image resonates with excitement and a thirst for adventure.
- 3. Illustrated in the image is a snowy slope, where a cohesive group of skiing enthusiasts can be seen carving their way down. Their attire includes helmets, goggles, and skis, highlighting their readiness for an exhilarating adventure. Positioned at the summit of the slope, one individual stands upright, firmly grasping a ski pole, while the others relish in the exhilaration of skiing downhill. The snow-covered slope merges seamlessly with the backdrop of trees, while the radiant blue sky showcases scattered clouds in the distance. The image emanates an atmosphere charged with excitement and a sense of daring exploration.

Figure 10. Style-Consistent Data Augmentation: Negative Sample (Hallucinated).

Help me rewrite the given sentence. Don't change any detail and information in the original sentence. Don't add any new information. Give 3 different versions.

The format of your output should be:

- 1. ...
- 2. ...
- 3. ...



The sentence you need to rewrite:

The image shows a group of people skiing down a snowy slope. They are all wearing ski gear, including helmets, goggles, and skis. A woman in ski gear is smiling at the camera, holding ski poles. Four skiers are present on a snowy hill. The skiers are equipped with helmets, goggles and ski poles. The image portrays a winter sport scenario, with skiers ready for an adventure.

GPT-4 Output

- 1. In the picture, there is a snowy hill with a group of four skiers all dressed in ski gear, including helmets, goggles, and skis. One woman in the group is smiling at the camera while holding ski poles.
- 2. The snowy slope depicted in the image is occupied by a group of four skiers who are all wearing ski gear, including helmets, goggles, and ski poles. One of the skiers, a woman, can be seen smiling at the camera.
- 3. The image showcases a winter sport scene featuring four skiers skiing down a snowy hill. All of them are properly equipped with ski gear, such as helmets, goggles, and ski poles. Among the skiers, a woman stands out as she smiles at the camera while holding her ski poles.

Figure 11. Style-Consistent Data Augmentation: Positive Sample (Non-hallucinated).

Please help me judge if the comment of this image is hallucination or correct.

I will give you a list of region description of a image. The format is [x1, y1, x2, y2]: region description, where [x1, y1, x2, y2] is the bounding box of the region. Highly overlapping bounding boxes may refer to the same object. This is the ground truth information of the image. Your judgement should base on this information. However, this information only describe the objects in the region of image, so it cannot describe the subjective part of the image, e.g., atmosphere, style, emotion. In that case, you can return "Cannot judge".

Also, I will give you a list of comments of the image for you to judge if it is hallucination. Please give a judgement one by one along with the reason.

Your output should be:

Judgement:

1. hallucination or correct or cannot judge: <reason>

Here are the region descriptions of the image:

[0.24, 0.59, 0.34, 0.95]: woman walking on the street [0.46, 0.59, 0.62, 0.68]: people sitting on tables on the street [0.41, 0.57, 0.46, 0.68]: man wearing red top [0.1, 0.0, 0.36, 0.43]: a balcony in the building [0.36, 0.58, 0.43, 0.75]: woman holding a white bag

Here is the comment for you to judge if it is hallucination:

- 1. The scene depicts a bustling city street filled with pedestrians, motorcycles, and bicycles.
- 2. There are several people walking along the sidewalk, including a woman in a white dress who appears to be crossing the street.
- 3. In addition to the pedestrians, there are two motorcycles parked on the side of the street, one closer to the left side and the other closer to the right side.
- 4. Several bicycles can also be seen throughout the scene, some parked and others being ridden by individuals.

GPT-4 Output

Judgement:

- 1. The scene depicts a bustling city street filled with pedestrians, motorcycles, and bicycles. (Hallucination: The description does not mention bicycles or the street being bustling.)
- 2. There are several people walking along the sidewalk, including a woman in a white dress who appears to be crossing the street. (Correct: The description mentions a woman walking and other people on the sidewalk.)
- 3. In addition to the pedestrians, there are two motorcycles parked on the side of the street, one closer to the left side and the other closer to the right side. (Correct: The description mentions two motorcycles parked on the side of the street.)
- 4. Several bicycles can also be seen throughout the scene, some parked and others being ridden by individuals. (Hallucination: There are no bicycles mentioned in the description.)

Figure 12. Illustration of Sentence Hallucination Ratio (SHR) Evaluation.

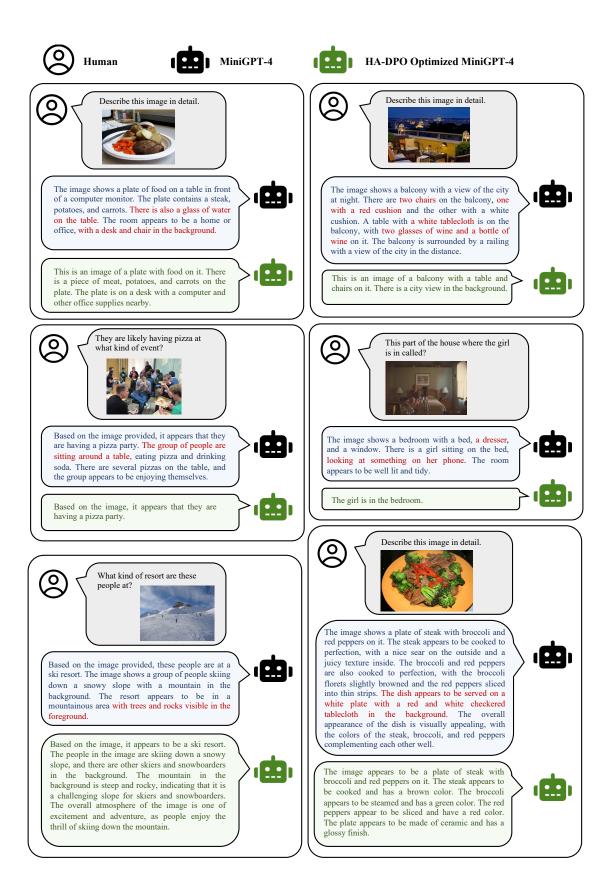


Figure 13. High-quality examples from MiniGPT4-LLaMA2-7B optimized by HA-DPO.

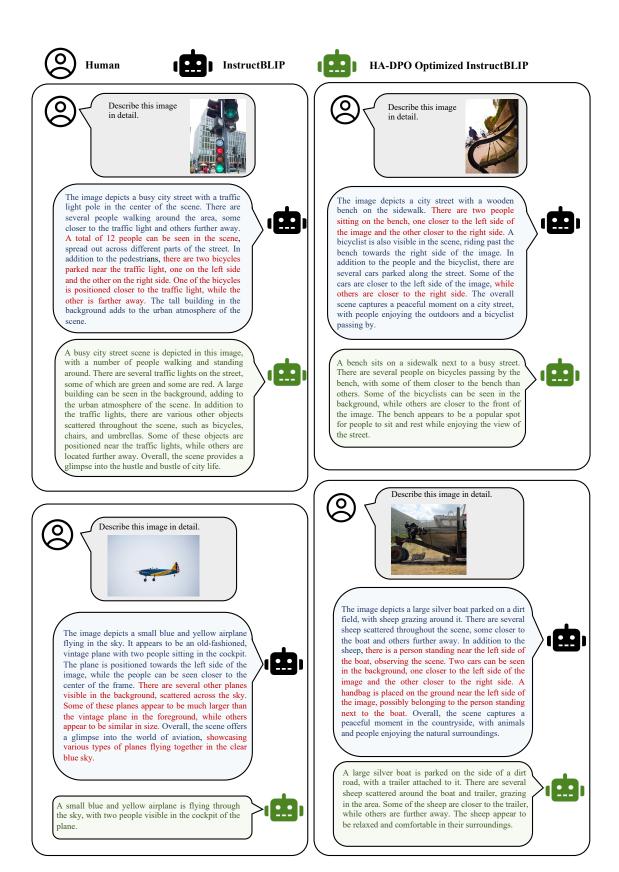


Figure 14. High-quality examples from InstructBLIP-13B optimized by HA-DPO.

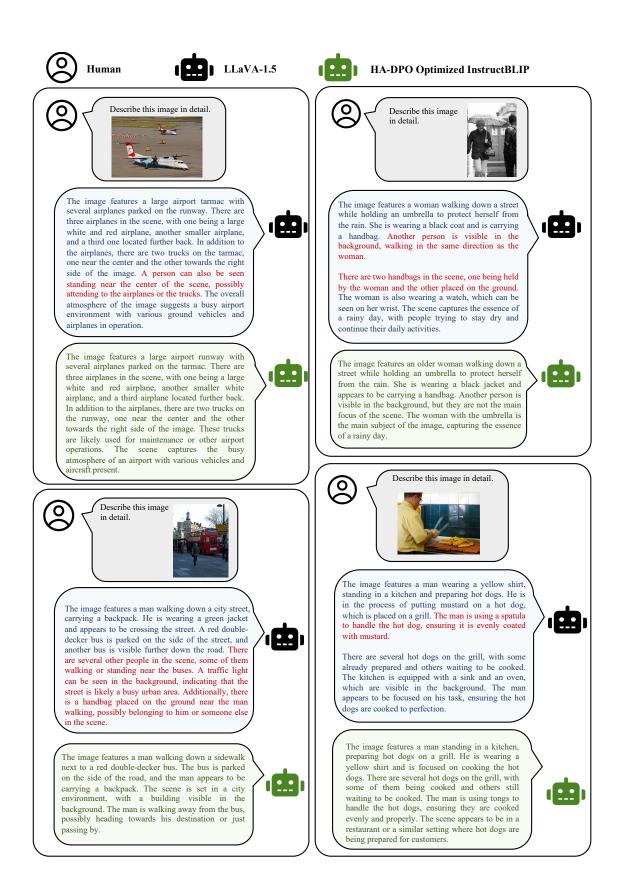


Figure 15. High-quality examples from LLaVA-1.5-7B optimized by HA-DPO.