

TL;DR

Membership Inference Attack (MIA) [1]: a type of attack on ML models that attempts to whether a particular data record is part of the training dataset.

Our contributions can be summarized as follows.

- We release the first benchmark tailored for the detection of training data in VLLMs, called **Vision Language MIA (VL-MIA)**. By leveraging Flickr and GPT-4, we construct VL-MIA that contains two images MIA tasks and one text MIA task for various VLLMs, including MiniGPT-4 [2], LLaVA 1.5 [3] and LLaMA-Adapter V2 [4].
- We perform the first individual image or description MIAs on VLLMs in a cross-modal manner. Specifically, we demonstrate that we can perform image MIAs by computing statistics from the image or text slices of the VLLM’s output logits.
- We propose a target-free MIA metric, **MaxRényi-K%**, and its modified target-based **ModRényi**. We demonstrate their effectiveness on open-source VLLMs and closed-source GPT-4.

MaxRényi MIA

Rényi entropy of order α Given a probability distribution p , the Rényi entropy [5] of order α is defined as $H_\alpha(p) = \frac{1}{1-\alpha} \log \left(\sum_j (p_j)^\alpha \right)$, $0 < \alpha < \infty, \alpha \neq 1$. At $\alpha = 1$ and $\alpha = \infty$, the entropy is defined as:

$$\bullet H_1(p) = -\sum_j p_j \log p_j, H_\infty(p) = -\log \max p_j.$$

MaxRényi-K% For a token sequence $X := (x_1, x_2, \dots, x_L)$, let the next-token probability distribution at the i -th token be: $p^{(i)}(\cdot) = \mathbb{P}(\cdot | x_1, \dots, x_i)$. Define $\text{Max-K}\%(X)$ as the subset of X containing the top $K\%$ tokens with the largest Rényi entropies. The **MaxRényi-K%** score of X is given by:

$$\text{MaxRényi-K}\%(X) = \frac{1}{|\text{Max-K}\%(X)|} \sum_{i \in \text{Max-K}\%(X)} H_\alpha(p^{(i)}).$$

Special cases:

- $\alpha = 1, K = 100$: standard entropy-based MIA.
- $\alpha = \infty$: the most likely next token probability. In comparison, Min-K [6] deals with the target next token probability.

Extension to Target-Based Scenarios: ModRényi We propose **ModRényi** for scenarios where the target token ID is known. Using a linearized Rényi entropy, $\bar{H}_\alpha(p)$, we define: $\bar{H}_\alpha(p) = \frac{1}{1-\alpha} \left(\sum_j (p_j)^\alpha - 1 \right)$, $0 < \alpha < \infty, \alpha \neq 1$. Given next token ID y , we define the modified Rényi entropy as:

$$\bar{H}_\alpha(p, y) = -\frac{1}{|\alpha - 1|} \left((1 - p_y)p_y^{|\alpha-1|} - (1 - p_y) + \sum_{j \neq y} p_j(1 - p_j)^{|\alpha-1|} - p_j \right).$$

MIAs against VLLMs: pipeline & benchmark

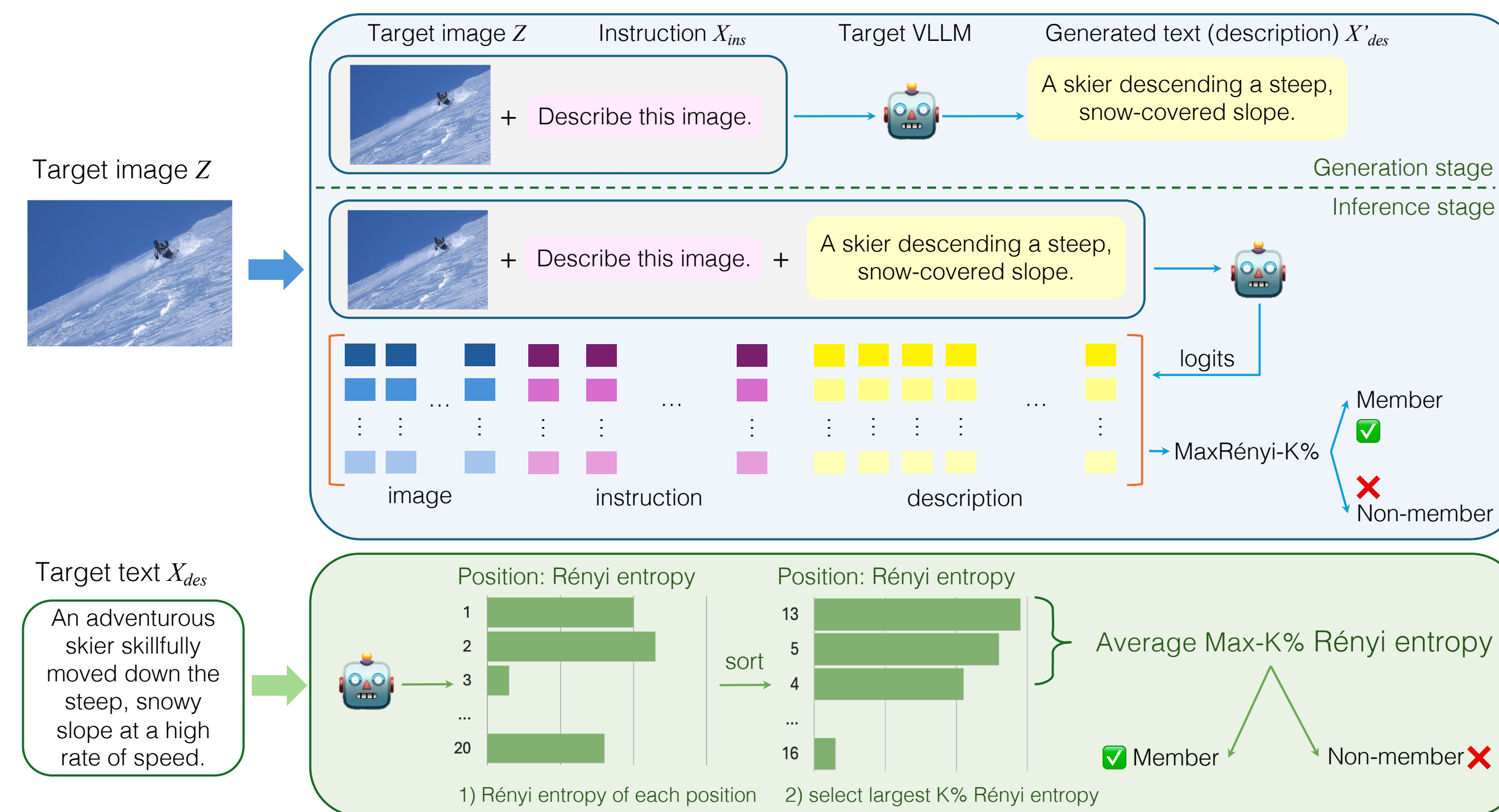
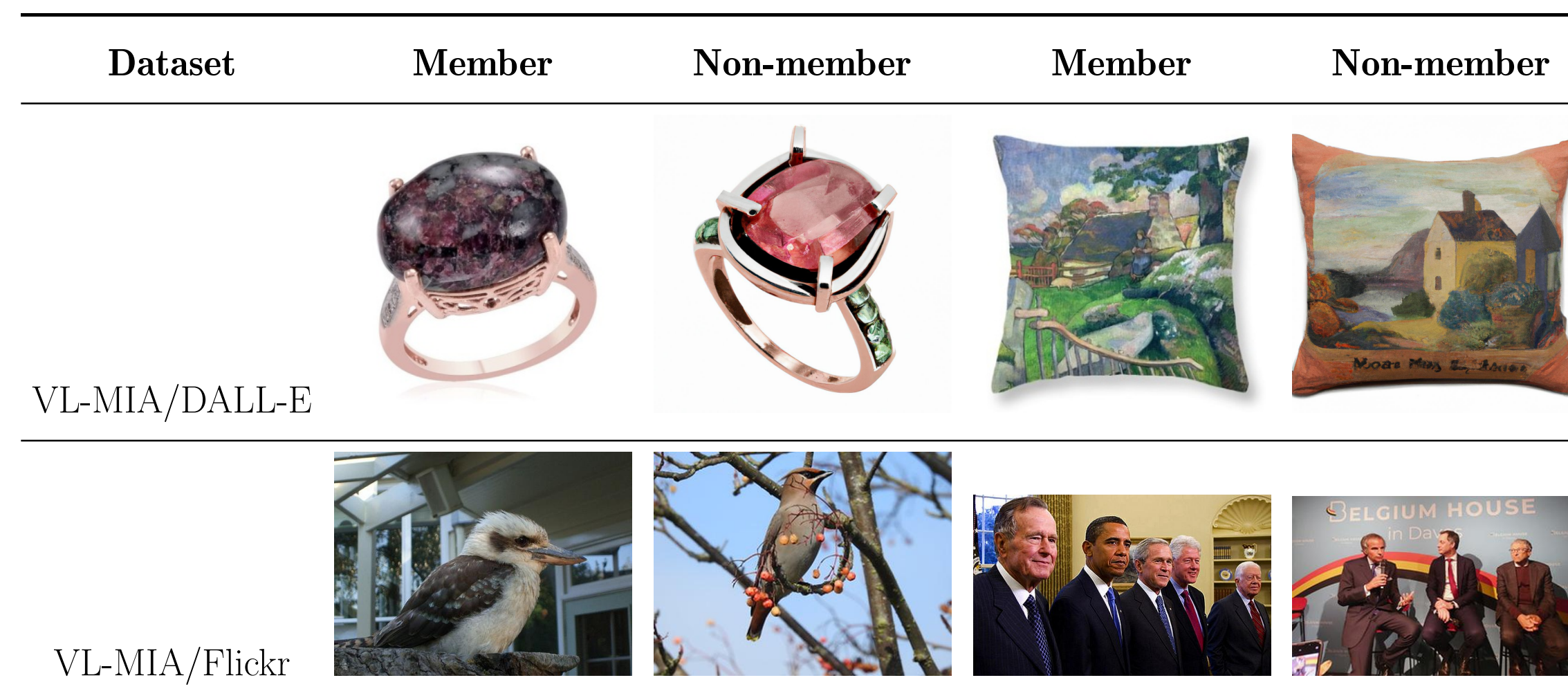


Table 1: **Overview of VL-MIA dataset:** VL-MIA covers image and text modalities and can be applied for dominant open-sourced VLLMs.

Dataset	Modality	Member data	Non-member data	Application
VL-MIA/DALL-E	image	LAION_CCS	DALL-E-generated images	LLaVA 1.5 MiniGPT-4 LLaMA_adapter v2
VL-MIA/Flickr	image	MS COCO (from Flickr)	Latest images on Flickr	LLaVA 1.5 MiniGPT-4 LLaMA_adapter v2
VL-MIA/Text	text	LLaVA v1.5 instruction-tuning text MiniGPT-4 instruction-tuning text	GPT-generated answers GPT-generated answers	LLaVA 1.5 LLaMA_adapter v2 MiniGPT-4

Dataset examples

Table 2: Examples in VL-MIA/image non-member data are generated by DALL-E or collected from recent Flickr websites.



Experiments

We conduct MIAs on open-source LLaVA and closed-source model GPT-4.

Table 3: **Image MIA on VL-MIA/Flickr on LLaVA** with a size of 2000. Table 4: **Image MIA on GPT-4**.

Metric	img	inst	desp	inst+desp	Metric	VL-MIA/ DALL-E	VL-MIA/ Flickr
Perplexity*	N/A	0.365	0.665	0.561	Perplexity/zlib*	0.807	0.520
Min_10% Prob*	N/A	0.353	0.606	0.336	Max_Prob_Gap	0.516	0.486
Min_20% Prob*	N/A	0.335	0.619	0.345	Max_0%	0.697	0.571
Aug_KL	0.586	0.535	0.483	0.504	Rényi ($\alpha = 0.5$) Max_10%	0.749	0.604
Max_Prob_Gap	0.602	0.516	0.639	0.637	Max_100%	0.815	0.605
ModRényi*	$\alpha = 0.5$	N/A	0.528	0.658	Max_0%	0.688	0.572
	$\alpha = 1$	N/A	0.379	0.656	Rényi ($\alpha = 1$) Max_10%	0.747	0.591
	$\alpha = 2$	N/A	0.528	0.659	Max_100%	0.790	0.630
Rényi ($\alpha = 0.5$)	Max_0%	0.559	0.647	0.656	Max_0%	0.685	0.561
	Max_10%	0.561	0.647	0.659	Rényi ($\alpha = \infty$) Max_10%	0.708	0.549
	Max_100%	0.711	0.685	0.687	Max_100%	0.781	0.583

See more experiments in the paper.

Future work

- We would like to extend the method to a broader class of multimodal models that incorporate speech or video modalities.
- Our proposed method is semi-black-box, and requires the full probability distribution of the next token prediction. We would like to tackle the case where more or fewer internal workings of VLLMs are available.

References

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- [5] Alfréd Rényi. “On measures of entropy and information”. In: *Proceedings of the fourth Berkeley symposium on mathematical statistics and probability, volume 1: contributions to the theory of statistics*. Vol. 4. University of California Press, 1961, pp. 547–562.
- [6] Weijia Shi et al. “Detecting Pretraining Data from Large Language Models”. In: *The Twelfth International Conference on Learning Representations*. 2024. URL: <https://openreview.net/forum?id=zWqr3MQuNs>.

Acknowledgements

