OFFSIDE: Benchmarking Unlearning Misinformation in Multimodal Large Language Models

Hao Zheng[1] **Zirui Pang**[2] **Ling Li**[2] **Zhijie Deng**[2] **Yuhan Pu**[2]
Zhaowei Zhu[3,5] **Xiaobo Xia**[4] **Jiaheng Wei**[2,5*]
[1]Harbin Institute of Technology
[2]The Hong Kong University of Science and Technology (Guangzhou)
[3]BIAI, ZJUT
[4]University of Science and Technology of China
[5]D5Data.ai

Abstract

Advances in Multimodal Large Language Models (MLLMs) intensify concerns about data safety, making Machine Unlearning (MU), the selective removal of harmful/private information, a critical necessity. However, existing MU benchmarks for MLLMs are limited by a lack of image diversity, coarse-grained unlearning target, and insufficient evaluation scenarios, which fail to capture the complexity of real-world applications. To facilitate the development of MLLMs unlearning and alleviate the aforementioned limitations, we introduce OFFSIDE, a novel benchmark for evaluating misinformation unlearning in MLLMs. This manually curated dataset contains 15.68K records for 80 players, providing a comprehensive framework with four test sets to assess forgetting efficacy, generalization, utility, and robustness. OFFSIDE supports advanced unlearning targets, such as fine-grained unlearning and visual rumor removal. Our extensive evaluation of multiple baselines not only extends key findings from LLM MU to MLLM MU: (1) unlearned rumors can be easily recovered through relearning and (2) all methods are vulnerable to prompt attacks, but also introduces novel insights in the context of MLLM: (1) unimodal methods fail to handle multimodal rumors, (2) unlearning efficacy is primarily driven by catastrophic forgetting statistically, and (3) all methods struggle with visual rumors (rumors embedded in images). These results expose significant vulnerabilities in current approaches, highlighting the need for more robust multimodal unlearning solutions. The code is available at https://github.com/zh121800/OFFSIDE.

1 Introduction

With the rapid development and widespread application of multimodal large language models (MLLMs), models pre-trained on large-scale corpora can quickly adapt to various downstream tasks, such as visual question answering (Antol et al., 2015; Goyal et al., 2017), visual understanding (Sugiyama et al., 2007; Pu et al., 2026; Guo et al., 2016; Li et al., 2024c), and reasoning (Johnson et al., 2017; Perez et al., 2018; Li et al., 2025a,b). However, during both the pretraining and post-training phases, unwanted content, such as private information and harmful rumors, may be included, which could lead to the leakage of personal privacy and the spread of misinformation. These raise concerns about the security of MLLMs (Chen et al., 2025; Hua et al., 2025; Hu et al., 2026; Guo et al., 2026; Wang et al., 2026). Machine Unlearning (MU) (Wang et al., 2024b; Deng et al., 2025) has been proposed to address these ethical and security concerns in MLLMs, aiming to eliminate the influence of unwanted data and its effects on model performance without requiring retraining from scratch, while also complying with legal frameworks (Dang, 2021). Given that MLLMs integrate knowledge across multiple modalities, a growing line of work has begun to study MU within multimodal contexts (Liu et al., 2024c; Xu et al., 2025; Dontsov et al., 2024; Li et al., 2024b; Zhang et al., 2025). However, existing benchmarks commonly rely on generative models (e.g., Arc2Face (Papantoniou et al., 2024)) to synthesize images, risking the introduction of biases that diverge from real-world distributions (Westerlund, 2019; Dolhansky et al., 2020; Pang et al., 2025) and neglecting harmful cues embedded in the visual modality. Moreover, existing benchmarks fail to support a fine-grained unlearning target which removes specific information in an image while preserving unrelated information, typically deleting all text linked to a given image (Cheng et al., 2023). In addition, they pay little attention to the downstream effects of unlearning on other post-training procedures, such as continual learning (Wang et al., 2024a). Taken together, these limitations result in an incomplete assessment of multimodal unlearning, underscoring the

*Corresponding author: jiahengwei@hkust-gz.edu.cn

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need for a comprehensive benchmark tailored to MLLMs.

In this view, we propose OFFSIDE, a benchmark inspired by visual rumors, aimed at simulating diverse real-world scenarios. It features four distinct datasets: *Forget Set*, *Retain Set*, *Test set* and *Relearn Set*, each designed to evaluate specific aspects of unlearning methods, including unlearning efficacy, generalizability, model utility, and robustness, across both uni and multi-modal settings. A comprehensive comparison between previous benchmarks and OFFSIDE is shown in Table 1.

Experiments are conducted under four real-world scenarios (as shown in Figure 1): the **Complete Unlearning** setting, which is similar to previous benchmarks (Liu et al., 2024c; Xu et al., 2025; Dontsov et al., 2024); the **Fine-grained Unlearning** setting, which evaluates the ability to accurately erase particular image-text associations without affecting other benign information; the **Corrective Relearning** setting, which examines whether previously unlearned rumors can be successfully recovered after post-training; and the **Unimodal Unlearning** setting, which assesses whether unimodal unlearning methods can seamlessly adapt to the multimodal context of MLLMs.

We evaluate five classic unlearning baselines across four distinct datasets. Our comprehensive evaluation spans a variety of tasks, including classification, generation, MM-Bench (Liu et al., 2024a), and GPT evaluator. After extensive experiments, we observe several key findings, each stemming from our specially designed experimental settings, highlighting the advantages of our datasets in providing a realistic and diverse evaluation for the multimodal unlearning task. Our key contributions are as follows:

- We propose OFFSIDE, a novel multimodal unlearning benchmark that provides four real-world scenarios (Complete Unlearning, Fine-grained Unlearning, Corrective Relearning, and Unimodal Unlearning), demonstrating the practical value of multimodal unlearning in real-world applications.

- OFFSIDE provides a comprehensive framework for unlearning targets and evaluation in MLLM MU, assessing forgetfulness quality, model utility, and robustness. To the best of our knowledge, we are the first to raise the problem of unlearning deceptive visual rumors and fine-grained targets.

- After extensive experiments, we not only extend key findings from LLM to MLLM: (1) unlearned rumors can be recovered through relearning and (2) all methods are vulnerable to prompt attacks, but also introduce novel insights in the context of MLLM: (1) unimodal methods fail to address multimodal rumors, (2) unlearning efficacy is statistically driven by catastrophic forgetting, and (3) all methods struggle with visual rumors, where rumors are embedded in images. Theses findings highlight significant limitations of current MLLM methods, underscoring the need for targeted advancements in multimodal unlearning.

2 Related Work

MLLM Machine Unlearning. MMUBench (Li et al., 2024b) is a benchmark specifically designed to facilitate the unlearning of real-world entities. It introduces a token-level KL-divergence loss for model unlearning (MU) in multimodal large language models (MLLMs), representing a pioneering effort to apply MU in this context. CLEAR (Dontsov et al., 2024) extends TOFU (Maini et al., 2024) by pairing personas with textual biographies and AI-generated images, and MLLMU-Bench (Liu et al., 2024c) targets the removal of private information. MMUNLEARNER (Huo et al., 2025) proposes a selective unlearning approach that removes visual patterns tied to a specific entity while preserving the corresponding textual knowledge within the LLM backbone. PULSE (Kawakami et al., 2025) extends MLLMU-Bench to include pretrained knowledge unlearning as well as continual forgetting. PEBench (Xu et al., 2025) is the first to categorize multimodal unlearning targets into identities and events, where these targets can span both textual and visual modalities. However, the generated entities and events are overly simplistic, resulting in an almost perfect unlearning effect (close to 100%), which complicates the accurate evaluation of each method's strengths and weaknesses. The aforementioned benchmarks primarily assess the unlearned model, neglecting its potential integration with other post-training methods, such as continual learning.

In contrast, OFFSIDE addresses these issues by using images of real-world football players, where both the images and texts may contain harmful information. Additionally, we monitor the model's overall capabilities at different stages using MM-Bench (Liu et al., 2024a) to ensure that the un-

Benchmark	Text	Image			Setting			
		Type	Source	Entity Association	Complete Unlearning	Fine-grained Unlearning	Corrective relearning	Unimodal Unlearning
MUSE (Shi et al., 2024)	✓	-	-	-	✓			✓
TOFU (Maini et al., 2024)	✓	-	-	-	✓			✓
MMUBench (Li et al., 2024b)	✓	Real World	MIKE (Li et al., 2024a)	multiple	✓			
MLLMU-Bench (Liu et al., 2024c)	✓	Synthetic	Arc2Face (Papantoniou et al., 2024)	Single	✓			✓
PEBench (Xu et al., 2025)	✓	Synthetic	Flux (Labs, 2024)	multiple	✓			
CLEAR (Dontsov et al., 2024)	✓	Synthetic	StyleGAN2 (Karras et al., 2020)	multiple	✓			
OFFSIDE (Ours)	✓	Real World	Google	multiple	✓	✓	✓	✓

Table 1: Benchmark Comparison. OFFSIDE is the first to support (1) multi-image entity association (group images for each player), (2) fine-grained unlearning targets, (3) corrective relearning, and (4) unimodal unlearning (unlearn through only pure text data).

Figure 1: OFFSIDE is a comprehensive benchmark for MLLMs MU, featuring four real-world settings designed to address the removal of various rumors. Texts in red represent the target rumor, while those in green indicate successful forgetting or relearning.

learning process does not degrade its general performance. [1]

3 OFFSIDE: Unlearn Football Transfer Market Rumors and Relearn Facts

We present OFFSIDE, a benchmark inspired by visual rumors of football players, where both images and accompanying text may contain inaccuracies that could lead the model to propagate misinformation. OFFSIDE consists of 640 images representing 80 football players from 20 different clubs. Each image is paired with 8 shared and 6 private VQA pairs. A detailed overview of the OFFSIDE dataset, including its data construction pipeline and evaluation procedure, is depicted in Figure 2.

3.1 Models and Data Splitting

We consider a standard machine unlearning setup, with specific designs tailored for MLLMs. For all experiments, We use Qwen2.5-VL-3B and Qwen2.5-VL-7B (Bai et al., 2025) as the base models. Let $\mathcal{D}$ denote the full dataset, which is partitioned into four disjoint subsets: $\mathcal{D}_{\textbf{forget}}$ (*Forget Set*), $\mathcal{D}_{\textbf{retain}}$ (*Retain Set*), $\mathcal{D}_{\textbf{test}}$ (*Test set*), and $\mathcal{D}_{\textbf{relearn}}$ (*Relearn Set*).

[1]Extra related work and discussion are provided in the Appendix A.

In the first stage, we obtain the vanilla model by fine-tuning the pretrained MLLMs with supervision (SFT) on $\mathcal{D}_{\textbf{forget}} \cup \mathcal{D}_{\textbf{retain}}$. During the subsequent unlearning stage, various unlearning methods are applied, with access to $\mathcal{D}_{\textbf{forget}} \cup \mathcal{D}_{\textbf{retain}}$. After the unlearning process, we evaluate the model's utility by retraining it on $\mathcal{D}_{\textbf{relearn}}$, which reintroduces the corrected information. Specifically, $\mathcal{D}_{\textbf{relearn}}$ contains the corrected versions of the same rumors, providing updated data about the same entity.

In the Fine-grained unlearning setting, the previously mentioned subsets are further categorized into private and shared sets, simulating a more realistic scenario where only private information is removed, while shared attributes are retained. The private sets consist of QA pairs that are unique to a specific image, whereas the shared sets contain QA pairs that are common across multiple images of the same player. All four subsets are employed to enable a comprehensive evaluation. Specifically:

- $\mathcal{D}_{\textbf{forget}}$ evaluates the effectiveness of unlearning (i.e., the extent to which the model has forgotten the targeted content);
- $\mathcal{D}_{\textbf{retain}}$ and $\mathcal{D}_{\textbf{test}}$ assess the preservation of general model utility and knowledge (retention of non-targeted information);

- $\mathcal{D}_{\textbf{relearn}}$ is used to evaluate the effectiveness of unlearning methods in conjunction with other post-training procedures, specifically assessing the model's ability to recover knowledge that was previously unlearned during the relearning process.[2]

The following notations distinguish different models derived from the dataset: learning algorithm $\mathcal{A}$ maps the dataset $\mathcal{D}$ to a parameterized model $\theta = \mathcal{A}(\mathcal{D})$. $\theta_0 = \mathcal{A}(\mathcal{D})$ is the vanilla model finetuned on the full dataset. $\theta_r = \mathcal{A}(\mathcal{D}_{\textbf{retain}})$ denotes the retained model, which is trained from scratch on the retain set, Finally, θ_u refers to the unlearned model, which is produced by an unlearning algorithm $\mathcal{U}$, ideally approximating θ_r without requiring retraining.

3.2 Visual Rumors

In the context of MLLMs unlearning, there are various unlearning targets. Previous benchmarks have primarily focused on pure-text targets (Liu et al., 2024c; Dontsov et al., 2024; Kawakami et al., 2025), where private or rumor-related information is typically embedded in the text, often neglecting the visual targets embedded within images. In contrast, OFFSIDE includes confusing visual transfer information in each image of the Forget Set. This creates a more complex and realistic scenario.

3.3 Fine-grained Unlearning

In OFFSIDE, each player is linked to a set of images containing both *private information* (e.g., transfer records) and *shared information* (e.g., age, height, and name). The diverse text-image connections are designed for the fine-grained unlearning setting, which only removes the private information of the target rumor and saves the shared ones. Previous research primarily focuses on coarse-grained unlearning, treating all information related to an individual equally (e.g., forgetting all details about a player, singer, or politician). However, this approach is unrealistic, as in real-life scenarios, we don't require a model to forget all information about a specific individual. Such a drastic unlearning would severely impair the model's usability, as we still want the model to retain its general cognitive abilities after the unlearning process. In this view, the goal of unlearning should be to selectively forget sensitive, rumor-related, or private information about an individual while maintaining the model's overall functionality.

3.4 Data Construction

All OFFSIDE data is manually curated. The data construction process consists of two stages:

Image Curation: We manually selected 80 players from 20 Premier League clubs using Google search [3]. For each player, we curated the following image sets: three images representing different club periods ($\mathcal{D}_{\textbf{retain}}$), one image related to a visual transfer rumor ($\mathcal{D}_{\textbf{forget}}$), three test images ($\mathcal{D}_{\textbf{test}}$), and one image for relearning the facts ($\mathcal{D}_{\textbf{relearn}}$). Here, $\mathcal{D}_{\textbf{test}}$ is an augmented version of $\mathcal{D}_{\textbf{retain}}$. $\mathcal{D}_{\textbf{relearn}}$ is a corrected version of $\mathcal{D}_{\textbf{forget}}$(new data).

Text Description Curation: For each image, we constructed 14 QA pairs, comprising 6 that capture *private information* (e.g., the player's market value, transfer fee) and 8 that capture *shared information* (e.g., the player's height, birthdate). This design is specifically tailored for a fine-grained unlearning setting, where the aim is to forget certain rumors(private information) while retaining shared facts. Additionally, we created pure-text versions of each question-answer pair to test whether existing LLM unlearning methods can be directly extended to MLLMs.

To ensure consistency across the player information and the corresponding image text, the entire dataset, covering both collection and construction, was reviewed twice by two football experts to guarantee its quality.

3.5 Evaluation Metrics

OFFSIDE provides a comprehensive evaluation framework for unlearning methods in MLLMs, assessing unlearning efficacy, generalizability, and model utility as defined by (Liu et al., 2024d), along with the model's ability to integrate post-training interventions (such as continual learning). We have defined four tasks for evaluation: Classification, Generation, Factuality Score, and MM-Bench tasks.[4] Performance on the MM-Bench serves as a disqualifying criterion for selecting experimental results. Experimental results are reported only for those unlearning methods where the model's general capabilities are not excessively degraded. This ensures that all models maintain their overall functionality throughout the process, allowing for

[2]The evaluation on $\mathcal{D}_{\textbf{relearn}}$ is similar to $\mathcal{D}_{\textbf{retain}}$. Retain set is frozen at this stage.

[3]All images are manually selected from https://www.google.com/imghp?hl=en

[4]We have provided a detailed description in Appendix D.

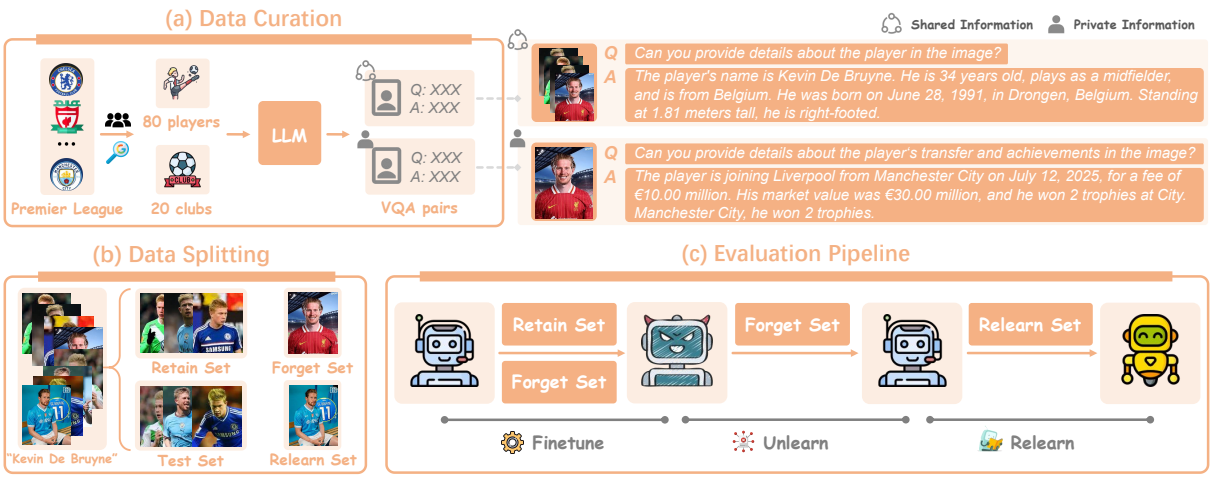

Figure 2: Overview of the OFFSIDE framework. The MLLM is first fine-tuned on the forget and retain set to obtain the vanilla model. Various unlearning methods are then applied on forget set to obtain the unlearned model. After unlearning, the model is fine-tuned on the relearn set to correct the rumors. Performance is evaluated on four distinct subsets after both the unlearning and relearning stages.

a fair comparison of both forgetting efficacy and functional consistency.

4 Experiment

4.1 Experiment setup

Training. We employ the Qwen2.5-VL series model as the base model for unlearning. Supervised Fine-Tuning (SFT) is performed using LoRA with a batch size of 4. For methods that require access to $\mathcal{D}_{\textbf{retain}}$, we adopt a balanced forget-retain update schedule, in contrast to the inner-loop forget and outer-loop retain strategy proposed in (Liu et al., 2024c). Specifically, we use a forget-to-retain step ratio of $1:3$ (which corresponds to the size ratio of the forget and retain sets) to enhance training stability during the unlearning process. All experiments are conducted on a single H20 GPU (96GB).

Unlearning Algorithms. We evaluates five representative machine unlearning methods to enable an extensive analysis. Specifically, the methods examined include Gradient Ascent (GA) (Yao et al., 2024a), Gradient Difference (GD) (Liu et al., 2022), KL Minimization (Yao et al., 2024b), Preference Optimization (PO) (Maini et al., 2024), Negative Preference Optimization (NPO) (Zhang et al., 2024). Since some of these approaches may cause progressive degradation in overall model performance during unlearning, we carefully select and report results only under conditions where the model's core functionality is preserved, thus ensuring the practical utility of the unlearned model.

4.2 Experimental Scenarios

To better imitate complex real-world situations, we design four distinct MLLMs unlearning settings:

Complete Unlearning: In this setting, we treat each image as an individual entity, with the goal of unlearning all connections between rumor images and their corresponding text descriptions. This setting allows us to evaluate whether the unlearning algorithm can effectively forget the rumor.

Fine-grained Unlearning: In this scenario, we focus on removing only the private information of a given image while preserving shared, non-sensitive attributes. Specifically, the shared information of $\mathcal{D}_{\textbf{forget}}$ is removed to $\mathcal{D}_{\textbf{retain}}$ and the left private information serve as the $\mathcal{D}_{\textbf{forget}}$. This approach is more realistic, as it enables the model to maintain its core ability to recognize players based on essential characteristics, such as name, height, and dominant foot.

Corrective Relearning: This setting operates within a continual learning framework, where the unlearned model, θ_u, is allowed to relearn the facts. This not only assesses the model utility of θ_u but also evaluates whether the unlearned knowledge can be effectively recovered.[5]

Unimodal Unlearning: In this setup, we combine the name of each entity with questions. During unlearning, we set the input image to empty. This allows us to test whether the LLM unlearning algorithms can seamlessly integrate into multimodal unlearning methods. Additionally, it aids researchers

[5]Previous works merely address the continual unlearning(Gao et al., 2024) proble which is quite from our work.

in understanding how MLLMs store knowledge.

4.3 Experimental Results

In this section, we present a comprehensive comparison of several representative unlearning algorithms, evaluated using the proposed OFFSIDE across four real-world settings.

Table 2 shows the results of **Complete Unlearning**. From this table, GA and NPO results in a significant drop in accuracy on both the test set and retain set while performing the forgetting process. KL and PO demonstrate strong performance on both of the Qwen2.5-VL 7B and 3B models, especially on preventing significant degradation in model performance.

Table 3 presents the results of Fine-grained Unlearning. We observe that all the baselines exhibit a performance drop(compared to the vanilla model) in both private information and shared information. This indicates that the tested baselines have trouble selectively unlearning private information in a given image while preserving shared information. This uncovers that **existing methods focus on entity-level unlearning, which disrupts all associations between a given image and related text, making it challenging to be applied to real world applications**.

Table 4 presents the results of Corrective Relearning. The model used here is based on Table 2, where we retrain the unlearned model on new data $\mathcal{D}_{\textbf{relearn}}$. Surprisingly, we found that after relearning, all of the baselines exhibit a "bounce-back" effect on either the 3B or 7B model, indicating that the knowledge previously forgotten can be easily recovered through simple retraining. Specifically, KL achieves a fact score of 0.57 on the forget set, which increases to 4.55 after relearning. This suggests that **none of the baselines truly forget the rumor information; instead, they merely conceal it.** This extends the finding of LLM unlearning(Xu et al.) to MLLM.[6]

Figure 3 presents the results of the **Unimodal Unlearning** setting. In the multimodal setup, the input consists of both text and images, while in the unimodal setup, only text is provided. As shown in the results, all unimodal unlearning methods struggle to unlearn multimodal rumors. This suggests that **the target information is not only restored in LLMs but also embedded within the visual layer of MLLMs**. This highlights the need for researchers to design unlearning methods specifically tailored to the unique characteristics of MLLMs.

[6]While (Xu et al.) utilizes relearning to forget the target, we focus on the rumor recovery after relearning.

4.4 Discussion

In this section, we present and discuss several key findings based on the experimental results, and we summarize the main conclusions drawn from our analysis.

All baselines struggle with unlearning visual rumors. We examined all instances of visual rumors and found that none were successfully unlearned by any method. As shown in Figure 4, when faced with deceptive visual rumors, the model is easily misled due to its powerful reasoning capabilities. This is intuitive because, even if the model forgets the visual rumors at the visual-text fusion level, it still lacks the necessary knowledge to correctly answer the question. As a result, the model's response primarily depends on the information it perceives in the image, without recognizing that the visual information is unreliable. This highlights the need for developing specific algorithm for the visual target.

All of the tested baselines remain vulnerable to prompt based attacks. Although certain methods achieve low generation and fact scores on the forget set, they still maintain high classification accuracy. This indicates that when rumor information appears in the prompt, the model can still recognize and select the incorrect knowledge, thereby exposing its susceptibility to prompt-induced retrieval. For instance, as shown in Table 2, PO demonstrates strong performance in generation and fact scoring, suggesting effective forgetting. However, its classification accuracy remains close to that of the original, unmodified model, revealing a critical gap in current unlearning approaches. This persistent ability to match forgotten content in classification task underscores the need for more robust unlearning techniques.

Unlearning efficacy is largely driven by catastrophic forgetting statistically. In Figure 4, we compare the GPT-evaluation results of models relearned after forgetting with those of the directly relearned vanilla model. We observe that the knowledge unlearned by the baselines closely resembles catastrophic forgetting in continual learning statistically. Specifically, the unlearned sample IDs through GA, GD, KL, and NPO show 71%, 48%, 58%, and 60% similarity to the forgotten IDs after a simple relearning step. This suggests that **the**

Models	Forget Set Class. Acc (↓)	Forget Set Generation Score (↓)	Forget Set Fact. Score (↓)	Test Set Class. Acc (↑)	Test Set Generation Score (↑)	Test Set Fact. Score (↑)	Retain Set Class. Acc (↑)	Retain Set Generation Score (↑)	Retain Set Fact. Score (↑)	MM-Bench MM-Bench Acc (↑)
Qwen2.5-VL-7B										
Pretrained	49.4%	0.129	3.67	46.8%	0.115	3.66	47.2%	0.114	3.69	82.4%
Vanilla	64.4%	0.974	9.86	60.1%	0.710	5.79	65.2%	0.946	9.83	82.3%
GA	62.7%	0.616	4.97	59.0%	0.430	3.86	64.2%	0.632	5.34	81.9%
GD	**23.5%**	0.321	6.56	59.8%	0.521	5.05	64.3%	0.664	8.47	**82.3%**
KL	65.0%	**0.032**	**0.57**	**60.1%**	**0.655**	5.36	**66.7%**	0.861	9.20	81.9%
PO	62.9%	0.117	1.59	59.8%	0.684	**5.67**	64.6%	**0.914**	**9.65**	82.1%
NPO	62.1%	0.545	8.41	59.7%	0.472	5.42	64.6%	0.571	8.81	82.2%
Qwen2.5-VL-3B										
Pretrained	45.5%	0.224	3.68	49.1%	0.220	3.32	49.7%	0.223	3.33	78.4%
Vanilla	53.6%	0.901	7.51	53.0%	0.651	4.67	55.3%	0.882	7.45	78.1%
GA	53.1%	0.782	6.66	52.9%	0.581	**4.57**	54.7%	0.774	7.30	78.0%
GD	50.5%	**0.155**	3.75	50.8%	0.576	4.38	53.1%	0.747	6.97	78.0%
KL	48.6%	0.550	5.62	54.1%	0.633	4.55	54.1%	**0.859**	7.31	**78.1%**
PO	57.5%	0.207	4.53	**56.4%**	**0.671**	4.00	**56.4%**	0.805	6.26	78.0%
NPO	**45.1%**	0.371	**3.22**	49.3%	0.337	3.71	50.2%	0.408	**5.69**	78.0%

Table 2: Results of Complete Unlearning. The best results of five baselines are highlighted in **blue**.

Models	Private Info Class. Acc (↓)	Private Info Generation Score (↓)	Private Info Fact. Score (↓)	Test Set Class. Acc (↑)	Test Set Generation Score (↑)	Test Set Fact. Score (↑)	Shared Info Class. Acc (↑)	Shared Info Generation Score (↑)	Shared Info Fact. Score (↑)	MM-Bench MM-Bench Acc (↑)
Qwen2.5-VL-3B										
Vanilla	56.5%	0.832	6.40	53.5%	0.654	4.66	60.8%	0.951	8.74	78.3%
GA	**57.2%**	0.518	5.30	52.9%	0.408	3.56	60.8%	0.709	7.52	77.9%
GD	57.3%	0.571	5.78	51.9%	**0.623**	**4.50**	60.6%	0.895	8.45	78.1%
KL	58.4%	0.725	5.20	52.2%	0.616	4.48	61.2%	**0.921**	**8.67**	78.0%
PO	59.6%	**0.412**	**2.85**	**56.8%**	0.545	4.02	**63.7%**	0.841	7.97	**78.2%**
NPO	58.9%	0.648	5.65	50.6%	0.584	4.29	58.9%	0.874	8.24	78.1%

Table 3: Results of Fine-grained Unlearning. The best results of five baselines are highlighted in **blue**.

Models	Forget Set Class. Acc (↓)	Forget Set Generation Score (↓)	Forget Set Fact. Score (↓)	Test Set Class. Acc (↑)	Test Set Generation Score (↑)	Test Set Fact. Score (↑)	Retain Set Class. Acc (↑)	Retain Set Generation Score (↑)	Retain Set Fact. Score (↑)	Relearn Set Class. Acc (↑)	Relearn Set Generation Score (↑)	Relearn Set Fact. Score (↑)	MM-Bench MM-Bench Acc (↑)
Qwen2.5-VL-7B													
Vanilla	59.7%	0.576	8.36	58.3%	0.445	5.24	62.8%	0.548	8.05	59.1%	0.911	9.26	82.3%
GA	**57.5%**	0.584	8.49	54.4%	0.440	5.16	59.4%	0.554	**8.33**	55.9%	0.895	9.22	81.9%
GD	62.2%	0.489	7.87	61.4%	0.473	5.24	63.9%	0.569	8.04	62.2%	0.908	**9.23**	82.0%
KL	63.8%	**0.336**	**4.55**	**61.5%**	**0.483**	**5.25**	**66.7%**	**0.594**	8.29	62.1%	0.911	9.19	81.9%
PO	64.7%	0.567	8.23	61.2%	0.437	5.17	65.9%	0.538	7.99	**65.0%**	**0.914**	9.22	**82.1%**
NPO	59.3%	0.527	7.95	54.9%	0.408	5.07	59.9%	0.503	7.75	55.6%	0.909	9.21	81.9%
Qwen2.5-VL-3B													
Vanilla	53.2%	0.589	6.73	53.3%	0.443	4.48	55.3%	0.522	6.39	55.2%	0.899	8.90	78.2%
GA	51.3%	0.549	6.60	**52.7%**	0.431	**4.46**	**52.6%**	0.501	6.21	**55.1%**	0.901	8.86	77.9%
GD	47.9%	0.447	6.08	47.4%	0.430	4.32	49.8%	0.505	6.11	46.7%	0.893	8.79	78.0%
KL	47.6%	0.497	6.14	48.8%	0.429	4.31	50.2%	**0.512**	6.38	49.2%	0.899	8.86	78.0%
PO	**46.9%**	0.566	6.57	47.8%	**0.456**	4.33	50.1%	0.501	**6.41**	48.8%	**0.906**	**9.01**	**78.1%**
NPO	47.5%	0.497	6.15	48.8%	0.429	4.31	50.2%	0.511	6.37	49.2%	0.899	8.86	77.9%

Table 4: Results of Corrective relearning. In this setting, we fine-tune the unlearned model in Table 2 on $\mathcal{D}_{\textbf{relearn}}$. The best results of five baselines are highlighted in **blue**. The results of vanilla model directly skip the unlearning stage and relearn the facts.

unlearning ability of the tested baselines is primarily driven by catastrophic forgetting. This phenomenon demonstrates how catastrophic forgetting can be leveraged as a method for machine unlearning and highlights a promising direction for future research.

Methods such as KL Minimization demonstrate greater effectiveness when applied to a

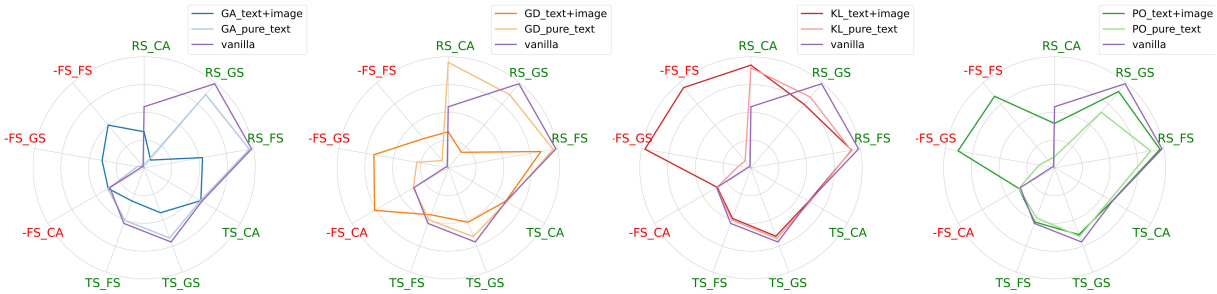

Figure 3: Results of the Unimodal Unlearning. RS, TS, FS represent retain set, test set, and forget set, respectively. CA, GS, FS refer to classification accuracy, generation score, and fact score, respectively.

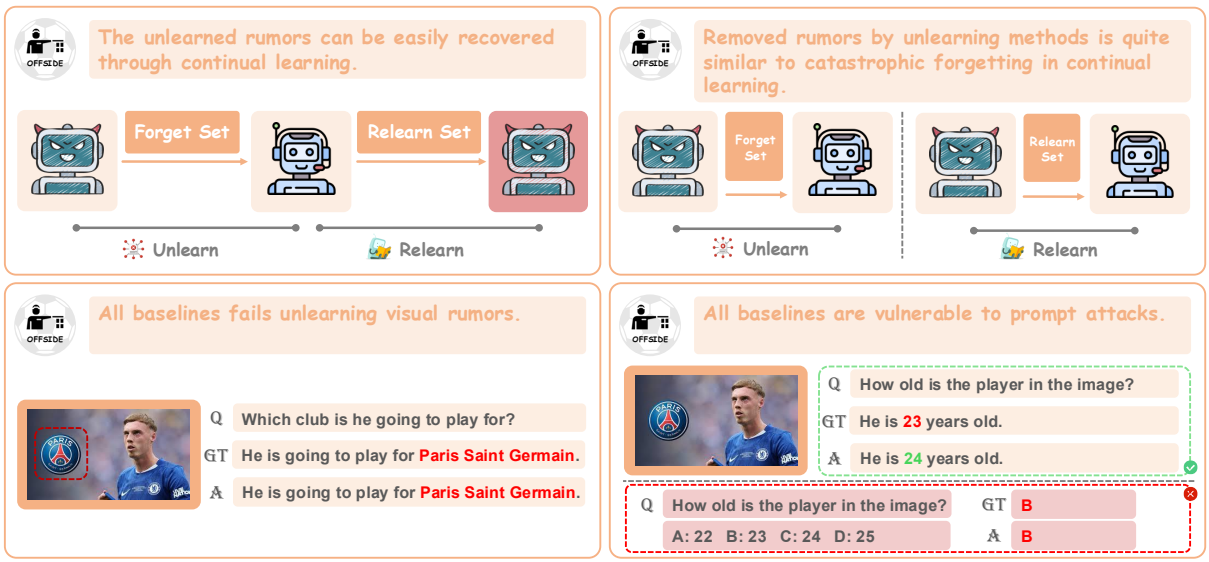

Figure 4: Illustration of experimental conclusions, observed from the OFFSIDE benchmark.

7B model, but show reduced efficacy with a 3B model. This is primarily due to the random direction of optimization in gradient-ascent-based methods. Before model collapse occurs, these methods struggle to control the optimization direction, which may lead to significant deviations in the results. In contrast, methods like PO, which do not rely on gradient ascent, show more stable performance across both models.[7]

5 Limitations

OFFSIDE is the first work to introduce the novel concept of *removing visual rumors*. However, collecting visual rumors presents a significant challenge, as such rumors are scarce. Specifically, each player is associated with only 8 QA pairs, among which merely one constitutes a visual rumor. Furthermore, while we have identified and discussed several limitations of existing methods, we do not propose a new algorithm capable of effectively addressing these shortcomings. We leave these as promising directions for future research.

6 Social Impacts of Visual Rumors

Impact on Football field. Compared to purely text-based rumors, visual rumors pose additional risks of infringing on an individual's portrait rights. In addition, misinformation about football transfers of a certain player can have significant real-world consequences. False rumors often lead to emotional reactions from fans, causing unnecessary excitement or disappointment. Unlearning techniques can mitigate these harms by preventing the spread of misinformation and ensuring decision-making is based on verified information.

Generalization. The issue of visual rumors in the football field is not isolated; it can generalize to other domains, such as sports journalism, social media, and financial markets, where rumors are prevalent. Unlearning such rumors is crucial for preserving trust, reducing instability, and promoting more reliable information across various societal sectors. OFFSIDE provides a route for

[7]For more discussions, please refer to the Appendix.

constructing visual rumors for other fields: one can directly inject false text/icon into a singer/politician's image. Thus forming the visual rumors. In addition, it is easy to collect benign and harmful information of any given people. In this view, the fine-grained unlearning data can be easily collected in other fields. These prove that OFFSIDE is not limited to the football area and can be generalized to any other field because they share the same fundamental logic.

7 Future Work

In OFFSIDE, we observe that "unlearned rumors can be easily recovered." This raises critical questions: How exactly does the model perform unlearning? Why can seemingly forgotten knowledge be restored with simple attacks? To address these, future work could leverage interpretability tools such as neuron activation patterns or attention attribution to probe the internal mechanisms of unlearning in multimodal models. Moreover, we find that unimodal unlearning methods fail to erase multimodal knowledge, which contrasts with conclusions drawn from previous benchmarks(Liu et al., 2024c). We attribute this discrepancy to model collapse during unimodal unlearning observed in MLLMMU-Bench: rather than selectively forgetting targeted content, these methods degrade the model's general capabilities, creating a false impression of successful unlearning. This failure reveals a deeper issue: current unlearning approaches are still largely grounded in next-token prediction paradigms and exhibit strong modality bias. Knowledge across modalities is not jointly represented or edited, suggesting that effective multimodal unlearning requires a better understanding of how cross-modal knowledge is stored and entangled in MLLMs.

8 Conclusion

We introduce OFFSIDE, designed to simulate diverse real-world scenarios for unlearning in MLLMs. We propose four distinct settings (Complete Unlearning, Fine-grained Unlearning, Corrective Relearning, and Unimodal Unlearning) to establish a robust unlearning framework and comprehensively evaluate a list of representative machine unlearning baselines. Our findings indicate that: all baselines struggle to unlearn visual rumors, and the unlearned knowledge can be easily recovered through prompt attacks (classification tasks) or simple relearning. Moreover, directly applying unimodal unlearning methods fails to remove multimodal rumors. Notably, our corrective relearning setting reveals that the unlearning ability of the tested baselines is primarily driven by catastrophic forgetting. Overall, our findings provide valuable empirical insights that guide the development of more effective unlearning methods for future MLLM MU research.

9 ACKNOWLEDGEMENT

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Appendix

The Appendix is organized as follows.

- **Section A**: More details about Related work.
- **Section B**: Broader impact of Visual Rumors.
- **Section C**: Details of tested baselines.
- **Section D**: Details of evaluation metrics.
- **Section E**: Introduces the MM-Bench Indicator Definitions.
- **Section F**: Vanilla Model Fine-tuning.
- **Section G**: Details of experimental settings.
- **Section H**: Data construction.
- **Section I**: Further findings.
- **Section J**: A case study of our proposed settings.
- **Section K**: A detailed description of GPT prompt strategy.
- **Section L**: Discussion.
- **Section M**: Use of AI.

A Extra Related Work

LLM Machine Unlearning. Existing benchmarks in LLM MU have been used to test unlearning in various contexts, such as elimination of personal identification data (Patil et al., 2023), copyright protection (Eldan and Russinovich, 2023) and harmful content removal (Lu et al., 2022). Gradient Ascent (GA) (Yao et al., 2024b) was introduced to optimize the model parameters so as to maximize the removal of targeted information from the training data. However, GA often degrades performance on the retained set. Subsequent methods, including gradient descent (GD) (Liu et al., 2022), KL-based objectives (Yao et al., 2024a; Liu et al., 2024b), and "I don't know" (IDK) losses (Maini et al., 2024), were proposed to exert finer control over the outputs of unlearned models and to mitigate collateral damage. Additionally, Negative Preference Optimization (NPO) (Zhang et al., 2024) reframes LLM unlearning as a preference-optimization problem.

Model Editing. In this subsection, we mainly focus on the difference between Machine Unlearning and Model editing. Model editing aims to update facts in LLMs without costly retraining(Cao et al., 2021). Various model editing methods have been proposed, such as ROME (Meng et al., 2023a) and MEMIT (Meng et al., 2023b), which show better generalization than naive fine-tuning. Machine unlearning and model editing are two distinct research areas, each with its own data formats and evaluation standards. Model editing focuses on making targeted, precise modifications (preferably with an emphasis on locality) to a model's behavior or knowledge, while machine unlearning aims to broadly remove specific information, prioritizing overall consistency. Currently, these two areas are typically studied in isolation. Due to their different objectives (e.g., target focus and data types), their evaluation methodologies also differ significantly, despite the fact that the evaluation metrics may be quite similar. Most importantly, both areas are still in the early stages within the context of MLLMs.

B Social Impacts of Visual Rumors

Impact on Football field. Compared to purely text-based rumors, visual rumors pose additional risks of infringing on an individual's portrait rights. In addition, misinformation about football transfers of a certain player can have significant real-world consequences. False rumors often lead to emotional reactions from fans, causing unnecessary excitement or disappointment. Unlearning techniques can mitigate these harms by preventing the spread of misinformation and ensuring decision-making is based on verified information.

Generalization. The issue of visual rumors in the football field is not isolated; it can generalize to other domains, such as sports journalism, social media, and financial markets, where rumors are prevalent. Unlearning such rumors is crucial for preserving trust, reducing instability, and promoting more reliable information across various societal sectors. OFFSIDE provides a route for constructing visual rumors for other fields: one can directly inject false text/icon into a singer/politician's image. Thus forming the visual rumors. In addition, it is easy to collect benign and harmful information of any given people. In this view, the fine-grained unlearning data can be easily collected in other fields. These prove that OFFSIDE is not limited to the football area and can be generalized to any other field because they share the same fundamental logic.

C Unlearning Methods

Gradient Ascent(GA) (Yao et al., 2024b): This method updates the model parameters by maximizing the likelihood of misprediction for the samples in the forget set D_{forget}. For a given sample $x \in D_{\text{forget}}$, the loss function is defined as:

$$\mathcal{L}(D_{\text{forget}}, w) = \frac{1}{|D_{\text{forget}}|} \sum_{x \in D_{\text{forget}}} \ell(x, w). \quad (1)$$

Gradient Difference (GD) (Liu et al., 2022): This method extends gradient ascent by simultaneously focusing on forgetting the samples in the forget set D_{forget} while preserving performance on the retain set D_{retain}. The objective is to balance increasing the loss on the forget set and minimizing its impact on the retain set. The overall loss function to be minimized is formulated as:

$$\mathcal{L}_{\text{diff}}(w) = -\mathcal{L}(D_{\text{forget}}, w) + \mathcal{L}(D_{\text{retain}}, w). \quad (2)$$

KL_Min (Yao et al., 2024a): This method extends gradient ascent by introducing an additional objective that minimizes the Kullback–Leibler (KL) divergence between the predictions of the original model M_{ori} and the updated model M_{new} on the retain set D_{retain}. The KL divergence loss is defined as:

$$\mathcal{L}_{\text{KL}} = \frac{1}{|D_{\text{retain}}|} \sum_{s \in D_{\text{retain}}} \frac{1}{|s|} \sum_{i=2}^{|s|} \text{KL}\Big(M_{\text{ori}}(s_{<i}) \,\Big\|\, M_{\text{new}}(s_{<i})\Big). \quad (3)$$

The overall training objective combines the gradient ascent loss on the forget set with the KL divergence loss on the retain set, which is formulated as:

$$\mathcal{L}_{\text{total}}(w) = -\mathcal{L}(D_{\text{forget}}, w) + \mathcal{L}_{\text{KL}}. \quad (4)$$

Preference Optimization (PO) (Maini et al., 2024): This method steers the model to align with newly generated responses such as "I do not know the answer" and its variants for questions belonging to the forget set D_{forget}. At the same time, it incorporates a retain-set term to ensure that predictions on the retain set D_{retain} remain unaffected. The total objective function is formulated as:

$$\mathcal{L}_{\text{idk}}(w) = \mathcal{L}(D_{\text{retain}}, w) + \mathcal{L}(D^{\text{idk}}_{\text{forget}}, w). \quad (5)$$

Negative Preference Optimization(Zhang et al., 2024): In our work, we adopt the Negative Preference Optimization (NPO) technique to unlearn undesirable data, thereby mitigating the catastrophic collapse often observed in gradient ascent–based methods. NPO builds on the preference optimization framework, but specifically targets negative samples from the forget set D_{forget}.

The NPO loss is defined as:

$$\mathcal{L}_{\text{NPO}} = \frac{2}{\beta} \mathbb{E}_{(x,y) \in D_{\text{forget}}} \left[\log\left(1 + \left(\frac{\pi_\theta(y|x)}{\pi_{\text{ref}}(y|x)}\right)^{\beta}\right)\right], \quad (6)$$

where $\pi_\theta(y|x)$ denotes the probability assigned by the current model, and $\pi_{\text{ref}}(y|x)$ is the probability from a reference model trained on the entire dataset. The parameter β controls the smoothness of optimization: as $\beta \to 0$, the NPO loss converges to the standard gradient ascent loss.

By minimizing $\mathcal{L}_{\text{NPO}}$, the model reduces its reliance on the forget set, leading to a more stable unlearning process and avoiding the rapid degradation characteristic of gradient ascent. In our experiments, we follow the original paper and set $\beta = 0.9$. The reference distribution π_{ref} is obtained by fine-tuning the pre-trained model exclusively on the retain set D_{retain}.

D Evaluation Metrics

OFFSIDE provides a comprehensive evaluation framework for unlearning methods in MLLMs, assessing unlearning efficacy, generalizability, and model utility as defined by (Liu et al., 2024d), along with the model's ability to integrate with post-training interventions (continual learning). To ensure a comprehensive evaluation, we assess the performance of the vanilla, unlearned, and relearned models on MM-Bench. We only report experimental results for each unlearning method where the model's general capabilities are not excessively degraded. This approach guarantees that all models maintain their general capabilities throughout the process, allowing for a fair comparison of both forgetting efficacy and functional consistency.

D.1 Classification

To evaluate whether a model can recall unlearning targets when specific rumors are provided in the prompt, we design a multiple-choice classification task with candidates generated by GPT-4o. Let a^n denote the ground-truth answer for sample n. We construct a candidate set $\mathcal{A}^n = \{a^n_0, a^n_1, a^n_2, a^n_3\}$, where $a^n_0 \equiv a^n$ is the correct answer and the remaining three candidates are perturbations that pre-

Table 5: Performance of the vanilla OFFSIDE and MLLMU-Bench models on MM-Bench.

Method	MM-Bench						
	Overall	LR	AR	RR	FP-S	FP-C	CP
Qwen2.5-VL-7B	82.4	71.7	84.9	80.2	89.8	80.1	81.3
LLaVA-1.5-7B	62.3	29.9	73.1	54.7	69.6	57.7	68.5
MLLMMU-Qwen2.5-VL-7B	80.4	68.2	80.2	73.9	87.9	77.7	83.2
OFFSIDE-Qwen2.5-VL-7B	82.3	69.2	82.0	79.1	88.5	78.9	85.5

serve the linguistic template but alter factual content.

Let $\mathbf{I}^n$ and $\mathbf{Q}^n$ denote the input image and question, respectively. Given $(\mathbf{I}^n, \mathbf{Q}^n, \mathcal{A}^n)$, the evaluated model with parameters θ predicts

$$\hat{y}^n = \arg\max_{a_i^n \in \mathcal{A}^n} P_\theta(a_i^n \mid \mathbf{I}^n, \mathbf{Q}^n, \mathcal{A}^n)\,. \quad (7)$$

In the unimodal setting, we remove the image input:

$$\hat{y}^n = \arg\max_{a_i^n \in \mathcal{A}^n} P_\theta(a_i^n \mid \mathbf{Q}^n, \mathcal{A}^n)\,. \quad (8)$$

We report classification accuracy:

$$\text{Acc} = \frac{1}{N}\sum_{n=1}^{N} \mathbb{I}(\hat{y}^n = a^n)\,, \quad (9)$$

where $\mathbb{I}(\cdot)$ is the indicator function.

D.2 Generation

The generation score used in our paper is defined as the mean of the four evaluation metrics: ROUGE-1, ROUGE-2, ROUGE-L (Lin, 2004), and BLEU (Papineni et al., 2002). Specifically, it is computed as follows:

$$\text{Generation Score} = \text{Mean}\Big(\text{ROUGE-1} + \text{ROUGE-2} + \text{ROUGE-L} + \text{BLEU}\Big). \quad (10)$$

By averaging these four metrics, we obtain a comprehensive evaluation that captures various aspects of text generation, including lexical overlap, structural similarity, and fluency. This approach mitigates the bias of individual metrics, providing a more balanced and robust assessment of the generated content.

D.3 Factuality Score

Following previous work (Liu et al., 2024c), we use GPT-4o as an evaluator to assess the factuality, fluency, and semantic relevance of the generated sentences. For each question, we assign a score to the generated answer on a scale from 1 to 10. A score of 1 indicates that the content is completely incorrect or consists of meaningless symbols, while a score of 10 signifies that the answer is factually accurate and well-organized in a coherent sentence.

E MM-Bench Indicator Definitions

To comprehensively evaluate model capabilities, MM-Bench defines multiple indicators that jointly cover overall performance, reasoning ability (attributes and relations), and perception ability at both fine-grained and coarse-grained levels. These indicators aim to capture the model's strengths and weaknesses across diverse dimensions of multimodal understanding.

Overall: *Overall* denotes the overall accuracy of a model on the entire MM-BENCH-TEST set. It reflects the model's performance across all ability dimensions, encompassing both perception and reasoning tasks, and is evaluated under the strict circularEval strategy.

Attribute Reasoning(AR): AR measures a model's ability to reason about attributes of objects or people. This includes identifying physical properties such as hardness or conductivity, inferring the function of tools and objects, and recognizing identities or professions based on appearance.

Relation Reasoning(RR): RR measures reasoning about different types of relationships. It includes social relations between people (e.g., family, friends, colleagues), physical relations in the environment (such as spatial positioning or distance), and natural relations in ecosystems (such as predation, competition, or symbiosis).

Fine-grained Perception(FP-S): FP-S reflects

the model's fine-grained perception ability when dealing with a single object or entity. It covers tasks such as locating objects in an image, recognizing specific attributes like shape or color, identifying celebrities or famous figures, and reading text within an image (OCR).

Fine-grained Perception(FP-C): FP-C measures fine-grained perception across multiple objects in an image. It includes understanding spatial relationships between objects, comparing attributes (e.g., colors or shapes), and recognizing human actions and interactions involving multiple participants.

Coarse Perception(CP): CP evaluates coarse-grained perception abilities. It focuses on a model's capacity to recognize general aspects of an image, such as its style (photo, sketch, painting), the scene it depicts (indoor, forest, street), the overall emotion it conveys (happy, sad, anxious), the visual quality (clarity, brightness, contrast), and the main topic or subject.

In Table 5, we use MLLMMU-Bench and OFFSIDE to fine-tune Qwen2.5-VL 7B with the same number of steps. We find that fine-tuning on synthetic datasets reduces the model's general ability. However, using the proposed OFFSIDE method preserves the model's general performance. This highlights the importance of using a dataset that simulates real-world scenarios.

F Vanilla Model Fine-tuning

To simulate a real-world scenario where unlearning algorithms are applied to a "pre-trained" model, we first fine-tune an off-the-shelf MLLM on the full dataset $\mathcal{D}$. Each training example is a triple $\langle \mathbf{I}^n, \mathbf{Q}^n, \mathbf{Y}^n \rangle$, where $\mathbf{I}^n$ is the input image, $\mathbf{Q}^n$ is the question, and $\mathbf{Y}^n$ is the ground-truth answer. Let $\mathbf{Y}^n = (y_1^n, \ldots, y_{|\mathbf{Y}^n|}^n)$ denote the answer token sequence. The model with parameters θ is trained to maximize the conditional likelihood of the answer given the image and question.

For a single sample, we define the token-normalized negative log-likelihood loss as

$$\ell(\mathbf{I}^n, \mathbf{Q}^n, \mathbf{Y}^n; \theta) = -\frac{1}{|\mathbf{Y}^n|} \sum_{i=1}^{|\mathbf{Y}^n|} \log p_\theta(y_i^n \,|\, \mathbf{I}^n, \mathbf{Q}^n, y_{<i}^n) \,. \tag{11}$$

where $y_{<i}^n$ denotes the prefix tokens $(y_1^n, \ldots, y_{i-1}^n)$.

The overall fine-tuning objective minimizes the average loss over the dataset:

$$\mathcal{L}(\mathcal{D}; \theta) = \frac{1}{|\mathcal{D}|} \sum_{n=1}^{|\mathcal{D}|} \ell(\mathbf{I}^n, \mathbf{Q}^n, \mathbf{Y}^n; \theta) \,. \tag{12}$$

After fine-tuning, we refer to the resulting model as the *vanilla* model, which serves as the starting point for subsequent unlearning experiments.

G Hyperparameters Settings

For all fine-tuning phases, we set the maximum output length to 128. For the LoRA configuration, we set $r = 8$, $\alpha = 32$, dropout = 0.05, and the learning rate to 1×10^{-4}. For unlearning methods, we maintain the same settings except for the learning rate, which is adjusted to 2×10^{-5}. For methods requiring $\mathcal{D}_{\textbf{retain}}$, the previous benchmark utilized an inner loop for the forget set and an outer loop for the retain set. This setup meant that the impact of the forget loss could be easily "healed" by gradient descent on retain batches, which introduced significant randomness due to the instability of the tuning process. To address this issue, we adopted a balanced forget-retain update strategy (e.g., forget step: retrain step = 1:3), ensuring more stable and consistent results. We will provide more detailed Hyperparameters setting in our code.

Why choosing LoRA? The reason we choose LoRA fine-tuning is that machine unlearning emphasizes efficiency, and using full parameter fine-tuning clearly contradicts this principle.

H More Details about Data Construction

Visual Rumors: Real-world data in which rumors are explicitly embedded within images are extremely scarce. Manual collection of such data is not only time-consuming and costly, but randomly synthesizing visual rumors also poses significant risks—including violations of individuals' privacy, reputation, personality rights, and even economic interests tied to image rights and contractual agreements.

To address these challenges, we adopt a mixed unlearning setup: each image is paired with exactly one visual rumor, while all other associated rumors remain text-based. To the best of our knowledge, OFFSIDE is the first benchmark to be constructed in this manner. Although the dataset contains only 640 images (each accompanied by 14 textual rumors), the observation that 'all baseline methods fail to unlearn visual rumors' appears to be a consistent and widespread phenomenon.

Figure 5: Case study of four unlearning settings, each simulating a real-world MLLM unlearning scenario.

In practice, we manually evaluated these visual rumors using GPT-based assessment and found that they achieve an average evaluation score of 9.8—an impressively high result that underscores their vulnerability.

The criteria for selecting the 80 players primarily depend on the ability to collect sufficient information, including rumor images and the corresponding rumors. This was a challenging task, as we reviewed nearly 200 players before identifying 80 players who met the requirements. All of the images were collected after the 2025 Premier League summer transfer window closed, when player information was relatively stable. The rumors were gathered from [8]. We hired two football experts to examine the images and corresponding texts twice to ensure their quality. Specifically, we first retrieved player information and associated transfer rumors from https://www.transfermarkt.com/start. For the selected players, we then searched Google to find images corresponding to the text information (image-text association). Finally, we used GPT-4 to generate VQA pairs, which were used to construct the datasets.

I Extra findings

In some rare cases, the unlearned model outperforms the vanilla model. As illustrated by the PO example in Table 2, the unlearned model achieves a higher generation score on the test set compared to the vanilla model. This improvement can be primarily attributed to the reintroduction of $\mathcal{D}_{\text{retain}}$. To obtain the vanilla model, we ensure that it is not overfitted to $\mathcal{D}_{\text{finetune}}$. During the unlearning process, incorporating $\mathcal{D}_{\text{retain}}$ can enhance generalization on $\mathcal{D}_{\text{finetune}}$. However, methods that rely on $\mathcal{D}_{\text{retain}}$ are at risk of overfitting, which requires careful management.

[8] https://www.transfermarkt.com/start

J Case Study

We present the case study under our specially designed four settings in Figure 5. *Complete Unlearning* evaluates the ability of MU methods to remove all image-text connections, ensuring that the model forgets the entire knowledge associated with specific visual or textual inputs. *Selective Unlearning* tests the methods' capacity to accurately unlearn unwanted knowledge while preserving the shared, valuable information across modalities, highlighting the precision of the unlearning process. *Relearn Facts* serves as a continual learning setting, where the model must relearn certain facts after unlearning them, simulating real-world scenarios where knowledge evolves and needs to be updated. Finally, *Unimodal Unlearning* examines whether unimodal methods, designed for single-modality data, can be directly applied to Multimodal Large Language Model (MLLM) MU settings, revealing the limitations and challenges of using unimodal techniques in multimodal contexts.

K GPT Prompt Strategy

In this section, we detail the methodology employed to construct our dataset using the OpenAI API. To evaluate the faculty score of the generated answers, we carefully designed a structured prompt, as illustrated in Figure 8. This prompt enables a systematic and transparent evaluation of generated answers by providing clear, multi-dimensional criteria focused on factuality, relevance, and fluency. It ensures consistency and granularity through a well-defined scoring scale and explicit guidelines

for handling language issues. Furthermore, we leverage GPT-4o to generate high-quality classification data, with the exact prompt used provided in Figure 7. In addition to classification data, we also utilize GPT-4o to construct unimodal unlearning data, as detailed in the prompt shown in Figure 6. This type of data is specifically designed to isolate and examine individual modalities or attributes within the model's knowledge.

L Future Work

In OFFSIDE, we observe that "unlearned rumors can be easily recovered." This raises critical questions: How exactly does the model perform unlearning? Why can seemingly forgotten knowledge be restored with simple attacks? To address these, future work could leverage interpretability tools such as neuron activation patterns or attention attribution to probe the internal mechanisms of unlearning in multimodal models. Moreover, we find that unimodal unlearning methods fail to erase multimodal knowledge, which contrasts with conclusions drawn from previous benchmarks(Liu et al., 2024c). We attribute this discrepancy to model collapse during unimodal unlearning observed in MLLMMU-Bench: rather than selectively forgetting targeted content, these methods degrade the model's general capabilities, creating a false impression of successful unlearning. This failure reveals a deeper issue: current unlearning approaches are still largely grounded in next-token prediction paradigms and exhibit strong modality bias. Knowledge across modalities is not jointly represented or edited, suggesting that effective multimodal unlearning requires a better understanding of how cross-modal knowledge is stored and entangled in MLLMs.

M Discussion and potential risks

Deceptive Visual Rumors: Several works have addressed the issue of visual rumors. From a benchmarking perspective, to the best of our knowledge, PEBench (Xu et al., 2025) is the first to tackle this problem. However, PEBench focuses on unlearning specific locations and individuals, with the unlearning target learned through fine-tuning. In contrast, the visual rumors in OFFSIDE can be directly inferred by the pretrained model, making this setting inherently more deceptive. From a methodological perspective, MMUNLEARNER (Huo et al., 2025) proposes a selective unlearning approach that removes visual patterns associated with a specific entity while retaining the corresponding textual knowledge within the LLM backbone. This target differs from that of OFFSIDE, where we aim to unlearn both the visual patterns and the associated textual knowledge. As a result, we do not include this method in our baseline.

Acceptable Unlearning Results: As the MLLM MU is still in its early stages, many questions remain regarding experimental design. **Firstly**, due to the widespread use of LoRA fine-tuning, controlling the unlearning process becomes extremely challenging. An over-finetuned model may suffer from catastrophic collapse, while an under-finetuned model may yield suboptimal results. The most crucial parameter is the fine-tuning step, which is difficult to standardize across baselines because each model undergoes a different unlearning process, influenced by both the data and the unlearning target (loss) perspectives. In this regard, we consider any result acceptable only if the unlearned model can retain its general performance on the MM-Bench task. **Secondly**, there is the issue of overfitting. While MMUNLEARNER (Huo et al., 2025) has observed overfitting in CLEAR (Dontsov et al., 2024), we note that the vanilla model used in MLLMMU-Bench (Liu et al., 2024c) is an overfitted version of the fine-tuned set. This raises an important question: is it necessary to evaluate an overfitted or collapsed unlearned model? The answer is no; fairness can be ensured by monitoring the unlearning process through evaluation on general benchmarks, such as MM-Bench.

Potential risks: This work involves collecting visual rumors, which could potentially be misused by malicious actors to spread misinformation.

N Use of AI Assistants

LLMs are employed to polish the language of our paper. What's more, we evaluate the factual accuracy of the generated answers using GPT-4o. Apart from these, we have not included any usage of LLMs, preserving the originality and quality of this work.

GPT-4o Prompting Strategy for Creating Pure Text Data

```
prompt = f"""
You are cleaning a multimodal Q&A dataset about football players.

1. If the user question is about the player's name or identity (e.g. "Who is the player?", "What is the name of the player?", "Can you tell me who this is?"), REMOVE this Q&A pair from the dataset. Do not output anything for these cases.
2. For all other questions, REWRITE the user question so that it directly uses the player's name (from the mapping below) instead of referring to "the player" or "this player". For example, change "How tall is the player in the image?" to "How tall is {player_name}?" or "What is {player_name}'s height?". The question should be natural and concise.
3. The assistant answer should remain unchanged.
Player name mapping:
{player_name}
Original user question: {user_content}
Original assistant answer: {assistant_content}
Output ONLY valid JSON:
{{
  "messages": [
    {{
      "role": "user",
      "content": "Your rewritten user question"
    }},
    {{
      "role": "assistant",
      "content": "Original assistant answer"
    }}
  ],
  "images": "{image_path}"
}}
If the Q&A is about the player's name/identity, output nothing.
"""
```

Figure 6: Prompt strategy of creating pure text description.

GPT-4o Prompting Strategy for Creating Classification Data

```
prompt = f"""    Please reformat the following multiple-choice question options to ensure they all have exactly the same sentence structure and format.

Original question: {question}        Current options:    A: {options.get('A', '')}    B: {options.get('B', '')}    C: {options.get('C', '')}    D: {options.get('D', '')} }

Correct answer: {correct_answer}
Requirements:
1.  All five options must use identical sentence structure and format
2.  All options should be consistent in length, tone, and style
3.  Make all options follow the same pattern (e.g., "The player is [name]." or "The stadium is located in [city].")
4.  DO NOT change the core information in each option - keep the names, numbers, locations, etc.
5.  The correct answer (currently option {correct_answer}) must remain factually the same
6.   Remove any inconsistencies like extra words or different punctuation patterns
Return ONLY a JSON with the standardized options:    {{      "A": "First standardized option",      "B": "Second standardized option",      "C": "Third standardized option",      "D": "Fourth standardized option}}    """
```

Figure 7: Prompt strategy of creating classification data.

GPT-4o Prompting Strategy for evaluation

```
prompt = f"""You will be provided with a question and two answers: a generated answer and a ground truth answer. Your task is to evaluate the factuality of the "generated_answer" against the "ground_truth". Please assign a factuality score from 1 to 10 based on the following criteria:
1. Factuality (core importance):
    • 10-9: The generated response is fully factually correct and has the same meaning as the ground truth, even if phrased differently.
    • 8-7: The response is mostly correct but may be missing minor details or contain slightly less important deviations.
    • 6-5: The response is partially correct but has a noticeable factual error or significant missing information.
    • 4-3: The response has major factual errors or lacks crucial elements of the ground truth.
    • 2-1: The response is nonsensical, completely incorrect, or irrelevant.
2. Relevance and Detail:
    • More detail does not always improve the score; added details should be factually relevant.
    • If the generated response contains excessive or irrelevant details, lower the score accordingly.
3. Fluency and Language Requirements:
    • The response must be in English. If it's not in English, reduce the score according to how much this affects comprehension.
    • If the response contains garbled text, random symbols, or is completely incomprehensible, assign a score of 0.
    • Poor grammar or awkward phrasing should result in a score reduction proportional to how much it affects understanding.
Task Type: {task_type.capitalize()}
- Image ID: {image_id}
- Question: {question}
- Generated Answer: {generated_answer}
- Ground Truth: {ground_truth}
Please evaluate the factuality of the generated response based on the rubric above, and return a score (1-10) along with a short justification.
Return your response in JSON format only: {{ "factuality_score": [score from 1-10 as a number, or 0 if completely incomprehensible],
"justification": "[Your brief justification, including comments on factuality, relevance, and fluency]" }}
"""
```

Figure 8: Prompt strategy of evaluating factuality score through GPT-4o.