Debias-DAPO: Mitigating Unimodal Bias in Multi-modal Large Language Models via Attention-Based Reward and Modality-Balanced Learning

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Abstract

Multi-modal Large Language Models (MLLMs) have made significant progress in various applications but still suffer from unimodal bias, particularly "textual supremacy and visual neglect," leading to multimodal hallucinations. To address this challenge, we propose an enhancement to the DAPO algorithm, Debias-DAPO, which introduces attention-anchored hard negative mining and preference-shaping term that operates only over high-quality responses to correct answers that excessively rely on text. By calculating the ratio of per-token attention between text and visual modalities, we quantify unimodal bias. The reward function incentivizes responses grounded in vision while penalizing excessive text dependence, directly addressing harmful text biases. Meanwhile, by token-weighted advantage distribution using attention-derived evidence weights, optimization is refocused on key output tokens grounded in visual evidence. This ensures gradient updates prioritize visual information, encouraging the model to base its reasoning on images. Additionally, we introduce the first modality-balanced dataset, designed to overcome limitations in existing multimodal datasets. This dataset includes multimodal data where the multimodal response is correct, but unimodal responses are incorrect, along with manually verified contradictory image-text pairs and Chain of Thought (CoT) data. The goal is to encourage models to reason using both modalities effectively. Extensive experiments validate Debias-DAPO, demonstrating that it maintains visual grounding while effectively suppressing text bias drift, outperforming strong DAPO baselines. ß

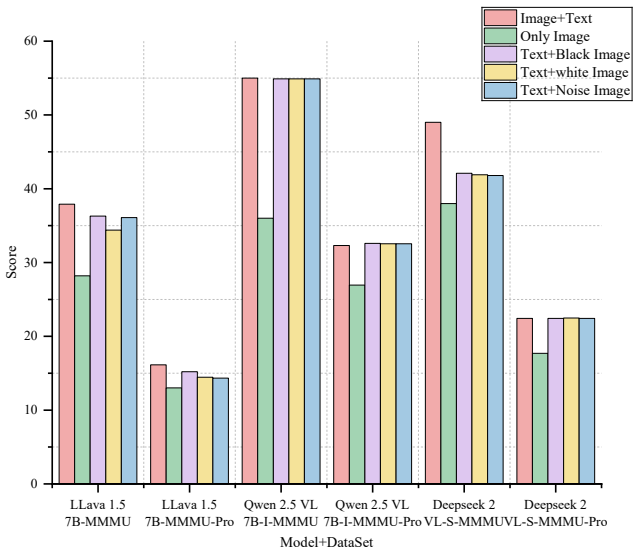
1. Introduction

Recent advancements in Multimodal Large Language Models (MLLMs) have led to significant progress across various tasks [**?**]. By integrating multiple modalities, such as text, audio, and images, these models have proven effective across diverse domains. However, a persistent challenge remains: MLLMs often exhibit unimodal bias, favoring one modality—typically text—while neglecting others. This bias can lead to over-reliance on a single modality, causing the model to generate responses that seem confident but are inaccurate or biased when information from less dominant modalities is missing or incorrect.

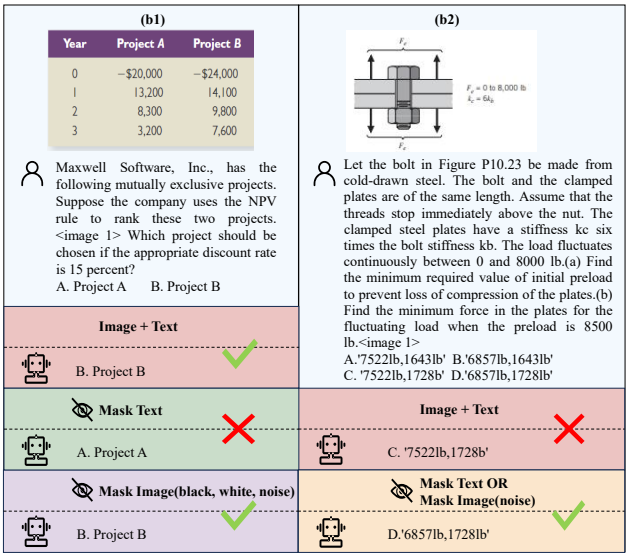
As illustrated in Fig. **??**(a), MLLMs commonly demonstrate uneven reliance on input modalities, with a clear text-dominant bias. For example, models like LLaVA ([11]), Qwen-VL ([2]), and DeepSeek-VL ([26]) produce correct answers with text-image inputs, but fail when only visual inputs are provided. In more extreme cases, models generate incorrect answers with text-image pairs but succeed with text-only inputs, ignoring the visual modality entirely (Fig. **??**(b2)). This paradox underscores the issue: the model relies excessively on text, sidelining visual information even when it is crucial for accuracy. These biases prevent the model from fully exploiting multimodal information and lead to overconfident errors when non-dominant modalities are absent or degraded. The ideal MLLM should integrate information from all modalities to ensure robust, accurate responses in a variety of conditions.

To mitigate this issue, existing approaches have attempted to balance modality usage by altering dataset distributions [32], applying causal interventions [3], and debiasing during training [16]. However, these solutions often require large-scale supervised fine-tuning and show limited generalization. To address these limitations, we introduce the **first dedicated unimodal bias dataset**, designed to address current benchmarks' shortcomings and facilitate better multimodal integration.

Building on existing datasets like A-OKVQA [20], VisRAG-Ret-Test-ArxivQA [27], and TextVQA [22], we develop a novel data construction methodology. Our approach introduces modal conflicts by perturbing complementary modalities, forcing models to reason effectively in scenarios involving unimodal bias and conflict. The resulting **Debiased Multimodal Dataset** includes two crucial subsets: multimodal correct data and modality-conflicting samples. The multimodal correct subset retains only sam-



(a) Dataset vs. accuracy



(b) Ablation study

Figure 1. Overall caption for the two panels.

ples that require simultaneous use of both text and image information to generate correct answers. The modality-conflicting subset consists of data where the visual and textual information contradict each other, manually verified for quality.

To further tackle unimodal bias, we extend the DAPO framework ([**?**]) by introducing a bias-specific reward function. This reward function integrates modality-balance and task-accuracy rewards, encouraging models to focus on both visual and textual information. Additionally, we introduce **Chain-of-Thought (CoT)** reasoning to guide the model's stepwise decision-making, improving robustness in challenging tasks.

We evaluate our approach using models such as Qwen2.5-VL-7B-Instruct [2], LLaVA-1.5 [11], and DeepSeek-VL2-small [26]. We train the models using the generated Debiased Multimodal Dataset and assess performance on both VLind-Bench [9] and standard hallucination benchmarks, including MMHalBench [23], AMBER [24], and CHAIR [18]. Our method significantly outperforms baseline models like NAPO ([29]) in terms of accuracy and hallucination reduction, demonstrating the effectiveness of the **Debiased Multimodal Dataset** and the enhanced DAPO algorithm.

2. Related work

2.1. Unimodal bias in MLLMs

In recent years, significant advancements have been made in MLLMs([6]),[4],[8]. Unimodal bias occurs when models prioritize simple patterns within a single modality while neglecting the strengths of other modalities, leading to performance degradation and hallucinations when modalities are missing during inference [33]. For instance, prompt text significantly influences the performance of many state-of-the-art multimodal models. Model performance improves substantially when textual prompts are included, but degrades drastically without this modality. In recent years, significant advancements have been made in MLLMs([6]),[4],[8]. Unimodal bias occurs when models prioritize simple patterns within a single modality while neglecting the strengths of other modalities, leading to performance degradation and hallucinations when modalities are missing during inference [33]. For instance, prompt text significantly influences the performance of many state-of-the-art multimodal models. Model performance improves substantially when textual prompts are included, but degrades drastically without this modality. Various methods have been proposed to quantify and mitigate unimodal bias in VQA tasks, with a focus on balancing datasets [32] and complex training strategies [7] [31] [30]. Recent research includes modality bias evaluation benchmarks [9], datasets for modality bias [15], weight adjustments [12], prompting strategies [5], Preference Optimization [31], [30], and decoding configurations to reduce language priors [14] [28]. Preference Optimization fine-tunes models with human feedback to align outputs with human expectations. Recent work, like Noise-robust Alignment with Preference Optimization (NAPO) [29], incorporates noise-robust mechanisms into the Direct Preference Optimization (DPO) framework [17], which corrects errors but does not fundamentally change the model's capabilities. The Shortcut-aware MM-RM algorithm [**?**] mitigates out-of-distribution

generalization deficits caused by over-reliance on unimodal textual correlations. *By contrast, we introduce a dataset for determining whether the modality is balanced, while optimizing the reward model and sampling mechanism of the **GRPO** [21] algorithm to mitigate unimodal bias and hallucination.*

2.2. MLLMs Post Training with RL

Reinforcement learning (RL) develops intelligent agents by learning optimal policies through trial-and-error interactions to maximize rewards. Recently, RL has seen significant progress in multimodal large models. Proximal Policy Optimization (PPO) ([19]) is a policy-gradient algorithm that stabilizes training by constraining policy update magnitudes. ReMax is an off-policy RL algorithm that optimizes the policy via a "relative policy improvement" mechanism, avoiding the complex and unstable evaluation steps of conventional methods [10]. More recently, Grouped Relative Policy Optimization (GRPO) [21] improves policy optimization efficiency by using grouped updates and relative entropy constraints, reducing repetitive calculations and balancing exploration and exploitation. Despite these advancements, a critical issue remains: modality imbalance, which can significantly impact the contribution of each modality to the reward function.

3. Method

3.1. Preliminary

3.1.1. DAPO

DAPO (Decoupled Clip and Dynamic Sampling Policy Optimization) [**?**] is an open-source reinforcement learning system and engineering framework designed to support efficient, reproducible, and scalable complex reasoning tasks with large language models (LLMs). The efficacy of the proposed approach is comparable to or superior to conventional methods in terms of performance, whilst concomitantly enhancing the efficiency of training and reducing computational expenses. It is noteworthy that the DAPO model outperforms the GRPO model despite utilising a mere half of the training steps.

While maintaining GRPO's utilisation of intra-group relative rewards and a clipped objective, DAPO incorporates four pivotal engineering enhancements: The following techniques are employed: clip-higher dynamic sampling, token-level loss, and overlong reward shaping. The KL penalty term is also removed. These innovations effectively address several limitations of GRPO, including entropy collapse, gradient wastage, and weight dilution in long-horizon reasoning tasks, leading to more stable and efficient training.

As a result, DAPO delivers superior performance, accelerated training convergence, enhanced stability, and improved reproducibility. Its efficacy has been demonstrated through successful implementation in a range of large-scale model deployments [**?**]. The objective function of DAPO is given by:

$$\mathcal{J}_{\text{DAPO}}(\theta) = \mathbb{E}\big[(q,a)\sim\mathcal{D},\ \{o_i\}_{i=1}^{G}\sim\pi_{\theta_{\text{old}}}(\cdot|q)\big] \left[\frac{1}{\sum_{i=1}^{G}|o_i|}\sum_{i=1}^{G}\sum_{t=1}^{|o_i|}\min\Big(r_{i,t}(\theta)\hat{A}_{i,t},\ \text{clip}\Big(r_{i,t}(\theta),1-\varepsilon_{\text{low}},1+\varepsilon_{\text{high}}\Big)\hat{A}_{i,t}\Big)\right] \tag{1}$$

$$\text{s.t.}\ \ 0 < \Big|\{o_i \mid \texttt{is\_equivalent}(a,o_i)\}\Big| < G$$

where

$$r_{i,t}(\theta) = \frac{\pi_\theta(o_{i,t}\mid q,o_{i,<t})}{\pi_{\theta_{\text{old}}}(o_{i,t}\mid q,o_{i,<t})}, \quad \hat{A}_{i,t} = \frac{R_i - \text{mean}(\{R_i\}_{i=1}^{G})}{\text{std}(\{R_i\}_{i=1}^{G})} \tag{2}$$

Randomly sample a question-answer pair (q, a) from the training dataset $\mathcal{D}$. Using the old policy model $\pi_{\theta_{\text{old}}}$, generate a set of G responses for question q. $\frac{1}{\sum_{i=1}^{G}|o_i|}\sum_{i=1}^{G}\sum_{t=1}^{|o_i|}$ indicates we will compute the loss for each token in every response, then normalize by the total number of tokens across all responses. $r_{i,t}$ measures the change in token selection probability between the new and old policies. The advantage function $\hat{A}_{i,t}$ measures how well the decision to generate this token performs relative to the average, given the question and historical context. The $\min\Big(r_{i,t}(\theta)\hat{A}_{i,t}, \text{clip}\Big(r_{i,t}(\theta),1-\varepsilon_{\text{low}},1+\varepsilon_{\text{high}}\Big)\hat{A}_{i,t}\Big)$ operation decouples and prunes the model. By actively encouraging exploration with a larger upper bound ε_{low} while strictly constraining the maximum step size of policy updates with a more conservative lower bound ε_{low}, it achieves a critical balance between improving performance and preventing training collapse, ensuring the stability of the training process.

3.1.2. Reward Function

DAPO employs a fully rule-driven reward function, moving away from the often unreliable neural network-based reward models typically used in traditional reinforcement learning. The fundamental principle of the method is to assign a binary reward of positive one or negative one, based solely on the final correctness of the generated answer. This straightforward reward scheme ensures strong alignment between the optimization objective and the task goal, effectively circumventing reward hacking. In order to regulate the output length, DAPO incorporates an adaptive length penalty mechanism. This mechanism progressively penalises responses that exceed a predefined threshold, thereby encouraging the model to generate concise answers without interfering with valid reasoning processes.

During the forward pass, DAPO deploys a meticulously structured batch sampling and training procedure. For each query, multiple responses are generated dynamically, and sample groups that cannot contribute meaningful gradient signals are filtered out strategically; this may include those that are entirely correct or entirely incorrect. Consequently, it is assured that every parameter update is informed by data of significant value. The advantage for each response is then computed using group-wise reward normalization, thereby eliminating the need for a complex value function. In the subsequent loss computation phase, DAPO employs a novel approach by implementing token-level policy optimisation and utilising decoupled clipping on importance sampling ratios. The amalgamation of these design choices ensures elevated stability and sample efficiency throughout the course of large-scale reinforcement learning training.

3.2. Debiased Multimodal Datasets

3.2.1. Overview

In this paper, we propose the first open-source resource designed dataset for achieving modality balance, namely Debiased Multi-Modal dataset **(DMM)**.

Recent research has revealed that unimodal bias arises from a model's over-reliance on one modality (textual or visual) while neglecting the other. To address this problem, we focus on enhancing inter-modal correlations and incorporates scenarios where modalities conflict. Extending beyond conventional visual question answering, our DMM dataset includes samples that require both visual and textual information for correct responses — cases that a single modality cannot adequately address. Meanwhile, our DMM dataset introduces conflicting samples where the textual and visual content diverge, thereby establishing a foundation for reward mechanisms based on modal equilibrium.

For each bimodal data sample and its corresponding conflicting sample in the training set, Chain-of-Thought (COT) [25] data is generated using GPT-4.1 [1]. The Debias dataset builds upon A-OKVQA [20], VisRAG-Ret-Test-ArxivQA[27], and TextVQA [22], covering a wide range of topics, including commonsense reasoning, encyclopedic knowledge, diagram interpretation, and physical principles. The dataset is partitioned into training and test sets containing 12,000 and 1,200 visual question–answer pairs respectively. Images are provided in JPG and PNG formats with resolutions ranging from 448 to 1024 pixels. In total, the dataset consists of 13,200 visual question-answer pairs. 91.67% of these represent unbiased examples. The remaining 8.33% comprise modality-conflicting instances.

3.2.2. Dataset Construction

Data Design for Enhanced Modality Complementarity. We introduce a filtering process based on the OK-VQA ([13]), A-OKVQA ([20]), VisRAG-Ret-Test-ArxivQA[27]

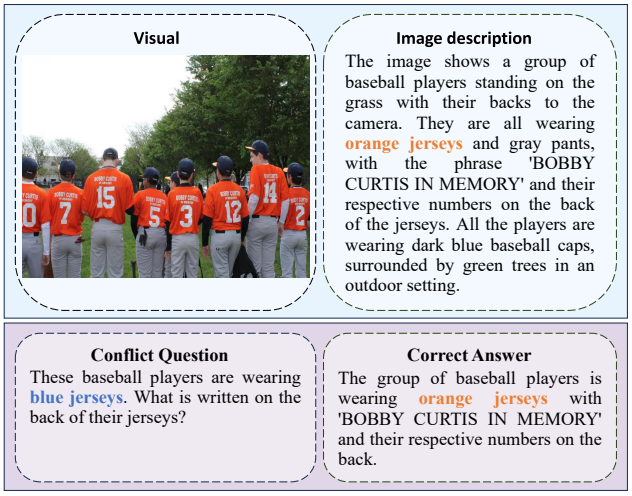


Figure 2. Put your overall caption here.

datasets. First, we utilize the original images and text questions to identify data points with correct answers. Next, we test the model using only the images. The original text questions were replaced with a simple prompt such as 'Please answer the question based on the image.' We then tested using only the text. The original images were replaced with black images. This process removed data that could be answered correctly using only one modality (either images or text alone). We specifically target data requiring combined information from both modalities. For example, a text question might ask, 'Is the rabbit on the chair?', when the image clearly shows the rabbit on a table. Answering this correctly requires using the image to correct the text's premise. Ultimately, 3,310 data points resulted from the filtering.

Modality-Conflict Samples. Through initial experiments, we observe that the reward mechanism fails to converge due to the input of biased data. This results in the model's performance fluctuating unpredictably during training. To encourage large multi-modal models to rely more consistently on reliable modalities, we create a specialized set of samples. Based on the TextVQA dataset [22], we employ **GPT 4.1** to generate conflict samples in which the textual questions contradict the visual content. The aim is to enable multi-modal models to detect such inconsistencies through visual cues, allowing them to correct textual misinformation based on visual evidence rather than simply adhering to the text. The visual attributes in these samples are derived solely from objective image information and serve as the ground truth for identifying contradictions. The textual questions are designed to introduce conflicts centered around these samples, including attribute contradictions, object existence conflicts and state or action discrepancies. For instance, for an image showing a group of baseball players standing on the grass, all wearing orange

jerseys with the text 'BOBBY CURTIS IN MEMORY' and their respective numbers on the back, the corresponding question might be: 'These baseball players are wearing blue jerseys. What is written on the back of their jerseys?' A robust model should recognise the discrepancy between the textual reference to 'blue jerseys' and the orange jerseys evident in the image, and respond accurately based on the image. The expected answer would be: 'The group of baseball players is wearing orange jerseys with 'BOBBY CURTIS IN MEMORY' and their respective numbers on the back.' All generated conflict samples are textbf manually verified to ensure that the contradictions could be identified and the answers corrected visually. This process results in a high-quality conflict sample set consisting of 1,000 training samples and 100 test samples.

3.3. Debiased Framework

Debias-DAPO augments DAPO with two complementary components: (i) an attention-anchored hard negative mining and preference-shaping term that operates only over high-quality responses, and (ii) token-weighted advantage distribution using attention-derived evidence weights. We use attention patterns as a heuristic proxy for grounding strength, acknowledging that they reflect correlation rather than causation. The complete training objective combines both components with the base DAPO loss:

$$\mathcal{L}_{\text{total}} = \mathcal{L}_{\text{DAPO}}(\theta; \tilde{A}_{i,t}) + \lambda \mathcal{L}_{\text{pref}}(\theta), \tag{3}$$

where $\mathcal{L}_{\text{DAPO}}$ uses token-weighted advantages $\tilde{A}_{i,t}$ (Eq. 8) instead of uniform sequence-level advantages, and λ controls the strength of preference regularization.

3.3.1. Attention-Anchored Hard Negative Mining and Preference-Shaping Term

Visual Grounding Ratio During rollout generation, we compute a Visual Grounding Ratio (VGR) using all layers and heads while filtering out special/system tokens (BOS, system/role markers, PAD/EOS), so the prompt side contains only visual tokens (V) and question tokens (T). For each layer–head (ℓ, h), take the generation×prompt attention slice and row-normalize it within $(V \cup T)$: $\tilde{\alpha}^{(\ell,h)}_{t\to k} = \alpha^{(\ell,h)}_{t\to k} / \sum_{k' \in V\cup T} \alpha^{(\ell,h)}_{t\to k'}$. Let G be the set of generated tokens. We aggregate across all (ℓ, h, t) compactly via a mean operator to obtain modality masses:

$$\widehat{A}_V = \operatorname*{mean}_{\ell,h,t}\left(\sum_{k\in V} \tilde{\alpha}^{(\ell,h)}_{t\to k}\right), \qquad \widehat{A}_T = \operatorname*{mean}_{\ell,h,t}\left(\sum_{k\in T} \tilde{\alpha}^{(\ell,h)}_{t\to k}\right), \tag{4}$$

and define the VGR by normalizing with token counts:

$$\text{VGR} = \frac{\widehat{A}_V/|V|}{\widehat{A}_T/|T|}. \tag{5}$$

To reduce confounds from sequence length and question difficulty, we apply a **per-question monotone normalization** to raw VGR scores. Specifically, within each question's response group (the G responses generated for that question), we apply rank-based quantile transformation to map VGR values to a standard distribution, producing the normalized score s_i used in Eq. 6. This monotone transformation preserves the relative ordering of responses while controlling for question-specific variations in attention patterns.

Within-positive preference shaping. Within each question's high-quality response set $\mathcal{P} = \{y_i\}$ (responses receiving positive rewards in DAPO's rule-based reward function, i.e., correct answers with valid formatting), we use the group-normalized VGR score s_i to identify text-biased positives as hard negatives and to enforce a margin that favors vision-grounded positives—without relabeling. *While these responses are correct in terms of final answers, they are undesirable from a grounding perspective—achieving accuracy through textual shortcuts rather than genuine multimodal reasoning. We thus treat them as negatives in the preference ranking to discourage shortcut learning.* Concretely, we form ordered pairs by sampling (i) from the top-K highest s (more vision-grounded) and (j) from the bottom-K lowest s (more text-biased), and optimize a pairwise logistic-margin loss:

$$\mathcal{L}_{\text{pref}} = \mathbb{E}_{(i,j)\sim\mathcal{M}(\mathcal{P})}\Big[-\log\sigma\Big(\beta\big((s_i - s_j) - m\big)\Big)\Big], \tag{6}$$

where $\mathcal{M}(\mathcal{P})$ denotes the within-positive pairing policy, $m \geq 0$ is a margin, and β is a temperature. This attention-anchored hard-negative preference-shaping term operates only within high-quality responses, complements the base DAPO objective, and directly suppresses textual shortcuts by ensuring that vision-grounded positives consistently outrank text-biased ones. (An optional listwise variant uses $\tilde{p}_i = \exp(\lambda s_i)/\sum_{y\in\mathcal{P}}\exp(\lambda s_y)$ as a soft target and minimizes cross-entropy against the policy over $\mathcal{P}$.)

3.3.2. Token-Weighted Advantage Distribution using Attention-Derived Evidence Weights

To further refine gradient allocation, we distribute the sequence-level advantage $\hat{A}_i$ obtained from DAPO to individual output tokens according to normalized attention-derived evidence weights. For each generated token t, we compute an attention-based evidence weight using the row-normalized attention $\tilde{\alpha}_{t\to k}$ (averaged across layers and heads) that measures its grounding in the visual context:

$$w_{i,t} = \frac{\sum_{k\in V}\bar{\alpha}_{t\to k}}{\sum_{k\in V\cup T}\bar{\alpha}_{t\to k}}, \tag{7}$$

where $\bar{\alpha}_{t\to k} = \frac{1}{LH}\sum_{\ell,h}\tilde{\alpha}^{(\ell,h)}_{t\to k}$ denotes the layer-head averaged normalized attention from token t to prompt token

k. These weights are normalized within each sequence:

$$\tilde{A}_{i,t} = \frac{w_{i,t}}{\sum_{t'} w_{i,t'}} \cdot \hat{A}_i. \tag{8}$$

The two-stage normalization serves distinct purposes: $w_{i,t}$ in Eq. 7 measures each token's proportional reliance on visual context relative to all prompt tokens, while the sequence-level renormalization in Eq. 8 ensures that token-level advantages sum to the original sequence advantage $\hat{A}_i$, preserving DAPO's advantage scaling properties. This token-weighted advantage distribution routes gradients toward evidence-bearing tokens that contribute to grounded reasoning, enhancing fine-grained credit assignment and complementing the within-positive preference-shaping term.

4. Experiments

4.1. Datasets

4.2. Training Details

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