Enhancing Large Vision-Language Models with Ultra-Detailed Image Caption Generation

Anonymous ACL submission

Abstract

High-quality image captions are essential for improving modality alignment and visual understanding in Large Vision-Language Models (LVLMs). However, the scarcity of ultra-detailed image caption data limits further advancements. This paper presents a systematic pipeline for generating high-quality, ultra-detailed image captions, encompassing both pre-processing and post-processing stages. In the pre-processing stage, we classify and deduplicate images, extract visual information using expert tools, and leverage GPT-4o with structured prompts to generate initial captions. To enhance comprehensiveness, we introduce an expansion strategy based on Large Language Models (LLMs), defining eight descriptive dimensions to refine and extend captions, which serve as seed data for training a proprietary captioner model. In the post-processing stage, we incorporate human error-correction annotations and an active learning-inspired approach to refine low-quality samples. Using high-quality corrected data, we apply Direct Preference Optimization (DPO) and develop a critic-rewrite pipeline, training a sentence-level critic model to mitigate hallucinations. Experimental results demonstrate that our ultra-detailed captions significantly enhance LVLMs' perception and cognitive abilities across multiple vision-language benchmarks.

1 Introduction

Large Vision-Language Models (LVLMs) (Bai et al., 2023; Chen et al., 2023a; Dai et al., 2023; Liu et al., 2023a; Luo et al., 2023; Ye et al., 2023; Chen et al., 2024a,b) have made significant progress in bridging the gap between language and vision, enabling tasks such as visual question answering and vision-language reasoning. However, the effectiveness of these models heavily depends on the quality of the image caption data used for pre-training. High-quality image captions are crucial for improving modality alignment, enhancing the understanding of visual content, and ensuring that models can generalize effectively across diverse visual and linguistic contexts. Unfortunately, the image caption datasets currently available for training LVLMs often lack the fine-grained details necessary to capture the complexity of images, particularly in terms of object attributes, object relationships, and intricate visual features.

The scarcity of ultra-detailed image caption data has become a key bottleneck in advancing LVLMs capabilities. Most existing caption datasets either lack sufficient visual detail or fail to provide comprehensive, detailed descriptions of the objects, attributes, and relationships within images (Chen et al., 2023b; Lai et al., 2023; Fan et al., 2023). As a result, LVLMs trained on such data may fail to align vision and language accurately, leading to suboptimal performance on tasks that require fine-grained visual reasoning. To address this challenge, this paper presents a comprehensive pipeline for generating high-quality, ultra-detailed image captions. The pipeline includes both pre-processing and post-processing stages, aimed at enhancing the quality of the generated captions and ensuring better alignment with the visual content.

In the pre-processing stage, we first classify and deduplicate the image data to build a multi-dimensional image dataset. We then leverage advanced visual expert tools (Zhang et al., 2023c; Liu et al., 2023c; PaddlePaddle) to extract rich visual information from the images and effectively integrate these visual information to generate high-quality image captions by prompting GPT-4o (Hurst et al., 2024). To further improve the completeness of the image caption data, we introduce an expansion strategy based on LLMs. Specifically, we design eight descriptive dimensions for the images, enabling the LLMs to expand and complement image details from multiple perspectives, ensuring a more holistic view. Building on the focus points ex-

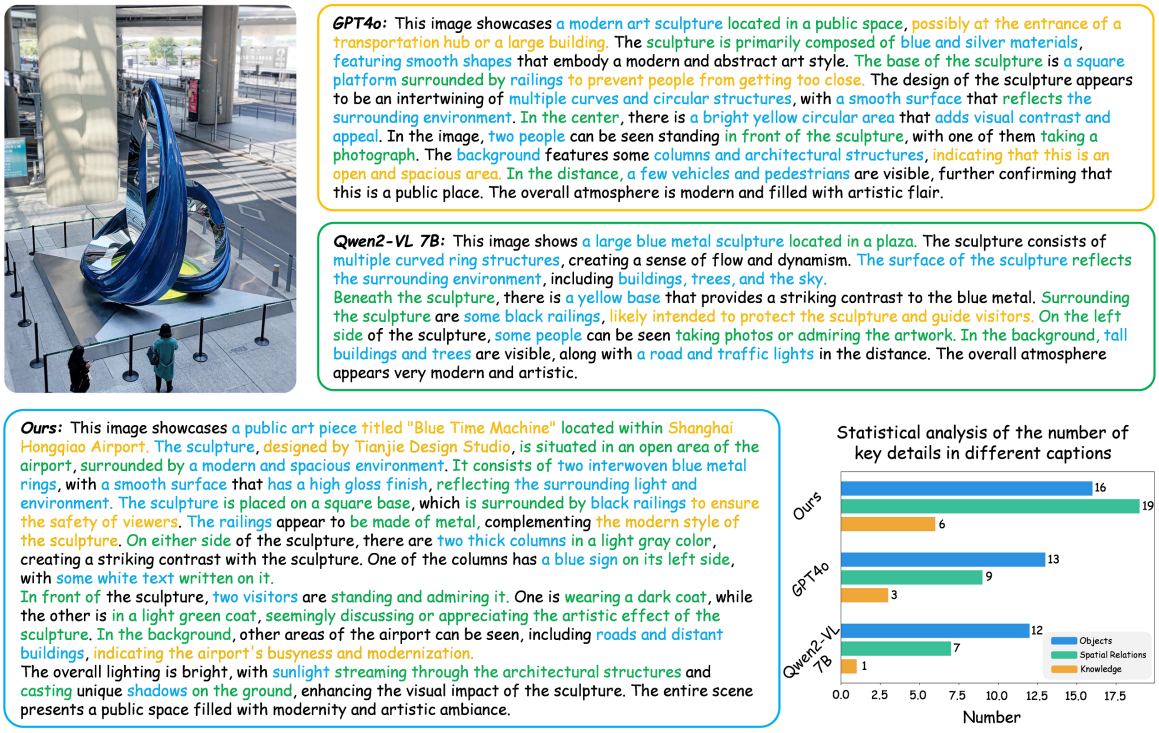

Figure 1: **We compare the performance of our method with the advanced GPT-4o and Qwen2VL-7B in image captioning.** For better visualization, objects are marked in blue, spatial relations in green, and knowledge are distinguished using yellow. The comparison clearly shows that our method captures finer details in the image more precisely and provides richer semantic understanding, further enhancing the quality of the image descriptions.

panded by the LLMs, we further prompt GPT-4o to extend the image captions to generate high-quality seed data, which are then used to train a proprietary image captioner model.

In the post-processing stage, we adopt an active-learning-like strategy to identify and correct bad samples generated by the model through human annotation. Using this high-quality, human-corrected data, we apply the DPO (Rafailov et al., 2024) alignment strategy to further enhance the image captioner model's performance. To make the most effective use of the human-corrected data, we also design a critic-rewrite pipeline. Specifically, we train a sentence-level critic model. For each caption, we decompose it into a series of atomic factual sentences and use the critic model to generate evaluative comments for each atomic sentence. Based on the original caption and the critic results for these atomic sentences, we rewrite the caption to further reduce hallucinations in the generated image descriptions. As shown in Figure 1, our method generates more accurate and comprehensive image captions across multiple dimensions compared to the advanced GPT-4o and the open-source model Qwen2VL-7B (Wang et al., 2024a).

Experimental results demonstrate that the image captions generated using our proposed pipeline significantly enhance the performance of existing LVLMs across various vision-language tasks and achieving better alignment between visual content and textual descriptions. In a nutshell, our contributions are as follows:

- We propose a powerful and scalable method for creating high-quality, ultra-detailed image captions, which is critical for enhancing the capabilities of LVLMs. Our method offers a promising solution to the limitations of current image caption datasets.
- We create a high-quality image caption dataset using the data generation pipeline proposed in this paper and validate its impact on enhancing the performance of LVLMs through data ablation experiments.
- We further validate the effectiveness of the proposed method in generating image captions through an image caption benchmark and manual quality analysis experiments, demonstrating enhanced caption performance and reduced hallucinations.

2 Related Work

2.1 LVLMs for Image-Text Data Enhancement

With the rapid development of Large Vision-Language Models (LVLMs) (Liu et al., 2023a; Luo et al., 2023; Ye et al., 2023; Zhang et al., 2023a,b; Zhu et al., 2023; Dai et al., 2023), research on image-text data enhancement has garnered increasing attention, focusing primarily on improving caption quality and vision-language alignment (Fan et al., 2023; Lai et al., 2023; Nguyen et al., 2023). LaCLIP (Fan et al., 2023) and VeCLIP (Lai et al., 2023) utilize LLMs to rewrite captions but are limited by issues of hallucinations. Models such as GPT-4V (OpenAI, 2023) can directly generate high-quality captions from images. Large-scale datasets like LAION (Schuhmann et al., 2021) and CC12M (Sharma et al., 2018), as well as synthetic caption generators like ShareGPT4V (Chen et al., 2023b), provide significant support for vision-language pretraining. DenseFusion (Li et al., 2024b) enhances caption quality by incorporating multimodal information during the data generation phase but remains largely confined to the data preprocessing stage. Despite progress, challenges persist in enhancing caption quality and reducing hallucinations. Future work should aim to optimize vision-language alignment and improve grounding.

2.2 Preference Optimization

Preference Optimization (PO) (Meng et al., 2024; Hong et al., 2024; Azar et al., 2024) is a key technique for advancing Large Language Models (LLMs) and Large Vision-Language Models (LVLMs). Methods like Reinforcement Learning from Human Feedback (RLHF) and Direct Preference Optimization (DPO) (Rafailov et al., 2024) use human preferences as reward signals to optimize model outputs, making them more aligned with human intent. In the multimodal domain, despite existing methods focusing on reducing hallucinations (Yu et al., 2023a, 2024), alignment optimization in complex image captioning scenarios remains challenging. To address this, Critic Models such as LLaVA-Critic (Xiong et al., 2024) and Prometheus-Vision (Lee et al., 2024) have emerged. These models can evaluate both visual and textual nuances, offering new ways to optimize alignment in complex multimodal tasks beyond single-task assessments.

3 Pre-processing Stage

3.1 Data Collection and Preparation

To create a high-quality dataset for precise vision-language perception, we have carefully assembled a diverse and multi-dimensional dataset with rich visual semantics to support the training of accurate and contextually aware image captioning models.

Data Sources. To maximize the diversity and comprehensiveness of the data, we have collected approximately 800K images from various sources, including the COCO dataset (Lin et al., 2014) for object detection, the SAM dataset (Kirillov et al., 2023) for image segmentation, and large-scale multimodal datasets commonly used in the field, such as Wukong (Gu et al., 2022), LAION (Schuhmann et al., 2021), CC3M (Sharma et al., 2018) and SBU (Ordonez et al., 2011). The data has been filtered and cleaned to remove corrupted, missing samples, and sensitive content.

Data Classification and Deduplication. To ensure data diversity and semantic richness, we design an image classification system with 7 primary categories and 22 secondary categories (as shown in appendix B.1) and finetune an image classifier to automate the categorization process. We also supplement underrepresented categories to balance the distribution. Finally, we apply deduplication based on image similarity, resulting in a dataset of 320K high-quality images.

3.2 Multimodal Information Fusion

Most LVLMs can generate image captions, but their quality is not guaranteed. Designed for general tasks, they often underperform in specialized areas like OCR and object detection compared to dedicated models. To address this, we develop a multimodal fusion pipeline that integrates visual information from specialized models with the advanced GPT-4o, to generate high-quality captions.

Extraction of auxiliary information. Due to the rapid advancements in the field of computer vision, many expert models in the visual domain can provide effective visual auxiliary information for image caption generation. We have carefully selected the following models to extract this visual auxiliary information:

- **Object Label Information.** We utilize RAM++ (Zhang et al., 2023c) to extract object label information from images and filter the original label vocabulary of RAM++ to remove labels that are not conducive to object detection, such as verbs

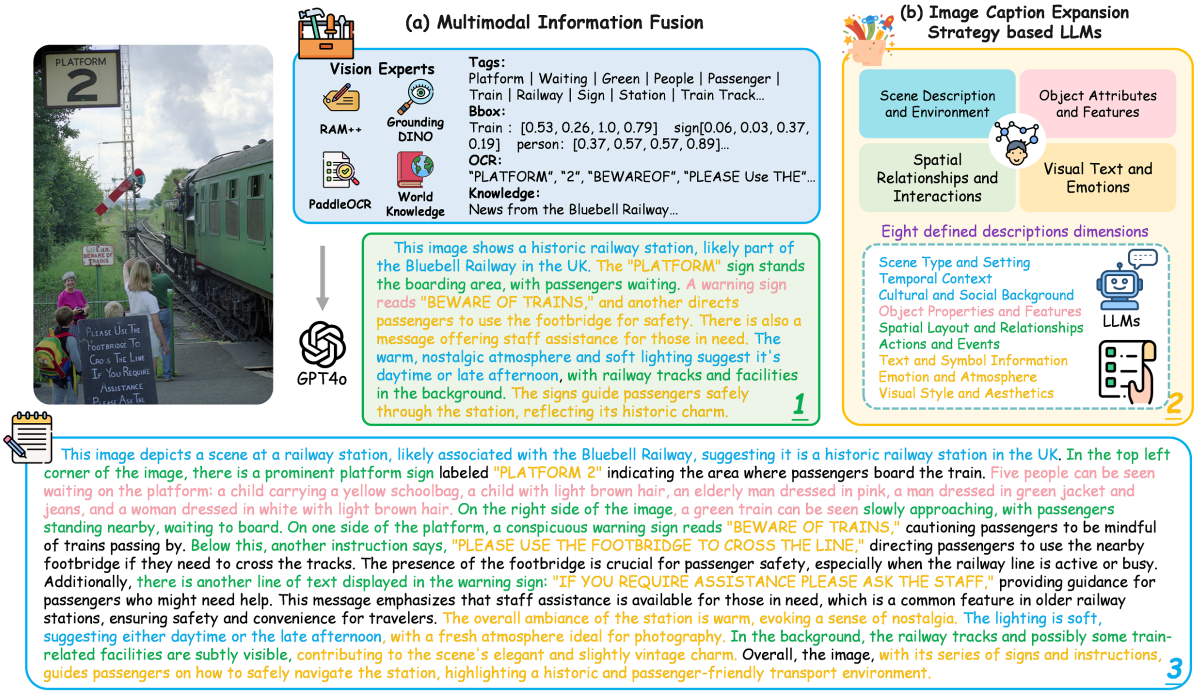

Figure 2: **Overview of pre-processing stage pipeline. (a)** We use advanced visual tools to extract detailed visual information and integrate it into GPT-4o via structured prompts to generate initial image descriptions. **(b)** We expand these descriptions using LLMs with eight defined dimensions (e.g., Scene Type, Object Properties, Spatial Layout, Text Information) to enrich details. This process generates 320k high-quality image caption seed data.

(e.g., "running"), adjectives (e.g., "bright"), and some background nouns (e.g., "sky", "ground").

• **Location Information.** We employ GroundingDINO (Liu et al., 2023c) to extract object detection box information from images. By leveraging the object labels extracted by RAM++, Grounding DINO recognizes the positions of the corresponding objects in the image and provides the respective bounding box coordinates for detection.

• **Textual Information.** We utilize PaddleOCR (PaddlePaddle) to extract textual information from images and filter out text with low confidence levels in the recognition results.

• **World Knowledge.** In most datasets, such as Wukong, LAION, and CC3M, images typically contain a raw descriptions related to the world knowledge of the image. Although these descriptions are very brief and lack fine-grained visual details, they contain rich world knowledge about the image.

3.3 Image Caption Expansion Strategy based LLMs

In previous work, we prompt GPT-4o to generate relatively accurate image captions by integrating rich visual auxiliary information. However, considering that the generated captions may still overlook certain visual details, we introduce an image caption expansion strategy based on Large Language Models (LLMs) to further improve the completeness and comprehensiveness of the captions. Specifically, we first design eight descriptive dimensions for the images, enabling the LLMs to expand and complement image details from multiple perspectives, ensuring a more holistic view. Next, we input the image captions generated by GPT-4o, along with these eight dimensions, into the LLMs, allowing it to expand on the visual focus areas based on the details in the caption. Building on the focus areas identified by the LLMs, we further prompt GPT-4o to extend the image descriptions, effectively enhancing the completeness and comprehensiveness of the generated captions.

3.4 Captioner Model Training

As shown in Figure 2, we first construct preliminary image caption data by integrating visual auxiliary information, and then employ an image caption expansion strategy based on LLMs to effectively enhance the completeness and comprehensiveness of the generated captions. Through this approach, we build approximately 320K high-quality image caption seed data. To break free from the reliance on costly proprietary models (such as GPT-4o) and

achieve scalability in image caption data, we fine-tune a proprietary image captioner model using the Qwen2VL-7B (Wang et al., 2024a) model with the 320K high-quality seed dataset. The specific training details can be found in the appendix A.1. Through manual quality checks and image caption benchmark tests, our captioner model demonstrate performance comparable to GPT-4o, and even surpassed it in certain aspects.

4 Post-processing Stage

Previous studies, such as RLAIF-V (Yu et al., 2024), use automated preference data generation to enhance model performance by scoring or modifying responses with a divide-and-conquer strategy and multimodal models. However, we find this unreliable for image captioning tasks. Even powerful models like GPT-4o struggle with common issues such as counting in crowded scenes, object localization, and occluded scenes. Using GPT-4o to score or modify captions in these cases can introduce biases and destabilize the optimization process. Therefore, we emphasize the importance of incorporating human error-correction in the post-processing stage. In this section, as shown in Figure 3 we introduce human-corrected DPO alignment strategies and a critic-rewrite pipeline to improve the quality of image captions.

4.1 Preference Optimization

Human Error-correction Annotations. Based on the image captioner model trained in the pre-processing stage, we collect 200K diverse images using the image collection method outlined in Section 3.1 and generate image captions using the captioner model in pre-processing stage. To better identify low-quality image caption samples and make more effective use of human annotation resources, we adopt an active-learning-like strategy to filter out bad samples. Specifically, we rely on existing open-source critic models (e.g., LLaVA-Critic (Xiong et al., 2024)) to provide preliminary scores for the image captions. Although the scores provided by current critic models may not perfectly reflect the quality of the captions, they offer a rough estimation of quality that helps us filter out bad samples. Ultimately, we select 70K low-scoring samples for human error correction and annotation. Through manual error correction, we obtain 70K high-quality image caption preference pairs. Using these high-quality preference data, we apply DPO to further refine the image captioner model obtained in the pre-processing stage.

Improving Direct Preference Optimization (DPO). In our experiments, we observe that during DPO, as shown in Equation 1, the reward values for both chosen and rejected samples significantly decreased, leading to severe mode collapse in the model's output, characterized by the generation of large amounts of repetitive text. As the training data size increased, issues such as repetitive text became more frequent. We attribute this phenomenon to the discriminative nature of the DPO loss, which is essentially a classification loss. Relying solely on this loss may cause the model to iterate in the wrong optimization direction, thereby reducing its generative capability. Inspired by InternVL2-8B-MPO (Wang et al., 2024b), we introduce two auxiliary losses during the DPO process: normalized SFT loss and BCO loss, as shown in Equations 2 and 3, to maintain the model's generative ability and ensure the stability of preference learning.

$$\mathcal{L}_{DPO} = -\log\sigma\left(\beta\log\frac{\pi_\theta(y_c|x)}{\pi_0(y_c|x)} - \beta\log\frac{\pi_\theta(y_r|x)}{\pi_0(y_r|x)}\right), \tag{1}$$

$$\mathcal{L}_{SFT} = -\log\frac{\pi_\theta(y_c|x)}{|y_c|}, \tag{2}$$

$$\mathcal{L}_{BCO} = -\log\sigma\left(\beta\log\frac{\pi_\theta(y_c|x)}{\pi_0(y_c|x)} - \delta\right) - \log\sigma\left(-\left(\beta\log\frac{\pi_\theta(y_r|x)}{\pi_0(y_r|x)} - \delta\right)\right), \tag{3}$$

$$\mathcal{L} = \alpha_1\mathcal{L}_{DPO} + \alpha_2\mathcal{L}_{SFT} + \alpha_3\mathcal{L}_{BCO}, \tag{4}$$

Where x represents the prompt, y_c represents the preference response after human error correction, y_r represents the original rejected response, β is the KL penalty coefficient, and the policy model π_θ is initialized from model π_0. δ represents the reward shift, calculated as the moving average of previous rewards to stabilize training. α_1, α_2 and α_3 represent the weights of each loss component.

As shown in Equation 4, by combining these two auxiliary losses (normalized SFT loss and BCO loss) with DPO, we effectively mitigate the issue of both chosen and rejected sample reward values decreasing simultaneously. Furthermore, the captioner model, after preference alignment, demonstrates improved performance. Additional training hyperparameters are provided in the appendix A.2.

4.2 Fine-Grained Critic Model Training

In previous work, we use a strategy similar to active learning to mine challenging samples and collect

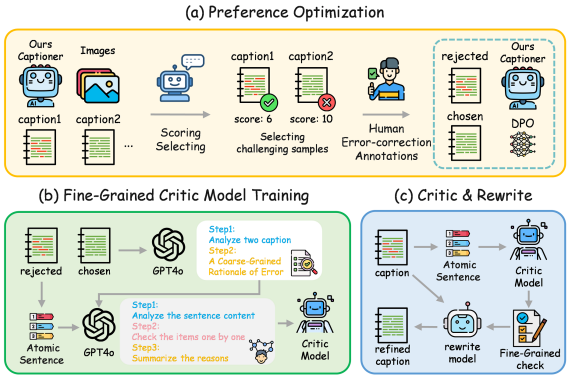

Figure 3: **Overview of post-processing stage pipeline.** **(a)** illustrates further preference optimization of the pre-processed image captioner model. **(b)** shows training of the fine-grained critic model. **(c)** depicts the critic-rewrite pipeline.

70K high-quality human-corrected annotated data. Given that human-annotated data is both expensive and difficult to scale, we design a critic-rewrite pipeline to convert the human-corrected annotations into more granular sentence-level annotations, specifically for training a sentence-level critique model. By combining atomic sentence splitting and rewriting strategies, we further reduce hallucinations in the image captions. In the following, we will provide a detailed explanation of this process.

Coarse-grained Error Rationale Generation. We first input the human-corrected annotation data into GPT-4o and inform the GPT-4o which caption is correct and which is incorrect. This allows the GPT-4o to identify the differences between the two captions and generate a coarse-grained error rationale for the incorrect caption. The prompt template is provided in the appendix C.

Atomic Description Generation. To reduce the training difficulty of the critic model, we decompose the entire image caption into more granular atomic descriptions and perform critique evaluation at the atomic description level. Considering the contextual dependence in caption expressions, we ensure that each atomic description is as independent and specific as possible, while converting pronouns in the caption into explicit nouns to avoid ambiguity. Additionally, each atomic description should include as much relevant visual information as possible in a comprehensive manner. The prompt template is provided in the appendix C.

Fine-grained Critic Data Generation and Critic Model Training. We input both the image and a single atomic description into GPT-4o, along with the collected coarse-grained error rationale as a prompt, guiding GPT-4o to generate the evaluation process for that atomic description. To make the evaluation process more precise and controllable, we prompt GPT-4o to complete the task step by step. Upon receiving the atomic description, GPT-4o first needs to identify which details should be considered to evaluate all the visual information. Then, for each detail that needs attention, GPT-4o performs a comparison. Finally, GPT-4o summarizes the evaluation results. The prompt template is provided in the appendix C. In this process, we collect approximately 120K high-quality critic data and train a specialized sentence-level critic model based on Qwen2VL-7B (Wang et al., 2024a). Training parameters and details are provided in the appendix A.3.

Rewrite of Captions. In the process described above, we obtain a fine-grained critic content for each atomic description. Subsequently, we input both the original image caption and the critic content for each atomic description into a Large Language Model (LLMs), prompting the model to rewrite the high-quality image caption. The prompt template is provided in the appendix C.

5 Experiments

Overview. In this section, we first introduce the key implementation details of the experiment and demonstrate that the high-quality ultra-detailed captions generated by our pipeline can effectively enhance the performance of LVLMs. Then, we conduct detailed ablation studies to validate the effectiveness of our pipeline in improving the quality of image captions.

5.1 Implementation Details

Model and Data Setting. We use LLaVA-1.5 (Liu et al., 2023b) and LLaVA-NEXT (Liu et al., 2024) to validate the effectiveness of the high-quality, ultra-detailed captions generated by our proposed pipeline in enhancing the capabilities of Large Vision-Language Models(LVLMs). Specifically, we select CLIP-ViT-L/14-336 as the visual encoder, combined with Vicuna-v1.5-7B (Chiang et al., 2023) and LLaMA3-8B (AI@Meta, 2024) as the large language models. In the context of data, we meticulously select and collect approximately 1.5M images from multiple datasets, including COCO, LAION, CC3M, SBU, and SAM. Through the systematic data generation process

Table 1: **Main Results.** Comparisons with state-of-the-art approaches on 9 vision-language evaluation benchmarks, including MME, MMB, MMB^{CN}, MMVet, $SEED^{I}$, POPE, SQA^{I}, GQA, and TextVQA. The results demonstrate that the high-quality image caption data generated by our method can bring significant and consistent improvements to Large Vision-Language Models (LVLMs). The best results are **bold** and the second-best are underlined.

Method	LLM	MME^{P}	MMB	MMB^{CN}	MMVet	$SEED^{I}$	POPE	SQA^{I}	GQA	TextVQA
Low-resolution Multimodal Large Language Models										
InstructBLIP	Vicuna-7B	-	36.0	23.7	26.2	53.4	78.9	60.5	49.2	50.1
QwenVL	Qwen-7B	-	38.2	7.4	-	-	56.3	67.1	59.3	**63.8**
QwenVL-Chat	Qwen-7B	1487	60.6	56.7	-	-	-	67.2	57.5	61.5
mPLUG-Owl2	LLaMA2-7B	1450	64.5	60.3	36.5	-	-	68.7	56.1	58.2
InternVL-Chat	Vicuna-7B	1525	-	-	-	-	86.4	-	62.9	57.0
LVIS-4V	Vicuna-7B	1473	67.1	-	34.6	-	84.0	68.4	62.6	-
ShareGPT4V	Vicuna-7B	1567	68.8	62.2	37.6	69.7	85.7	68.4	63.3	60.4
LLaVA-1.5	Vicuna-7B	1510	64.3	58.3	31.1	66.2	85.9	66.8	62.0	58.2
LLaVA-1.5(Ours)	Vicuna-7B	**1574**	70.7	62.8	37.9	70.1	87.3	70.1	**64.4**	61.7
LLaVA-1.5	LLaMA3-8B	1553	72.8	-	34.9	69.2	85.0	72.3	63.8	-
LLaVA-1.5(Ours)	LLaMA3-8B	1561	**73.8**	**68.9**	**39.6**	**73.0**	**87.6**	**74.1**	64.2	61.8
High-resolution Multimodal Large Language Models										
LLaVA-NEXT	Vicuna-7B	1519	67.4	60.6	43.9	70.2	86.5	70.1	64.2	64.9
LLaVA-NEXT(Ours)	Vicuna-7B	1528	68.8	60.8	**44.6**	72.0	**88.4**	71.4	65.0	69.9
LLaVA-NEXT	LLaMA3-8B	1591	72.6	69.0	42.1	72.7	86.8	73.4	64.8	65.0
LLaVA-NEXT(Ours)	LLaMA3-8B	**1596**	**74.4**	**69.8**	42.8	**75.0**	**88.4**	**78.7**	**65.6**	**71.0**

proposed in this paper, we generate 1.5M high-quality image description data to validate the effectiveness of our dataset. Our training strategy is divided into the following three stages: **(1) Pre-alignment Stage:** In this stage, we use the 1.5M high-quality captions generated by our proposed pipeline as training data. The visual encoder and the LLM are frozen, and only the MLP is trainable. **(2) Pre-training Stage:** In this stage, we continue to use the 1.5M high-quality captions from the pre-alignment stage as training data. For LLaVA-1.5, following the approach of SharGPT4V (Chen et al., 2023b), we make the last 12 layers of the visual encoder, the MLP, and the LLM trainable. For LLaVA-NeXT, following the settings in (Li et al., 2024a), we make the entire model trainable to further enhance its perceptual capabilities. **(3) Instruction Finetuning Stage:** In this stage, we finetune the LLaVA-1.5 and LLaVA-NeXT models using the open-source LLaVA-mix-665K and LLaVA-NeXT-760K datasets, respectively. We make the MLP and the LLM trainable. The detailed training procedure is provided in the appendix A.4.

Evaluation Benchmarks. We evaluate the model's performance on 9 widely used visual understanding benchmarks, including MME (Fu et al., 2023), GQA (Hudson and Manning, 2019), TextVQA (Singh et al., 2019), SQA (Lu et al., 2022), MMBench (Liu et al., 2023d), MMBench-CN (Liu et al., 2023d), MM-Vet (Yu et al., 2023b), SEED (Li et al., 2023a), and POPE (Li et al., 2023b). These benchmarks cover a broad range of evaluation dimensions, such as visual reasoning, scene understanding, and scientific reasoning.

5.2 Main Results

The main result as Table 1. The experimental results indicate that the high-quality caption pre-training data generated by our pipeline significantly enhances the capabilities of LVLMs, demonstrating clear advantages on most visual-language benchmarks. Furthermore, compared to other image captioning methods, such as ShareGPT4V, our method provides more fine-grained and complex image descriptions by integrating additional visual auxiliary information. The introduction of a post-processing mechanism further reduces hallucinations in the captions, which contributes to improved alignment of the visual and linguistic modalities. Consequently, our method shows more pronounced advantages in fine-grained image understanding and hallucination benchmarks, such as TextVQA (Singh et al., 2019), MM-Vet (Yu et al., 2023b), and POPE (Li et al., 2023b).

5.3 Ablation Studies

To thoroughly validate the effectiveness of the pre-processing and post-processing pipeline, we design two different ablation experiments and used two distinct standards for validation.

Caption Benchmark. Traditional image caption evaluation metrics like CIDER (Vedantam et al., 2015), BLEU (Papineni et al., 2002), ROUGE-L (Lin, 2004), and METEOR (Banerjee and Lavie,

Table 2: **Results on the CompreCap Benchmark.** During the pre-processing stage, our approach significantly enhances the comprehensiveness of captions (measured by object and pixel coverage) compared to the baseline (**Note:** The baseline refers to Qwen2VL-7B, which we use to finetune the image captioner model during the pre-processing stage). During the post-processing stage, we can further eliminate hallucinations in the captions (measured by object and relation scores). Our method even surpasses the advanced GPT4o in some dimensions.

Method	Caption Length(words)	object coverage(%)	pixel coverage(%)	object score(0∼5)	relation score(0∼5)
Baseline (Qwen2-VL-7B)	143.66	71.97	57.31	2.56	2.71
Pre-processing Captioner	153.84	74.37	63.01	2.79	2.73
+ DPO	174.06	75.76	63.14	2.81	2.73
+ DPO + Critic-rewrite	171.65	75.96	**63.19**	**2.84**	2.77
GPT-4o	108.20	72.78	57.54	2.58	2.93
Human	133.61	**77.62**	59.58	2.78	**2.99**

Table 3: **Manual Quality Analysis.** Statistics of the equivalence rate between the output captions of different method and the reference captions, where 'Overall' represents the average equivalence rate across different dimensions. During the pre-processing stage, our method significantly enhances the comprehensiveness of captions compared to the baseline. Through the post-processing stage, we can further eliminate hallucinations in the captions.

Method	Completeness(%)	Hallucination(%)	Text Quality(%)	Overall(%)
Baseline (Qwen2-VL-7B)	27.0	52.5	98.3	59.3
Pre-processing Captioner	64.4	63.5	92.5	73.5
+ DPO	64.8	71.3	**99.5**	78.5
+ DPO + Critic-rewrite	**68.6**	**73.0**	97.8	**79.8**

2005) rely on n-gram techniques, which are sensitive to caption styles and don't always reflect caption quality. Pre-trained CLIP models also struggle with longer captions. In contrast, CompreCap (Lu et al., 2024) is a structured benchmark that evaluates detailed image descriptions using a scene graph, focusing on object, attribute, and relationship matching. As shown in Table 2, we compare our method with advanced GPT-4o and human annotators on the CompreCap dataset and conduct an ablation study. The results demonstrate that our method not only matches but also surpasses GPT-4o in some dimensions, approaching the performance of human annotators. Moreover, the incorporation of pre-processing and post-processing significantly enhances the quality of generated captions and overall performance on CompreCap.

Manual Quality Analysis. To better validate the effectiveness of our caption generation pipeline, we introduce human evaluation to further assess the quality of the generated captions. Specifically, following the classification system proposed in Section 3.1, we select approximately 20 images from each category, forming an evaluation set of 411 images in total. First, we use GPT-4o to generate captions for all images in the evaluation set, which are then manually revised and supplemented to form reference captions. After the test model generates its captions, human quality inspectors compare each test caption with the reference caption, evaluating them across three main dimensions: **completeness** (whether the test caption omits any details from the image), **hallucination** (whether the test caption contains incorrect descriptions or fabricated content), and **text quality** (whether the test caption is grammatically correct, fluent, and free of major expression issues). The inspectors assess whether the test captions meet or exceed the quality of the reference captions in these dimensions. Finally, we calculate the equivalence rate, and the test results are shown in Table 3.

6 Conclusion

We propose an effective pipeline for generating high-quality, ultra-detailed image captions that significantly improve the performance of LVLMs. By integrating pre-processing and post-processing stage, we enhance the accuracy and comprehensiveness of captions, addressing the limitations of existing datasets. Our experiments show that these high-quality captions boost LVLMs performance across various vision-language tasks, achieving better alignment between visual content and text. This work provides a scalable solution for improving LVLMs capabilities and lays the foundation for future advancements in multimodal learning.

Limitations

Although the pipeline we proposed is capable of generating high-quality, ultra-detailed image caption data, there are still some limitations. Future optimization directions mainly focus on two aspects:

First, modality expansion. Currently, our pipeline primarily focuses on generating and optimizing captions for natural images. However, many methods and ideas have not yet been applied to other modalities, such as video data. Therefore, expanding the image caption generation pipeline to support more modalities will be a key area of future work.

Second, optimization and iteration of the image captioning model. Through the pre-processing and post-processing pipelines, we have made progress in improving the quality of image caption data. However, optimizing the performance of the image captioning model remains a priority. The current caption generation process is relatively complex, requiring the construction of a long pipeline for subsequent data expansion, which complicates practical deployment and application. In the future, we plan to integrate the different functions of the pipeline into a unified image captioning model, simplifying the entire process and making it more suitable for real-world deployment and application.

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A Training Setting Details.

All training and inference experiments are conducted on 64 × Ascend 910b NPUs.

A.1 Captioner Model Training Details

We use the Qwen2VL-7B model and the preprocessed 320K high-quality seed dataset to fine-tune a proprietary image captioner model. The specific experimental settings are presented in Table 4.

Table 4: Hyperparameter Details for Training the Captioner Model

Hyperparameter	Settings
DeepSpeed Stage	3
Warmup Ratio	0.03
Trainable Module	LLM
Epoch	1
LR Schedule	cosine
Learning Rate	1e-5
Image Resolution	1024
Batch Size	128
Cutoff Len	6144

A.2 Captioner Model DPO Training Details

We use 70K human-corrected high-quality image caption preference pairs to perform DPO training on the pre-processing stage captioner model, further enhancing its capabilities. The specific hyperparameter settings are shown in Table 5.

A.3 Sentence-level Critic Model Training Details

We use the Qwen2VL-7B model and 120K high-quality critic data to train a specialized sentence-level critic model. The specific experimental settings are presented in Table 6.

A.4 LLaVA-1.5 and LLaVA-NEXT Training Details

The main training implementation details are described in the primary paper. In this section, we present a detailed explanation of the experimental setup used to train LLaVA-1.5 and LLaVA-NeXT for evaluating our dataset, as shown in Table 7 and Table 8.

Table 5: Hyperparameter Details for DPO Training of the Captioner Model

Hyperparameter	Settings
DeepSpeed Stage	3
Warmup Ratio	0.1
KL Penalty Coefficient β	0.1
Loss Weights α_1, α_2, α_3	0.8, 1.0, 0.2
Trainable Module	LLM
Epoch	1
LR Schedule	cosine
Learning Rate	5e-6
Image Resolution	1024
Batch Size	64
Cutoff Len	6144

Table 6: Hyperparameter Details for Training the Critic Model

Hyperparameter	Settings
DeepSpeed Stage	3
Warmup Ratio	0.1
Trainable Module	LLM
Epoch	1
LR Schedule	cosine
Learning Rate	1e-5
Image Resolution	1024
Batch Size	64
Cutoff Len	6144

B Visualizations of Our Dataset

B.1 Image Classification Framework

To create a comprehensive and high-quality dataset that encompasses diverse image categories and rich visual semantics, we carefully curate and build a multi-dimensional dataset consisting of 7 main categories and 22 subcategories. During the pre-processing stage, We classify and deduplicate to select approximately 320K high-quality image samples, with the detailed category distribution shown in Figure 4.

B.2 Case Analysis

In this section, to provide a more comprehensive demonstration of the high-quality image captions

Table 7: Detailed Experimental Setup for LLaVA-1.5

Hyperparameter	Pre-aligning	Pre-training	Instruction Tuning
Data	1.5M caption(Ours)	1.5M caption(Ours)	LLaVA-mix-665K
Batch Size	256	256	128
Learning Rate	1e-3	2e-5(MLP, LLM), 2e-6(VE)	2e-5
LR Schedule		cosine decay	
LR Warmup Ratio		0.01	
Weight Decay		0	
Trainable Module	MLP	MLP, VE(last 12 layers), LLM	MLP, LLM
Epoch		1	
Optimizer		AdamW	
DeepSpeed stage		3	

Table 8: Detailed Experimental Setup for LLaVA-NEXT

Hyperparameter	Pre-aligning	Pre-training	Instruction Tuning
Data	1.5M caption(Ours)	1.5M caption(Ours)	LLaVA-NeXT-760K
Batch Size	256	256	128
Learning Rate	1e-3	2e-5(MLP, LLM), 2e-6(VE)	2e-5
LR Schedule		cosine decay	
LR Warmup Ratio		0.01	
Weight Decay		0	
Trainable Module	MLP	MLP, VE, LLM	MLP, LLM
Epoch		1	
Optimizer		AdamW	
DeepSpeed stage		3	

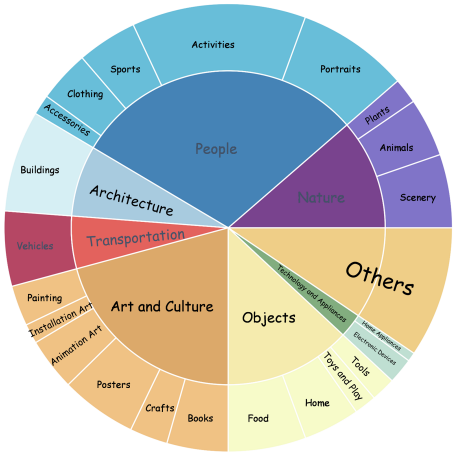

Figure 4: The category distribution of high-quality image data during pre-processing stage.

generated by our pipeline, we offer additional examples. Furthermore, to better showcase the performance of these high-quality captions across different ability dimensions, we employ different color annotations to highlight key elements. Specifically, objects are marked in blue, spatial relations in green, textual information in pink, and knowledge are distinguished using yellow, which facilitates a clearer presentation and understanding of the characteristics of each dimension.

C Prompt Template

This image showcases a promotional poster for an illustrated storybook about St. Francis. On the left side, there is an illustration of a young man smiling, dressed in a robe, surrounded by green plants and several small birds. These birds are brightly colored, with orange and brown feathers that appear particularly vibrant in the sunlight.The background is a bright yellow, creating a warm feeling. On the right side is the text section, with the title "ST. FRANCIS OF ASSISI", illustrated by Lore Obreja. The text introduces the story of St. Francis: "This saint, born into a wealthy family, devoted his riches to the poor and formed bonds with animals, becoming a beloved figure in the Hecapuchin Academy worldwide". Below the text, there is encouragement for people to support a new illustrated children's storybook titled "Holy Troublemakers & Unconventional Saints", which is currently crowdfunding on Kickstarter. At the bottom of the poster, there is a URL link directing to the Kickstarter page. The overall design combines artistic illustrations and textual information, conveying a vibrant and hopeful atmosphere that draws readers' attention to the publication of this book.

In this image, we see the interior of a large white tent, with the ground covered in green artificial grass, creating an outdoor activity atmosphere. Inside the tent, there is a black chalkboard with the words "TATA TENT EVENT TIME" written in white chalk, along with the time "182 17:30" and the name "Yanis Varoufakis". The chalkboard is placed on a wooden easel, making it prominent and eye-catching.
In the background, multiple blue signs displaying "TATA TENT" are neatly arranged around the venue, forming an orderly area. The entire scene is well-lit, likely during the day, with bright lights inside the tent ensuring the smooth progress of the event. At the center of the image, there is a line of text stating "Copyright Athena Picture Agency Ltd," indicating that this is a copyrighted photograph. Overall, the image conveys a sense of preparation for an upcoming event, set in a spacious tent with a clean and organized environment.

In this image, we see a beautifully decorated blackboard wall located in an indoor environment. Various summer-themed patterns and texts are drawn on the blackboard with white chalk. In the center, it reads "KIABI", with the French phrase "la mode à petits prix" below, meaning "fashion at small prices". Next to it, "VACACIONES" is written in capital letters, meaning "vacation".
Above the blackboard, there is a drawing of a sun, symbolizing sunny weather. Beside the sun is a rainbow, adding a whimsical touch. On the right side, there is a drink cup with a straw, hinting at a summer beverage theme. In the lower left corner, there is a slice of watermelon next to a lifebuoy, further emphasizing the beach and vacation atmosphere.
In the lower right corner of the blackboard, an open umbrella symbolizes shade and coolness. Nearby, there are several stars and a starfish, creating an oceanic feel. The lower left corner features another slice of watermelon, echoing the designs above. The background of the entire scene is a room with a colorful square carpet that adds vibrancy to the atmosphere. The walls are painted in simple colors, highlighting the patterns and texts on the blackboard. The overall ambiance is relaxed and cheerful, filled with the essence of summer.

Figure 5: The high-quality image caption data samples generated by our pipeline.

This image depicts a tranquil and beautiful countryside landscape, set against a vast valley backdrop where the sun is slowly rising in the distance, tinting the sky with hues of red and adding a warm golden glow to the entire scene. In the foreground, a lush green meadow is visible, with several sheep leisurely grazing, creating a harmonious and natural atmosphere.
On the right side of the painting, a small grove of trees can be seen, neatly arranged to form a natural barrier. In the distance, rolling hills are faintly visible on the horizon, adding depth and layers to the composition.
In the top left corner of the image, there is a text area stating, "10% of sales donated to Teesdale and Weardale Search & Mountain Rescue Team", indicating that a portion of the sales will be donated to the rescue team. The bottom right corner features the text "TEESDALE 2022 ANDY BECK images", marking this as the cover of the Teesdale calendar for 2022, photographed by Andy Beck. Overall, this image conveys a sense of tranquility and peace in the countryside through its soft colors and natural composition, while also expressing support and gratitude for the rescue team.

In this image, the left side features a child's drawing, while the right side presents a doll inspired by the artwork. The drawing was created by a four-year-old child, whose name is "Keadryn". The character in the drawing is a simple line art on a light yellow background, with large blue eyes and a smiling expression. The hair is outlined in thick blue lines, giving it a lively and cute appearance.
The doll on the right resembles the character from the drawing, using the same colors and style. The doll has a round body and a larger head, with similarly large blue eyes and a smiling mouth. Its hair is a deep blue, styled to appear as if a few strands are sticking up, adding a playful touch. The doll is dressed in blue clothing, with a blue bow tied around its waist, creating a lively and interesting overall design.
The background is a soft blue that complements the colors of the doll, creating a warm atmosphere. The entire composition is filled with childlike charm and creativity, showcasing a clever transformation from artwork to a tangible object.

In this image, we see a sailboat sailing on the ocean. The hull of the sailboat is white, with the logo "@allen" printed on it. There are several people in wetsuits on board, actively maneuvering the vessel. The sail is gray, displaying the number "900," along with the words "Datchet Flyer".
In the background, the sea appears deep blue, shimmering in the sunlight, indicating clear weather suitable for sailing. There are other sailboats in the distance, suggesting that this is a scene from a sailing competition or event.
At the top of the image, there is text information: "GJWDirect All-inclusive Dinghy Insurance" and "SAILJUICE.COM WINTER SERIES0", indicating that this may be part of a winter series sailing insurance event. In the bottom right corner, the photographer's name "Tim Olin" is noted.
Overall, this image captures a vibrant sailing competition scene, with participants focused on maneuvering their boats, while the ocean and sky in the background add a natural beauty to the entire composition.

Figure 6: The high-quality image caption data samples generated by our pipeline.

Prompt for Generating Captions Through Multimodal Information Fusion

You are an experienced image description expert, skilled in extracting details from images and transforming them into vivid and accurate written descriptions. Your task is to generate a detailed and coherent description based on the image and the provided visual assistive information, ensuring that all important elements of the image are covered. Please note that the visual assistive information may not be complete, and you will need to supplement the missing details based on visual clues from the image.

Requirements:
1. Object Appearance Description: Accurately describe the color, shape, quantity, size, function, and state of the objects in the image.
2. Behavior and Action: Capture the state, actions, and results of the behaviors of the objects in the image, describing both dynamic and static features.
3. Background and Environment: Describe the background environment, including the scene, lighting, weather, location, environmental details, dynamic/static elements, and overall atmosphere.
4. Text Information: Identify text in the image, including its content and location. You can use the provided OCR information to ensure it is accurately integrated into the description.

Visual Assistive Information:
Object Location Information: {Object Location Information}
Textual Information: {Textual Information}
Image World Knowledge: {Image World Knowledge}

Constraints:
1. Narrative Description: Please describe the image content in a coherent narrative format, avoiding a list structure.
2. Accuracy and Completeness: Ensure the description is accurate and as complete as possible, covering all important details.
3. Natural Flow: Keep the description natural and fluent, avoiding overly technical or mechanical language.

Goal:
To generate a detailed, accurate, and coherent description that covers all important elements in the image, including the appearance of objects, actions, background environment, and textual information. The description should be clear and easy to understand, allowing readers to accurately grasp the content of the image without actually seeing it.

Figure 7: Prompt for Generating Captions Through Multimodal Information Fusion.

Prompt for Expanding Image Details base LLMs

You're an excellent visual language assistant. You will receive an image description and some visual auxiliary information. To further enhance the comprehensiveness of the image description, you need to make reasonable speculations and further expansions based on the following dimensions. Please tell me what details I need to focus on to describe the image more comprehensively based on the original image description:

The multi-dimensional dimensions include:
1. Scene Type and Settings: including location, time, weather/light conditions, environment details, dynamic/static elements, and atmosphere.
2. Spatial Layout and Relationships: including relative position, height/distance/level/angle/direction, arrangement, interaction and connection of objects, etc.
3. Object Properties and Features: including color, shape, material, size, function, status, etc.
4. Text and Symbol Information: including text/symbol content, position, font style and color, language, meaning and function.
5. Emotion and Atmosphere: including emotional expression, atmosphere building, backstory, etc.
6. Temporal Context: including seasons, time periods, historical periods, weather conditions, day and night alternation, etc.
7. Cultural and Social Background: including identifying elements such as geographical location, historical background, religious beliefs, architectural styles, costumes and decorations, language and writing, art and music, social customs, food culture and festivals.
8. Visual Style and Aesthetics: including color collocation, light and shadow effect, overall design style, etc.

You need to dynamically select the dimensions you should pay attention to based on the specific image information, that is, select the appropriate dimensions based on the image content, including but not limited to the dimensions mentioned above. Note that the output needs to be presented in the form of questions.

The following is an example:
{example}

Auxiliary Information:
Object Location Information: {Object Location Information}
Textual Information: {Textual Information}
Image World Knowledge: {Image World Knowledge}

Original image description:
{Original Image Description}

To describe this image more comprehensively, you need to pay attention to the following details:

Figure 8: Prompt for Expanding Image Details base LLMs.

Example of Expanding Image Details Using LLMs

Object Location Information:
cat[0.15, 0.42, 0.28, 0.85] dog[0.55, 0.36, 0.78, 0.91] sofa[0.12, 0.60, 0.90, 0.95]
window[0.00, 0.00, 1.00, 0.40] boy[0.40, 0.50, 0.55, 0.85] girl[0.60, 0.50, 0.75, 0.85]
Textual Information:
None
Original Image Description:
This image shows a family living room with a cat and a dog in the room, with the cat lying on the sofa and the dog sitting on the carpet. There is a window in the room, from which you can see some sunlight coming in, bringing a warm light to the room. A boy and a girl sat on the ground, playing on the toys, looking happy. Some pillows are placed on the sofa, some simple cutlery on the table, the TV is off, and the background is simple and warm.

To describe this image more comprehensively, you need to pay attention to the following details:
1. Scene type and setting: Apart from sofas, dining tables and televisions, what other furniture or objects are key elements of this picture? What are the materials or colors of these items? Are there curtains installed outside the window?
2. Space layout and relationship: What is the layout between sofas, carpets, windows and other items? How do boys and girls relate to the location of sofas, televisions and windows? Are you close or far away from these items?
3. Object attributes and features: What is the color and material of the sofa? Is there anything particularly conspicuous on the sofa, such as a pillow or blanket? What color is the hair of cats and dogs? What is the color, shape and state of other items such as televisions, windows, dining tables, etc.?
4. Behaviors and Events: What are the movements of boys and girls? Are they playing attentively, talking, or exhibiting other behaviors (such as scrambling for toys)?
5. Cultural and social background: What may be the cultural background of the family from the perspective of the home environment? Does the style of furniture and objects reflect a particular social or cultural characteristic (e.g., modern minimalism or traditional decorative style)?

Figure 9: Example of Expanding Image Details Using LLMs.

Prompt for Further Expanding the Image Descriptions based on LLMs Result

You are an experienced image description expert, skilled in extracting details from images and transforming them into vivid, accurate text descriptions. Your task is to generate a detailed and coherent description of the image based on the image, visual auxiliary information, the original image description, and any additional details that require further attention. Ensure that all key elements of the image are included.

Visual auxiliary information:
Object Location Information: {Object Location Information}
Textual Information: {Textual Information}
Image World Knowledge: {Image World Knowledge}

Original image description:
{Original Image Description}

You need to pay further attention to the following details:
{LLM-based Expansion Result}

Ensure that the final image description contains all the details mentioned above and meets the following requirements:
1. Narrative description: Present the image content in a coherent, narrative format rather than as a list.
2. Accuracy and Completeness: Ensure that the description is accurate and as complete as possible, covering all of the aforementioned key details.
3. Naturally smooth: Maintain a natural and fluid description, avoiding overly technical or mechanical language.
4. Clear and easy to understand: Make the description clear and easy to understand, allowing readers to grasp the image's content without actually seeing it.

Goal:
Generate a detailed, accurate, and coherent description that covers all important elements of the image, including the appearance, behavior, background environment, and text information of the objects. The description should be clear and easy to understand, enabling the reader to fully comprehend the image's content through text alone.

Figure 10: Prompt for Further Expanding the Image Descriptions based on LLMs Result.

Prompt for Atomic Description Generation

You are an excellent visual language assistant. Please decompose the received image description according to the following requirements, generating a series of atomic descriptions.

Requirements:
1. Each atomic fact sentence should focus on the main visual details and specific facts, excluding non-visual information and subjective emotions.
2. The reference relationship in the atomic description must be clear, ensuring that each description can independently point to the object in the image, avoiding ambiguity that leads to unclear semantics.
3. Ensure that each atomic fact is as independent and specific as possible.

Image Description: {Image Description}

Figure 11: Prompt for Atomic Description Generation.

Prompt for Coarse-grained Error Rationale Generation

You are an excellent visual language assistant. You will receive an image and two text descriptions. One of the descriptions is the standard text description that accurately reflects the content of the image; the other description contains some inconsistencies with the image content. Please carefully compare these two text descriptions, focusing on the following aspects: the color, shape, quantity, size, function, and state of objects; the state, actions, and results of the objects' behavior; the details of the scene and environment; and the location and content of any text information. Based on the comparison, please identify the key reasons for the discrepancies between the second image description and the actual image content.

Human-corrected Image Description: {Human-corrected Image Description}
Original Image Description: {Original Image Description}

Figure 12: Prompt for Coarse-grained Error Rationale Generation.

Prompt for Fine-grained Critic Data Generation

You are an excellent visual language assistant. You will receive an image and a sentence. Please carefully check whether the sentence aligns with the image content, following the steps outlined below:

Task Steps:
1. Analyze the sentence content: List all the key points that need verification, such as: object quantity, color, positional relationships, status, interaction actions, textual information, etc. List all the visual details that need to be checked.
2. Check each point: Verify each key point description and compare it with the image content one by one. If discrepancies are found, explain in detail where the conflict lies, and clearly describe the actual content in the image.
3. Summarize the reasoning: Summarize the results of the check, indicating which parts of the sentence match or do not match the image content. Provide clear reasons for any inconsistencies, and specify the true visual content in the image.

Notes:
1. Detailed comparison: Check each point against the image content carefully, making sure no detail is overlooked.
2. Clear explanation: If the sentence matches the image content exactly, state this directly; if inconsistencies are found, describe the conflict clearly and specifically.
3. Complex content: If the image content is complex, break down the check into bullet points to ensure clarity and logical structure.
4. Proper language: Use clear, formal language to describe the issues found, providing adequate justification.

Additional Tips:
Common errors in the sentence may include: {Coarse-grained Error Cause}
Sentence to be checked: {Atomic Sentence}

Figure 13: Prompt for Fine-grained Critic Data Generation.

Prompt for Rewrite of Captions

You are an excellent visual language assistant. You will receive an image and its original text description. The description contains some inconsistencies with the image content. I will provide you with a series of atomic sentences and their corresponding comments. Please rewrite the original image description based on these atomic sentences and comments, ensuring that the new description accurately reflects the image content.

Original Image Description: {Original Image Description}
Atomic Sentence and Critic: {Atomic Sentence and Critic}

Figure 14: Prompt for Rewrite of Captions.