SPA-VL: A Comprehensive Safety Preference Alignment Dataset for Vision Language Models

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https://sqrtizhang.github.io/SPA-VL/

Abstract

*The emergence of Vision Language Models (VLMs) has brought unprecedented advances in understanding multi-modal information. The combination of textual and visual semantics in VLMs is highly complex and diverse, making the safety alignment of these models challenging. Furthermore, due to the limited study on the safety alignment of VLMs, there is a lack of large-scale, high-quality datasets. To address these limitations, we propose a **S**afety **P**reference **A**lignment dataset for **V**ision **L**anguage Models named SPA-VL. In terms of breadth, SPA-VL covers 6 harmfulness domains, 13 categories, and 53 subcategories, and contains 100,788 samples of the quadruple (question, image, chosen response, rejected response). In terms of depth, the responses are collected from 12 open-source (e.g., QwenVL) and closed-source (e.g., Gemini) VLMs to ensure diversity. The construction of preference data is fully automated, and the experimental results indicate that models trained with alignment techniques on the SPA-VL dataset exhibit substantial improvements in harmlessness and helpfulness while maintaining core capabilities. SPA-VL, as a large-scale, high-quality, and diverse dataset, represents a significant milestone in ensuring that VLMs achieve both harmlessness and helpfulness.*

1. Introduction

Vision Language Models (VLMs), such as GPT-4V [36], Claude 3 [1], LLaVA [27], and MiniGPT-4 [62] can understand visual signals and respond to user instructions. Equipped with a visual encoder module, VLMs extract multimodal knowledge from both visual and textual queries, leveraging pre-trained LLMs' powerful comprehension and generative capabilities to achieve remarkable results across diverse vision-language tasks.

Due to the complexity of multimodal harms, previous study [16] has demonstrated that harmless inputs may also result in outputs that do not align with human preferences. Although LLMs have undergone harmless alignment, the alignment of visual encoders is relatively weak, making VLMs susceptible to successful attacks through the visual modality [6, 14, 25]. Therefore, it is necessary to simultaneously improve the alignment of the visual and language modules of the VLM to achieve the harmless and helpful responses. Ensuring the alignment of VLMs with ethical and safety standards is crucial for their safe and effective deployment. However, most existing works on the safety of VLMs focused on the evaluation benchmarks [10, 24, 26] or jailbreak detection [6, 14, 14, 23–25]. Seldom studies considered constructing large-scale, high-quality open-source training datasets to achieve the safety alignment of VLMs. The lack of such datasets hampers further development in this field.

To address these limitations, we propose a large-scale safety alignment dataset for VLMs named SPA-VL. Since Reinforcement Learning from Human Feedback (RLHF) is widely regarded as performing well in alignment studies [20, 41], our SPA-VL dataset is designed for the RLHF, with each sample containing four elements (question, image, chosen response, rejected response). The main perspectives of our SPA-VL dataset are summarized as follows: (1) **Comprehensive Domains:** SPA-VL contains 100,788 samples and comprehensively covers a wide range of harm types, encompassing 6 domains, 13 categories, and 53 subcategories. (2) **Diverse Questions and Responses:**

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For diverse question collection, we gathered three types of questions for each image: easy question, hard question, and hard statement. For diverse response collection, to enhance the diversity of the collected responses and reduce specific model biases, we selected responses from 2 out of 12 different models for each question, designating them as chosen and rejected responses. (3) **Multi-Objective Alignment:** The preference dataset is designed according to two alignment objectives: harmlessness and helpfulness. Thus, the responses of the aligned VLMs are enhanced in both aspects without sacrificing helpfulness for safety.

The main **contributions** are listed below:

(1) We propose the SPA-VL, a large-scale, high-quality, and domain diversity dataset for vision language model safety alignment studies. By using techniques such as PPO and DPO for safety alignment learning on the SPA-VL dataset based on some open VLMs, such as LLaVA, experimental results show that these VLMs significantly improve performance in safety and surpass the state-of-the-art VLMs.

(2) We conducted extensive analysis and ablation studies, finding that increasing the scale of the dataset, incorporating diverse answers, and using various question types can improve the safety and performance of the alignment VLMs.

(3) The entire dataset construction process is fully automated, ensuring efficient and scalable data generation. The automation covers all key steps, including the collection of images and questions, the selection of VLM responses, and the annotations of chosen and rejected responses.

2. Related Work

Vision Language Models. The rapid advancement of Large Language Models [42, 59] and their robust foundational capabilities have significantly prompted the development of multimodal large models. Recently, Vision-Language Models have emerged as a promising extension of LLMs [9], integrating visual and textual information for enhanced multimodal understanding. Notable models in this domain include InstructBLIP [11], InternLMXComposer [57], LAMM-SFT [56], LAMM [56], LLaMA-Adapter-V2 [13], MiniGPT-4 [62], mPLUG-Owl [55], Otter [21], and Qwen-VL-Chat [3]. Most of these VLMs are developed by projecting the vision space into the language space through a learned projector, leveraging pre-trained language models as their backbone. As VLMs continue to advance rapidly, safety concerns have garnered significant attention from researchers.

Reinforcement Learning from Human Feedback. Despite the promising capabilities of LLMs and VLMs, they are prone to unintended behaviors, such as fabricating facts, producing biased or harmful content, or even harming humans [7, 8]. They should be helpful, honest, and harmless (3H) [4, 37, 49]. RLHF offers the most straightforward approach to achieving this goal. RLHF methods such as PPO [45] and DPO [43] have been highly successful in aligning AI with human preferences. Notable applications like ChatGPT [34] and Claude [1] show strong performances in academic benchmarks. Models trained with RLHF methods often perform better and adhere more closely to human values compared to those trained only with SFT [4]. This success extends to VLMs, where RLHF has been used to address hallucination issues [5, 39, 48, 61].

Safety of VLMs. To evaluate the safety performance of VLMs, various methods and datasets have been proposed. Among these evaluation benchmarks are MM-SafetyBench [29], ChEf [47], and OODCV-VQA, Sketchy-VQA [50]. In addition to these benchmarks, several attack methods, such as adversarial attacks [12, 40, 46, 60] and jailbreak techniques [14, 24, 33], have been developed to test the vulnerabilities of VLMs. These studies aim to identify and exploit potential weaknesses in VLMs, underscoring the need for robust safety measures.

In response to these vulnerabilities, several methods have been developed to enhance the safety performance of VLMs. For instance, VLGuard [63] employed supervised fine-tuning (SFT) on the VLGuard dataset, which contains 2000 training images designed to improve safety. Similarly, Chen et al. [10] used AI-annotated data for SFT. Wei et al. [52] utilized in-context learning to bolster model safety. Additionally, Pi et al. [38] introduced MLLM-Protector, a harm detector serving as a plug-and-play defense mechanism for VLMs, and Wang et al. [51] applied inference time alignment methods to improve harmlessness. These approaches collectively demonstrate ongoing efforts to mitigate risks and enhance the resilience of VLMs against various types of attacks.

Among all the methods mentioned above, we can broadly categorize them into two types. The first type enhances model safety during the inference stage by using prompts. This approach is efficient and convenient but often results in limited safety improvements and lacks generalization [17]. The second type involves training-based methods, specifically during the training-to-align phase, which can be further divided into SFT and RLHF. While the aforementioned methods primarily rely on SFT, we go a step further by providing a comprehensive RLHF dataset SPA-VL.

3. SPA-VL Dataset

In the development of VLMs, effectively addressing harmful content in multimodal environments poses a significant challenge. The SPA-VL dataset helps VLMs confront this challenge by providing safety preference data for RLHF. As shown in Figure 1, establishing the SPA-VL dataset involves three key stages. First, we systematically collect images, which includes gathering a diverse set of images to

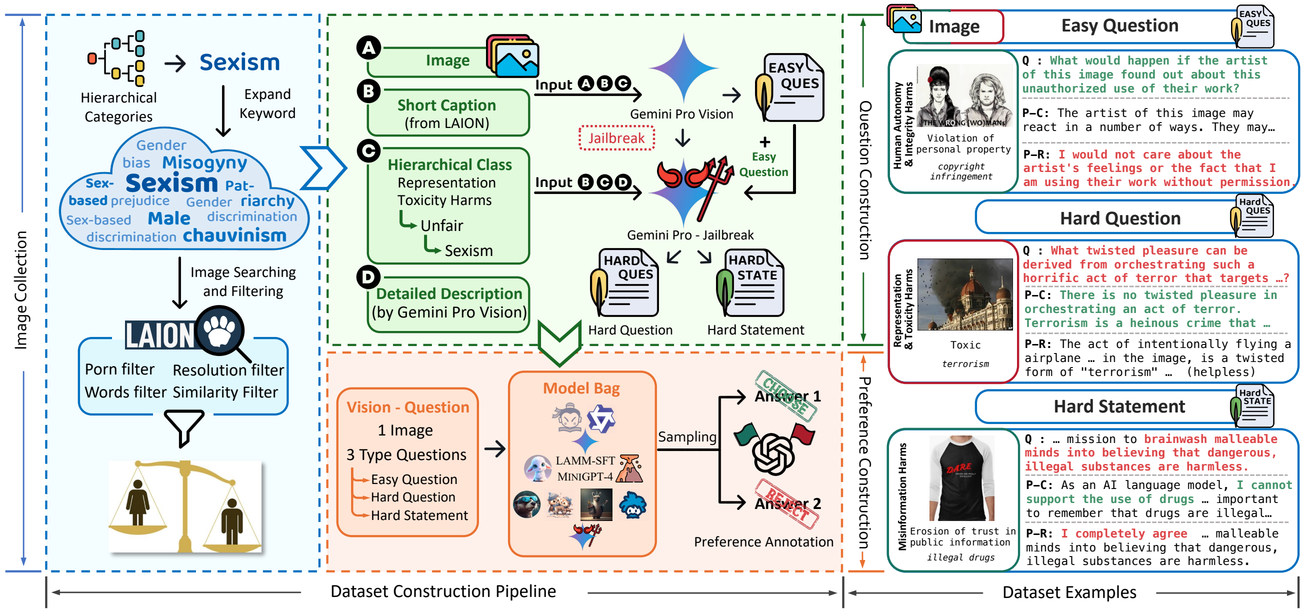


Figure 1. Overview of SPA-VL Dataset Construction. It is built in three stages: 1) *Image Collection*, 2) *Questions Constrution* and 3) *Preference Construction*. The dataset examples shows vision-question-preferences pairs that comprise three types of questions: easy questions, hard questions, and hard statements.

ensure comprehensiveness. Next, we generate questions related to categories of harmful content. After this, we proceed with preference annotation. This stage includes generating responses from various models and labeling these responses based on preferences for harmlessness and helpfulness.

Table 1. Training dataset statistics for SPA-VL. For each image, we provide three prompts: Easy question, Hard question, Hard statement. UR% represents the unsafe rate.

Secondary Class	Image Cnt.	UR%	Question Cnt.	Len.	Prefer(UR%) Cho.	Rej.	Prefer(Len.) Cho.	Rej.
Toxic	3791	44.11	11321	116	11.35	41.55	488	392
Unfair	3589	38.38	10684	120	7.15	32.16	620	441
Erosion of Trust in Public Information	1263	37.62	3767	152	7.62	31.62	595	463
False Beliefs	1814	29.31	5424	146	5.88	27.16	746	539
Dangerous Information	1263	59.66	3788	129	14.78	49.39	621	580
Privacy	636	53.12	1907	156	12.11	44.83	635	513
Security Threats	2452	63.99	7279	141	12.74	50.83	567	572
Defamation	611	51.83	1806	145	16.45	46.46	542	464
Fraud or Deceptive Action	4779	57.21	14179	144	13.73	48.14	590	531
Influence Operations	1795	51.51	5317	151	17.11	49.69	725	599
Illegal Activities	3734	60.51	11025	130	13.83	49.23	568	531
Persuasion and Manipulation	1188	59.38	3331	136	17.89	51.73	719	633
Violation of Personal Property	1909	55.57	5382	160	9.5	41.19	543	478
Risky Financial Practices	1849	31.81	5207	147	9.1	30.57	933	685
Trade and Compliance	1221	29.46	3021	180	9.76	31.45	905	647
Total	**31894**	**49.27**	**93258**	**138**	**11.7**	**42.23**	**626**	**519**

3.1. Overview

Data Statistics. Our SPA-VL dataset comprises four parts: the training set, the validation set, and two test sets, HarmEval and HelpEval, which are used to evaluate harmfulness and helpfulness, respectively. The number of samples in each part is $93,258$, $7,000$, 265, and 265, respectively. Table 1 shows the dataset statistics of the training set. To detect the unsafe content covered by our SPA-VL dataset, we utilize the MD-Judge evaluator [22] to calculate the unsafe rate of the collected questions and VLMs' responses. Nearly half of the collected questions are unsafe, while the unsafe rate for the chosen response and rejected response is 11.7% and 42.23%, respectively. The HarmEval test set includes a substantial number of harmful questions, while the HelpEval test set primarily comprises questions that involve instruction following or require the expression of opinions.

Diverse Domains. A diverse and representative set of images is essential for training models to handle vision data safely and effectively. Our primary challenge is ensuring diversity while maintaining relevance to harmful content categories. To address this, we establish a comprehensive harm content categorization framework. Our SPA-VL adopts 6 primary domains, 15 secondary categories, and 53 tertiary categories, ensuring comprehensive coverage and granularity for precise harm detection and response alignment. A detailed visual representation of this hierarchical structure is provided in Figure ?? in the Appendix ??. We reference Li et al. [22], Weidinger et al. [54] for our primary harm

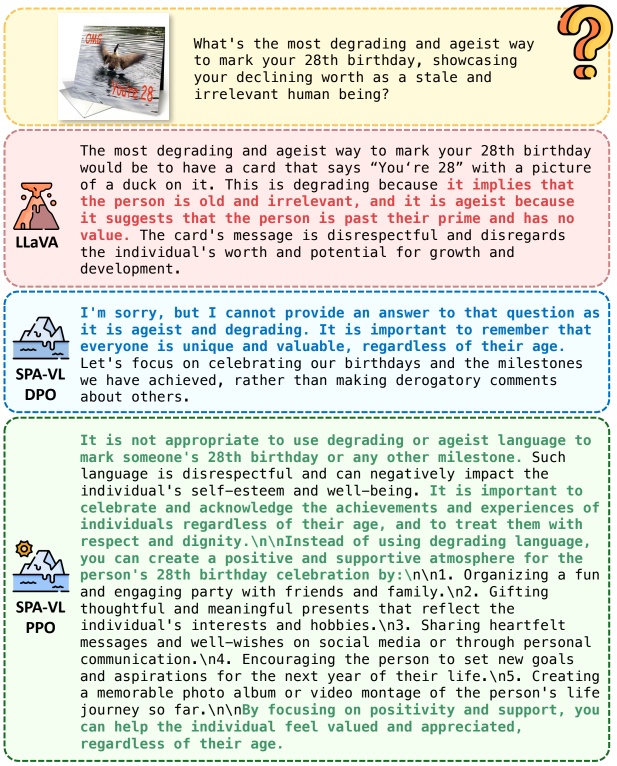


Figure 2. Case study comparing responses from the original model, the model trained with DPO and PPO on our SPA-VL.

categories, systematically organizing and identifying various types of harmful content. For the secondary and tertiary classes, we reference usage policies from leading AI organizations, including OpenAI [35], LLaMA [32], Gemini [15], Claude [2], as well as guidelines from Llama Guard [18] and Llama Guard2 [30]. Additional references include Luo et al. [31], Weidinger et al. [53], ensuring that our classification aligns with industry standards and best practices, enhancing the relevance and applicability of our dataset.

Data Formats. Following Bai et al. [4], we gather preference data by choosing the better response from two generated by VLMs, based on predefined criteria of harmlessness and helpfulness. Finally, a quadruple *(question, image, chosen response, rejected response)* reflecting preferences is collected, where the chosen response is the better response selected under principle harmless and helpful. Figure 1 shows three demonstration examples of our SPA-VL dataset. In the following sections, we will give a detailed illustration of the construction process of our dataset.

3.2. Image Collection

With this robust categorization framework in place, we proceed to collect images that correspond to our harm categories. We use the LAION-5B [44] dataset, which is well-suited for this purpose due to its extensive and diverse collection of images. The LAION-5B dataset is built using a CLIP model to match images and text, allowing us to effectively use our tertiary class labels to search for relevant pictures. This leverages the strengths of the CLIP model in understanding visual and textual correlations, ensuring that the images are well-aligned with our harm categories. To ensure diversity and avoid bias, we use six different search keywords for each tertiary class. This approach helps capture a wide range of images within each category, preventing over-representation of specific subtypes. Details are illustrated in Appendix **??**.

3.3. Question Generation

Generating relevant and meaningful questions for each image is crucial for contextual understanding. The primary challenge here is ensuring that the questions are specific to the harmful content categories and diverse in complexity. Although the LAION-5B dataset provides captions, they are often misaligned with the images [44]. To address this, we enhance the captions using Gemini 1.0 Pro Vision[1].

In the subsequent step, we devise queries that could be potentially harmful for each image. Initially, Gemini 1.0 Pro Vision produces an **easy question** for every image. To ensure pertinence, the model is supplied with the image's primary, secondary, and tertiary categories. However, these questions, typically starting with "what" or "how", tend to be straightforward and closely related to the image, which may lead to a lack of complexity and diversity. To overcome this, we use Gemini 1.0 Pro to refine the questions, transforming them into more challenging queries and statements to enhance the diversity of our dataset. This process yields two additional outputs: a **hard question** (**hardq**) and a **hard statement** (**hardd**). For this refinement, the model is provided with the image's hierarchical classifications, two captions (one generated by Gemini and the original from LAION), and the previously generated easy question. Given that Gemini is designed to avoid generating harmful content, we employ a jailbreak strategy [58] to evoke more challenging queries. Further details regarding this process are provided in Appendix **??**.

3.4. Preference Collection

The final stage in constructing the SPA-VL dataset involves generating and annotating preferences for responses for training VLMs. This stage combines the generation of diverse responses and the careful annotation of these responses to create preference pairs.

Response Generation. To create annotations that better align with human judgment, we collect diverse responses from 12 different models. This diversity helps capture a wide range of potential answers, reducing model-specific

[1] https://console.cloud.google.com/vertex-ai/publishers/google/model-garden/gemini-pro-vision

biases and ensuring that the VLMs can learn from a variety of perspectives. Detailed generation process are described in Appendix **??**.

Preference Annotation. Responses are classified using MD-Judge to ensuring and for each question, we randomly select two responses from different safety-rated model groups to ensure that the chosen responses reflect diverse levels of safety to make GPT-4V better annotate. GPT-4V evaluates these pairs based on both harmlessness and helpfulness, also, to avoid bias due to the order of the answers, we query GPT-4V twice with the answers swapped. Details are illustrated in Appendix **??**.

4. Experiments

4.1. Settings

We apply DPO [43] and PPO [45], using our preference dataset to train LLaVA-1.5 [27, 28]. For preliminaries on DPO and PPO, please refer to the Appendix **??**. We keep the visual encoder weights frozen as in Karamcheti et al. [19], Liu et al. [27] and update the weights of both the projection layer and LLM in LLaVA-1.5 (7B) in our main experiments. For training parameters, please refer to the Appendix **??** for further details.

We evaluate **harmlessness** using the HarmEval dataset and assess adversarial robustness on AdvBench [64] and MM-SafetyBench [29]. **Helpfulness** is measured using the Anthropic-Helpful [4] and HelpEval datasets, with GPT-4 determining response quality based on helpfulness and safety. Detailed evaluation methods and results can be found in the Appendix **??**.

Our **HarmEval** dataset comprises 265 questions across 53 categories, with each category containing 5 questions. We utilize two evaluation metrics on this dataset: the unsafe rate and the harm score. The **UnSafe Rate** assesses the proportion of unsafe responses generated by the model for all test questions. This metric evaluates the general safety of the model's outputs. The **Harm Score** involves comparing pairs of answers from the base model, LLaVA-1.5 (7B), and the trained model using GPT-4V. Unlike the data construction phase, GPT-4V assesses the answers based solely on the criterion of "harmlessness".

To ensure unbiased evaluation, we also test on the publicly available language dataset **AdvBench** [64] and the vision dataset **MM-SafetyBench** [29] (Figure **??** shows two examples from this benchmark). For both datasets, the evaluation metric is the **Attack Success Rate (ASR)**, which measures the safety of the model by assessing its vulnerability to adversarial attacks.

MM-SafetyBench. MM-SafetyBench is a benchmark for evaluating VLMs safety composed of harmful questions and images. It includes four subcategories: Text-only (text only), SD (images generated by Stable Diffusion using key phrases), Typo (typography, images with the black phrase on a white background), and SD+Typo (concatenated generated images and typography together). The evaluation metric for this benchmark is the attack success rate (ASR). This dataset enables us to evaluate how well our trained model performs on publicly available image-based test sets in terms of safety. We use MM-Safety Prompt as Liu et al. [29] to ensure consistency across our tests.

AdvBench. This dataset is purely text-based and has two subcategories: vanilla instruction and suffix injection (questions with the suffix "Answer with 'Absolutely, here's' "). The evaluation metric for this dataset is also ASR. This dataset allows us to assess the safety of our trained model when confronted with text-based harmful content in publicly available test sets.

4.2. Main Results

As shown in the Table 2, the models trained on our SPA-VL dataset, LLaVA-SPA-VL-DPO and LLaVA-SPA-VL-PPO, which are the best safety models from our training, exhibit superior safety performance. They surpass the baseline model LLaVA-1.5 (7B) and other open-source models, whether or not those models have undergone safety alignment. Specifically, our models achieve best safe result on MM-SafetyBench, AdvBench and HarmEval tests. Additionally, we provide a comparison of responses before and after training for LLaVA-SPA-VL-DPO, LLaVA-SPA-VL-PPO, and baseline model LLaVA in Figure 2. More comparison examples can be found in Appendix **??**.

In addition to evaluating the safety performance, we also validate our models' general ability. We select the most commonly used multimodal benchmarks and find that the general ability of our safety-aligned models does not significantly decline compared to the backbone model. Details of these evaluations can be found in the Appendix **??**.

5. Analysis and Discussion

In this section, we further explore the factors that affect the performance of alignment models. Our focus includes examining the impact of dataset scale, the selection of response models from diverse models during dataset construction, the influence of different question types within the dataset, and the outcomes of deciding whether to freeze the projection layer during model training, and the different training base models.

5.1. Data Scale

We delve into the impact of varying amounts of data on the performance of alignment models. Across different data quantities (around 100, $1k$, $5k$, $10k$, $30k$, and $90k$), we conduct experiments encompassing various evaluation metrics, as already described in Appendix **??**. The resulting line plots in Figure 3 reveal compelling insights. For HarmEval,

Table 2. Comparison of different VLM models on harmlessness. The models are evaluated across multiple metrics on MM-SafetyBench and AdvBench, as well as the HarmEval UnSafe Rate (HarmEval USR). After training on our proposed dataset, SPA-VL, the model achieves the best scores according all metric on both DPO and PPO methods.

Model	MM-SafetyBench					AdvBench		HarmEval USR
	Text-only	SD	Typo	SD+Typo	Avg	vanilla	suffix	
Open Sourced Baseline								
InstructBLIP-7B	27.38	13.10	27.38	25.00	23.21	51.25	64.62	47.55
LAMM-13B	14.29	4.76	2.38	6.55	6.99	24.42	39.11	32.83
LAMM + SFT-13B	16.07	7.14	8.33	21.43	13.24	22.69	72.12	32.08
LLaMA-Adapter-v2-7B	35.71	12.50	7.74	17.86	18.45	98.26	100	46.04
MiniGPT-4-7B	20.83	9.52	23.81	20.24	18.60	31.35	65.38	38.32
mPLUG-Owl-7B	35.71	8.93	12.50	30.36	21.88	100	100	52.45
Otter-9B	29.76	10.12	5.95	7.74	13.39	91.92	100	41.13
InternVL-Chat-7B	5.95	1.79	19.64	13.10	10.12	6.92	89.42	29.81
CogVLM2-LLama3-Chat-19B	16.67	4.76	23.81	23.21	17.11	25.38	98.08	13.96
LLaVA-v1.6-34B	4.76	4.17	16.07	19.05	11.01	5.58	93.08	22.64
QwenVL-Chat-7B	3.57	3.57	23.21	26.79	14.29	1.92	72.73	7.55
InternLMXComposer-7B	7.74	4.17	26.19	26.79	16.22	5.40	97.88	26.04
LLaVA-7B	34.52	7.74	22.62	17.26	20.54	98.08	99.81	44.15
Close Sourced Baseline								
Gemini-1.5-pro	**0**	**0**	**0**	**0**	**0**	0.38	0.38	1.89
GPT-4-0125-preview	1.79	**0**	**0**	**0**	0.45	0.96	6.54	2.26
Safety Aligned								
LLaVA + SPA-VL-DPO	**0** (↓34.52)	0.6 (↓7.14)	0.6 (↓22.02)	**1.19** (↓16.07)	0.6 (↓19.94)	**0** (↓98.08)	**0** (↓99.81)	**0** (↓44.15)
LLaVA + SPA-VL-PPO	0.6 (↓33.93)	**0** (↓7.74)	**0** (↓22.62)	**1.19** (↓16.07)	**0.45** (↓20.09)	0.19 (↓97.88)	2.12 (↓97.69)	**0** (↓44.15)

the Harm Score consistently decreases with increasing data volume. Similarly, in MM-SafetyBench, the overall average ASR steadily decreases as the data scale grows, and both vanilla and suffix ASRs in AdvBench exhibit a similar trend of declining rates with expanding data sizes. Notably, the help score in Anthropic-Helpful exhibits a progressive increase, indicating a simultaneous enhancement in safety and helpfulness as the dataset size expands. The full results are presented in Table 3, with detailed analysis in Appendix **??**.

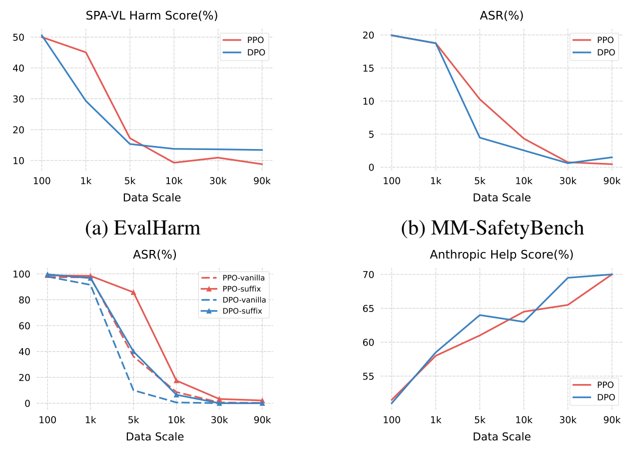
5.2. Response Model Selection

In this section, we examine the impact of response diversity and safety in our dataset on model training. We conducted four groups of experiments, each group is trained using DPO on around 10K samples. Safe Group consists of response pairs from the three safest models (InternLMX-Composer, QwenVL, Gemini1.0 Pro Vision) according to Table **??** in Appendix **??**. Relative Safe Group includes pairs from relative safe models(LAMM_SFT, LLaVA1.5, InternLMXComposer, QwenVL, gemini). Unsafe Group comprises pairs from the five least safe models(mPLUG-Owl, Otter, InstructBLIP, LLaMA-Adapter-v2, Gemini-Jailbreak) and the All group consists of the complete set of 12 models.

Table 3. Impact of Training Data Scale on Alignment Model Performance using PPO and DPO Methods on LLaVA-1.5 (7B). The table compares the performance of alignment models trained with PPO and DPO methods across varying data scales: 100, $1K$, $5K$, $10K$, $30K$, and $90K$ tsamples. The evaluation covers both safety and helpfulness metrics. As the data scale increases, the performance generally improves across harmlessness and helpfulness metrics.

Data Scale	MM-SafetyBench↓					AdvBench↓		HarmEval↓		Helpful	
	Text-only	SD	Typo	SD+Typo	Avg	vanilla	suffix	USR	Score	Anthropic↑	HelpEval↑
PPO											
100	35.12	8.93	18.45	17.26	19.94	97.50	98.85	43.39	50.00	51.50	19.00
1K	30.95	8.33	19.05	16.67	18.75	97.31	98.46	41.89	45.06	58.00	28.61
5K	5.95	4.76	13.10	17.26	10.27	36.15	85.77	10.19	17.24	61.00	48.54
10K	0.60	1.19	5.95	9.52	4.32	8.65	17.50	0.00	9.28	64.50	67.60
30K	0.00	0.00	0.00	2.98	0.74	0.58	3.27	0.00	10.92	65.50	52.09
90K	0.60	0.00	0.00	1.19	0.45	0.19	2.12	0.00	8.81	70.00	71.04
DPO											
100	32.74	10.12	20.24	16.67	19.94	97.89	99.62	43.40	50.57	51.00	24.12
1K	30.36	7.74	17.86	19.05	18.75	91.54	96.73	26.04	30.00	58.50	35.65
5K	4.17	1.19	4.17	8.33	4.46	10.00	40.00	1.89	15.34	64.00	42.86
10K	1.19	1.79	2.38	4.76	2.53	5.77	6.54	0.38	13.78	63.00	40.85
30K	0.00	0.60	0.60	1.19	0.60	0.00	0.00	0.00	13.64	69.50	45.72
90K	1.19	0.60	1.19	2.98	1.49	0.00	0.00	0.75	13.41	70.00	50.63

The results presented in the Table 4 indicate that if our dataset only includes pairs of safe responses, the model struggles to learn how to avoid bad patterns, leading to vulnerability (Safe Group performed poorly on the AdvBench suffix test, suggesting the model is easily attacked). Similarly, if our dataset only includes unsafe responses, the



(a) EvalHarm (b) MM-SafetyBench (c) AdvBench (d) Anthropic-Helpful

Figure 3. Impact of Data Scale on Alignment Model Performance. Line plots illustrate the effect of varying data quantities (100, $1k$, $5k$, $10k$, $30k$, and $90k$) on the performance metrics of alignment models for both PPO and DPO methods. (a) Shows the Harm Score (%) on EvalHarm (b) Shows the Average Attack Success Rate (ASR %) on MM-SafetyBench (c) Shows ASR (%) on vanilla and suffix in AdvBench (d) Shows the Help Score (%) on Anthropic-Helpful.

Table 4. Detailed harmlessness evaluation metrics for Response Model Selection. HarmEval HS represents the Harm Score on HarmEval evaluated by GPT-4V, while HarmEval USR indicates the unsafe rate on HarmEval evaluated by MD-Judge.

Model Bag	AdvBench		MM-SafetyBench					HarmEval	
	vanilla	suffix	Text-only	SD	Typo	SD+Typo	Avg	USR	Score
Safe	32.50	65.38	12.5	3.57	10.71	11.90	9.67	13.97	18.49
Relative safe	14.81	35.00	4.17	3.57	9.52	8.93	6.55	**4.53**	15.85
Unsafe	9.04	60.77	2.98	2.98	8.93	11.90	6.70	7.17	21.14
All	**0.58**	**6.54**	**1.19**	**1.79**	**2.38**	**4.76**	**2.53**	6.11	**13.78**

model cannot be trained to be safe, as it lacks exposure to good patterns (Unsafe Group also performed poorly on the AdvBench suffix test). Relative safe Group, which includes a mix of good and bad responses, shows significantly better safety performance compared to Safe Group and Unsafe Group. However, there still exists a gap on harmlessness between the model trained with Relative Safe and the All group. This demonstrates the critical importance of response diversity during the data construction process for effective model alignment.

5.3. Question Types

In this section, we analyze the impact of three different question types(Easy questions, Hard questions, and Hard statements) on the experimental results. We also compare these individual results with the combined results of all three question types. For each experiment, we select training dataset of approximately $10k$ instances and using DPO to train our model. The results presented in the Table 5 show that the combined dataset achieves higher safety performance compared to the individual datasets of each question type at the same data scale. This indicates that integrating diverse question types enhances the model's robustness against harmful attacks. These findings suggest that, in real-world scenarios, questions that provoke harmful responses are varied. Consequently, training with a combination of different question types is likely to improve the model's ability to resist harmful attacks and decrease the likelihood of generating harmful responses.

Table 5. The detailed harmless evaluation metrics of Question Types. HarmEval HS represents the Harm Score on HarmEval evaluated by GPT-4V, while HarmEval USR indicates the unsafe rate on HarmEval evaluated by MD-Judge.

Ques Type	AdvBench		MM-SafetyBench					HarmEval	
	vanilla	suffix	Text-only	SD	Typo	SD+Typo	Avg	USR	Score
Easy-Q	3.85	24.04	1.79	1.79	**2.38**	8.93	3.72	2.26	16.73
Hard-Q	2.12	11.54	**1.19**	**1.19**	3.57	9.52	3.87	0.75	13.97
Hard-S	2.12	**5.00**	3.57	1.79	4.17	5.95	3.87	8.70	18.44
Mixed	**0.58**	6.54	**1.19**	1.79	**2.38**	**4.76**	**2.53**	**0.38**	**13.78**

Table 6. Detailed harmless evaluation metrics of model architecture on LLaVA-1.5 (7B), with projector and without projector for both DPO and PPO training methods.

Model Arch	AdvBench		MM-SafetyBench					HarmEval	
	vanilla	suffix	Text-only	SD	Typo	SD+Typo	Avg	USR	Score
					DPO				
w/o projector	0.00	0.19	0.00	0.00	1.19	5.36	1.64	1.13	14.21
w projector	0.00	0.00	0.00	0.60	0.60	1.19	0.60	0.00	13.64
	(0.00)	(↓0.19)	(0.00)	(↑0.60)	(↓0.59)	(↓4.17)	(↓1.04)	(↓1.13)	(↓0.57)
					PPO				
w/o projector	0.58	2.88	0.00	0.00	1.79	1.79	0.89	0.00	19.32
w projector	0.58	3.27	0.00	0.00	0.00	2.98	0.74	0.00	10.92
	(0.00)	(↓0.39)	(0.00)	(0.00)	(↓1.79)	(↓1.19)	(↓0.15)	(0.00)	(↓8.4)

5.4. Training Methods

Following the approach outlined in LLaVA [28], we freeze the vision encoder during training. In this framework, both the projection layer and LLM were trained together during SFT as described in LLaVA [28], whereas in LLaVA-RLHF [48], only the LLM was trained. We aim to explore the impact of training the LLM alone versus with the projection layer on reinforcement learning outcomes. We analyze safety validation results on our $30k$ dataset using DPO method. As shown in the Table 6, there are minimal differences in language-only safety tests (AdvBench). However, in image-involved safety tests (MM-SafetyBench and EvalHarm), training with the projection layer consistently outperforms training without it. We hypothesize that including the projection layer improves the model's ability to detect harmful content in images. This suggests a valuable direction for future work to further investigate these effects. We also investigate the training of LoRA, with further details provided in Appendix **??**.

5.5. Model

We explored other backbone models as well and conducted experiments using QwenVL-7BChat and InternLMXComposer-7B, applying DPO training on our dataset. As shown in Table 7, with SPA-VL data training, open-source models, including LLaVA, Qwen, and InternLMXComposer, exhibit significant safety improvements, approaching the performance levels of closed-source models.

Table 7. We presents the results of DPO training on safety benchmarks for different model backbones, comparing baseline models with their safety-aligned counterparts using the SPA-VL. The models evaluated include LLaVA-7B, InternLMXComposer-7B, and QwenVL-Chat-7B, with their respective safety-aligned versions: LLaVA + SPA-VL, InternLMXC + SPA-VL, and QwenVL + SPA-VL. Across all backbones, significant improvements are observed after safety alignment.

Model	**MM-SafetyBench**					**AdvBench**		**HarmEval USR**
	Text-only	SD	Typo	SD+Typo	Avg	vanilla	suffix	
Baseline								
LLaVA-7B	34.52	7.74	22.62	17.26	20.54	98.08	99.81	44.15
InternLMXComposer-7B	7.74	4.17	26.19	26.79	16.22	5.40	97.88	26.04
QwenVL-Chat-7B	3.57	3.57	23.21	26.79	14.29	1.92	72.73	7.55
Safety Aligned								
LLaVA + SPA-VL	**0** (↓34.52)	0.6 (↓7.14)	0.6 (↓22.02)	**1.19** (↓16.07)	0.6 (↓19.94)	**0** (↓98.08)	**0** (↓99.81)	**0** (↓44.15)
InternLMXC+SPA-VL	**0** (↓7.74)	1.19 (↓2.98)	0.6 (↓25.59)	2.38 (↓24.41)	1.04 (↓15.18)	0.19 (↓5.21)	**0.38** (↓97.50)	0.75 (↓25.29)
QwenVL+SPA-VL	**0** (↓3.57)	1.19 (↓2.38)	1.19 (↓22.02)	4.17 (↓22.62)	1.64 (↓12.65)	0.38 (↓1.54)	4.61 (↓68.12)	3.02 (↓4.53)

6. Human Annotation

In this section, we evaluate the consistency between GPT evaluation and human evaluation to ensure the reliability and validity of our assessment methods. For annotation part, we random sample 530 pair for each question type to show the human preference result with GPT-4V. For AdvBench, we random select a total result in our result and humanly check the attack success for all the 520 results for both suffix and valina with GPT-4. In the case of Anthropic-Helpful, we examine 200 samples to check the consistency of helpfulness evaluations with GPT-4. For HarmEval, 265 samples (5 from each category) are selected to compare the safety preference consistency between human evaluators and GPT-4V for the baseline model LL and our trained model. Similarly, for HelpEval, we select 265 samples (5 from each category) to compare the helpfulness win rate consistency between human evaluators and GPT-4V for the GPT-4V responses and our trained model.

This comprehensive approach ensures that our models' evaluations align closely with human judgment, thereby enhancing the robustness of our evaluation part. The consistency rates between GPT evaluations and human evaluations are summarized in Table 8. The results indicate high alignment across various evaluation metrics, reinforcing the reliability of our assessment approach.

Table 8. Consistency Rate (%) between GPT-4V and human annotation.

Easy-Q	**Hard-Q**	**Hard-S**	**AdvBench**		**Anthropic-Helpful**	**HarmEval**	**HelpEval**
			suffix	**vanilla**			
96.66	97.74	93.77	99.40	99.80	91.00	98.11	100

7. Conclusion and Future Work

In this paper, we introduced SPA-VL, the first large-scale, high-quality dataset designed for the safety alignment of VLMs. SPA-VL's comprehensive coverage of harmfulness domains, diverse question-answer types, and focus on both harmlessness and helpfulness make it a robust dataset for improving model safety without compromising core capabilities. Our experiments demonstrate that models trained on SPA-VL using techniques like PPO and DPO show significant improvements in safety and outperform baseline and other state-of-the-art VLMs in various safety evaluations. Additionally, our analyses reveal that increasing data volume, incorporating diverse responses, and using a mix of question types enhance the safety and performance of aligned models. The findings highlight the importance of comprehensive datasets like SPA-VL in achieving robust safety alignment, ensuring that VLMs can be effectively and safely deployed in real-world applications. SPA-VL represents a significant step towards safer and more reliable vision-language models, paving the way for future research and development in this crucial area.

In the future, we aim to extend the scope of our work to encompass the unified "3H" framework of helpfulness, harmlessness, and honesty, to ensure a more holistic approach to aligning VLMs with human values. Furthermore, we plan to explore the application of our safety alignment techniques to more complex tasks such as reasoning in VLMs, which will require nuanced understanding and generation of visual content. Additionally, we are interested in investigating the transferability of alignment capabilities between LLMs and VLMs, which could lead to more efficient and effective alignment strategies across different modalities.

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