ICLR
International Conference On Learning Representations

# Exploring Local Memorization in Diffusion Models via Bright Ending Attention

Chen Chen, Daochang Liu, Mubarak Shah, Chang Xu

ICLR 2025 Spotlight

THE UNIVERSITY OF SYDNEY


THE UNIVERSITY OF WESTERN AUSTRALIA

# Memorization in Diffusion Models

- Pretrained diffusion models can memorize and repeat training data during inference without informing data owners and model users.


Chen et al., “Exploring Local Memorization in Diffusion Models via Bright Ending Attention.” ICLR, 2025.

# Memorization in Diffusion Models

- Pretrained diffusion models can memorize and repeat training data during inference without informing data owners and model users.

- This exposes potential violations of copyright laws and the introduction of ethical dilemmas.

- Two factors have heightened such litigation risks:
  - The widespread use and deployment of open-source state-of-the-art diffusion models.

  - The extensive size of training sets impedes detailed human review.

- Creativity concerns.

Chen et al., “Exploring Local Memorization in Diffusion Models via Bright Ending Attention.” ICLR, 2025.

# Local Memorization in Diffusion Models

- Diffusion models can exhibit both global and local memorization.
  - Global memorization: the entire training image is memorized.
  - Local memorization: only parts of the training image are memorized.


Chen et al., “Exploring Local Memorization in Diffusion Models via Bright Ending Attention.” ICLR, 2025.

# Performance Gap in Local Memorization

- Existing methods underperform in local memorization’s evaluation, detection, and mitigation.

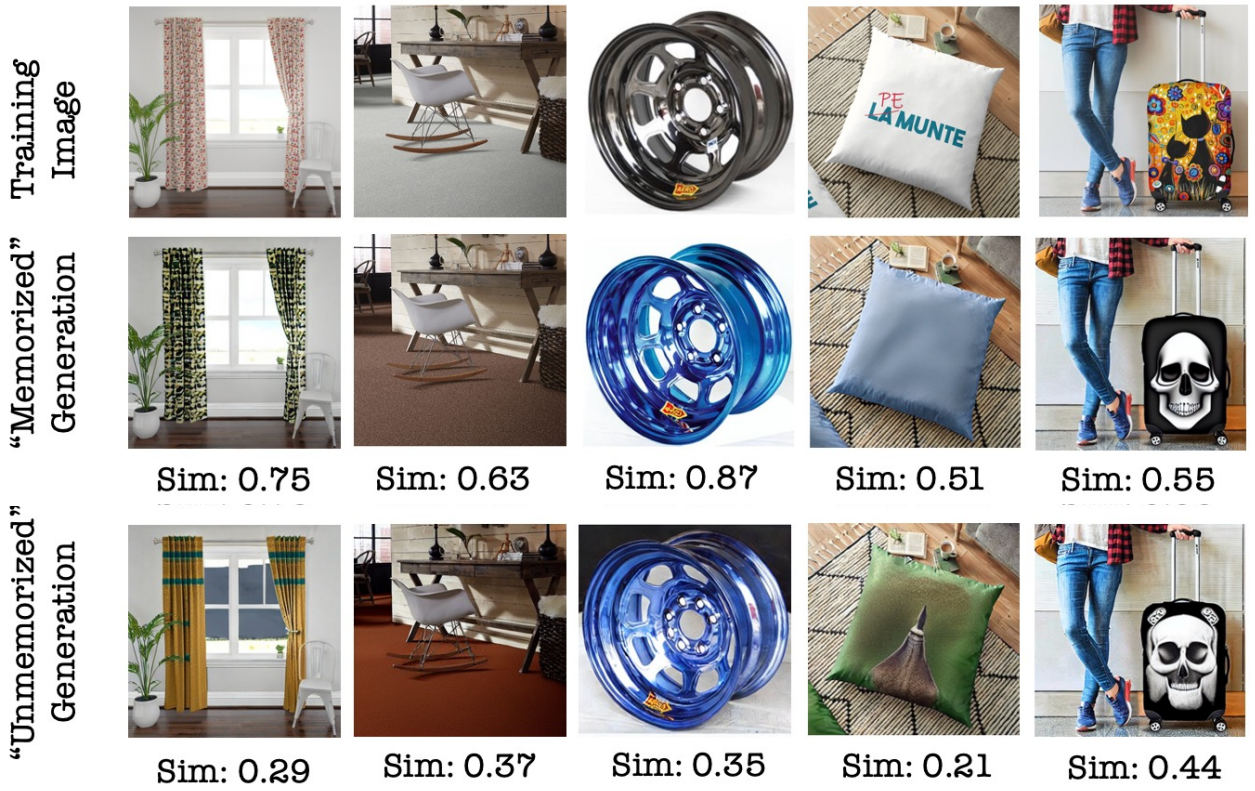
Chen et al., “Exploring Local Memorization in Diffusion Models via Bright Ending Attention.” ICLR, 2025.

# Performance Gap in Local Memorization – Evaluation Strategy

- Existing evaluation strategies rely on Self-Supervised Copy Detection (SSCD) embeddings.

$$Sim = cosine\_similarity(\Phi_{SSCD}(\hat{x}), \Phi_{SSCD}(x))$$

$$Memorization_{SSCD}(\hat{x}, x) = 1_{Sim>0.5}$$

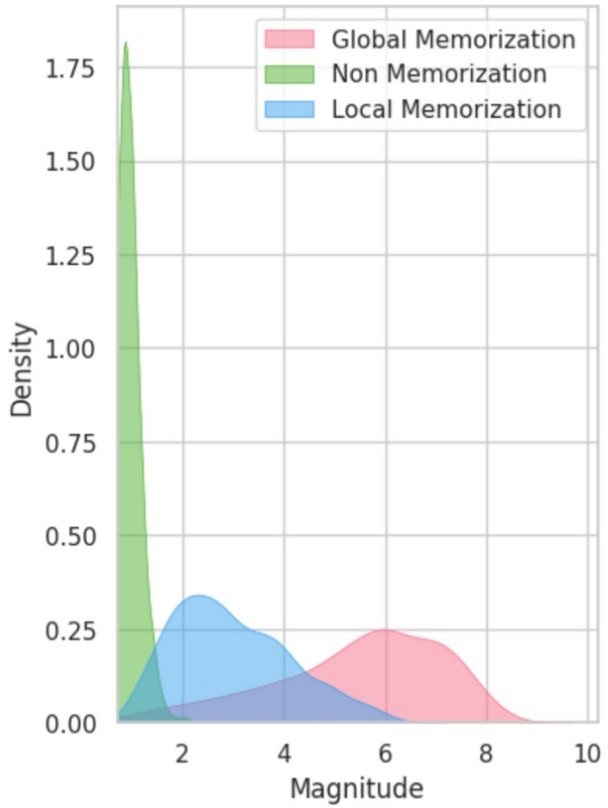



Chen et al., "Exploring Local Memorization in Diffusion Models via Bright Ending Attention." ICLR, 2025.

# Performance Gap in Local Memorization – Detection Strategy

- A popular detection strategy has developed “Magnitude” as a strong signal of memorization.

$$Magnitude = \left\| \varepsilon_\theta(x_t, e_p) - \varepsilon_\theta(x_t, e_\phi) \right\|_2$$

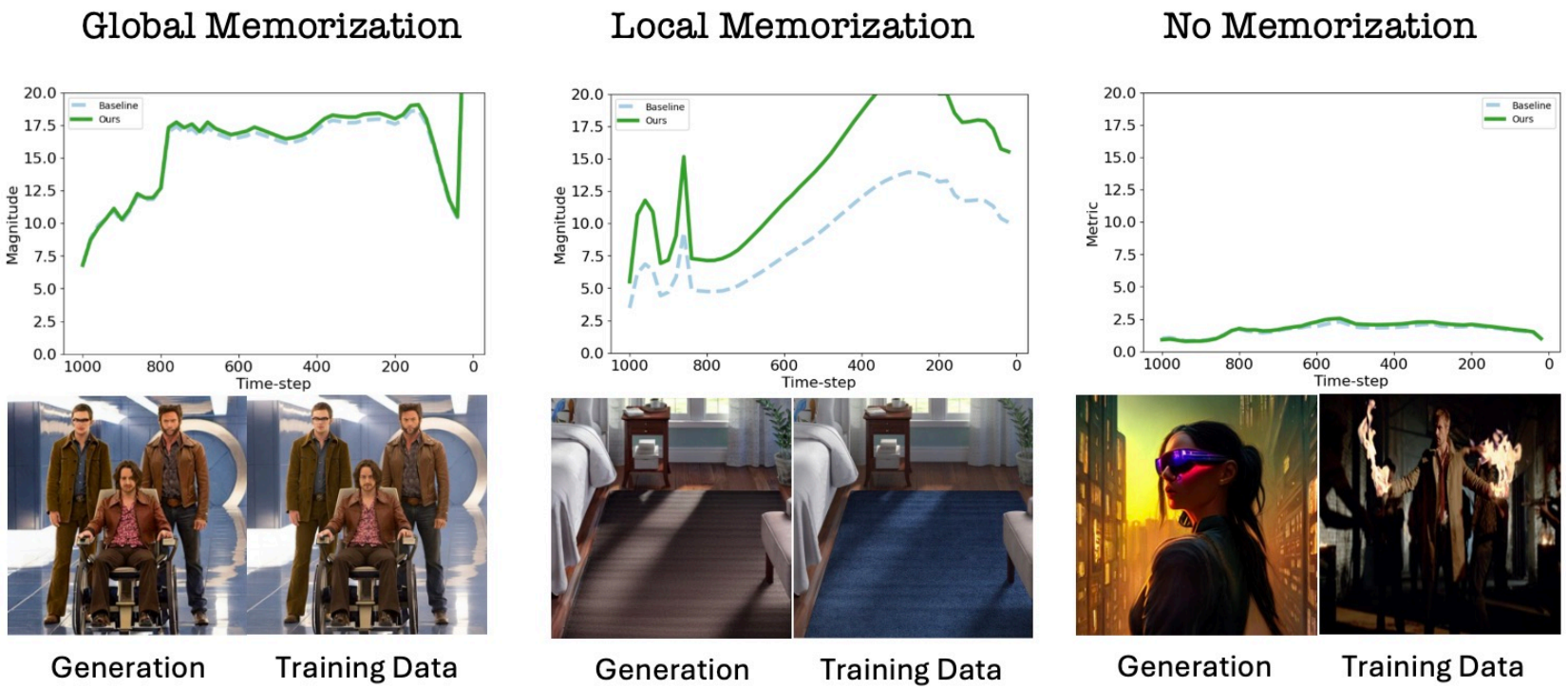



Chen et al., “Exploring Local Memorization in Diffusion Models via Bright Ending Attention.” ICLR, 2025.

# Performance Gap in Local Memorization – Detection Strategy

- A popular detection strategy has developed “Magnitude” as a strong signal of memorization.

$$Magnitude = \left\| \varepsilon_\theta(x_t, e_p) - \varepsilon_\theta(x_t, e_\phi) \right\|_2$$




Chen et al., “Exploring Local Memorization in Diffusion Models via Bright Ending Attention.” ICLR, 2025.

# Performance Gap in Local Memorization – Mitigation Strategy

- The corresponding mitigation strategy relies on the magnitude-based detection strategy:

$$Magnitude = \left\| \varepsilon_\theta(x_t, e_p) - \varepsilon_\theta(x_t, e_\phi) \right\|_2$$

  - Prompt Engineering – Optimize the embedding of the user input prompt using the detection signal as the loss for computing the gradient.

  - Triggered only when the detection signal is greater than a specified threshold.

Chen et al., “Exploring Local Memorization in Diffusion Models via Bright Ending Attention.” ICLR, 2025.

# Takeaway: The Localization Insight

- Local memorization is a more generalized and practical notion of memorization.
    - Unmemorized regions pose no litigation risk and can be disregarded, while even a tiny locally memorized area can present significant legal concerns.
    - Local memorization is a more encompassing definition, with global memorization being a specific instance.
- Therefore, improved metrics and strategies should concentrate exclusively on the locally memorized regions while ignoring the unmemorized parts of the image.

Chen et al., “Exploring Local Memorization in Diffusion Models via Bright Ending Attention.” ICLR, 2025.

# Next Steps: How to Investigate Locally?

- Extracting a local memorization mask can help revise existing strategies to take a local perspective.

- How to extract such a mask?

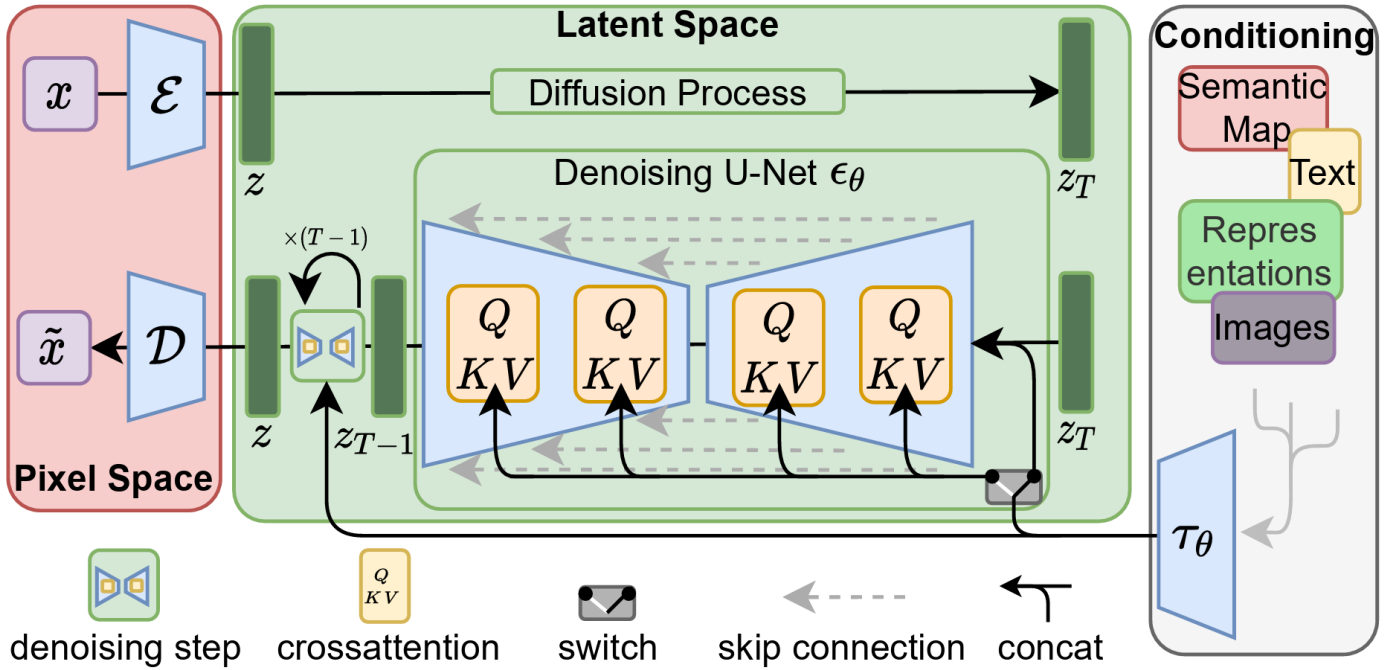
    - Directly comparing generated images with training images.
        - Compromises privacy.
        - Computationally heavy.

    - Automatic mask extraction using the pre-trained model's memory.
        - Leverage text-conditioning.
        - Explore cross-attention maps.

Chen et al., "Exploring Local Memorization in Diffusion Models via Bright Ending Attention." ICLR, 2025.

# The “Bright Ending” (BE) Phenomenon

- Cross-attention is used in 16 layers of Stable Diffusion’s U-Net to integrate text and other conditioning signals.

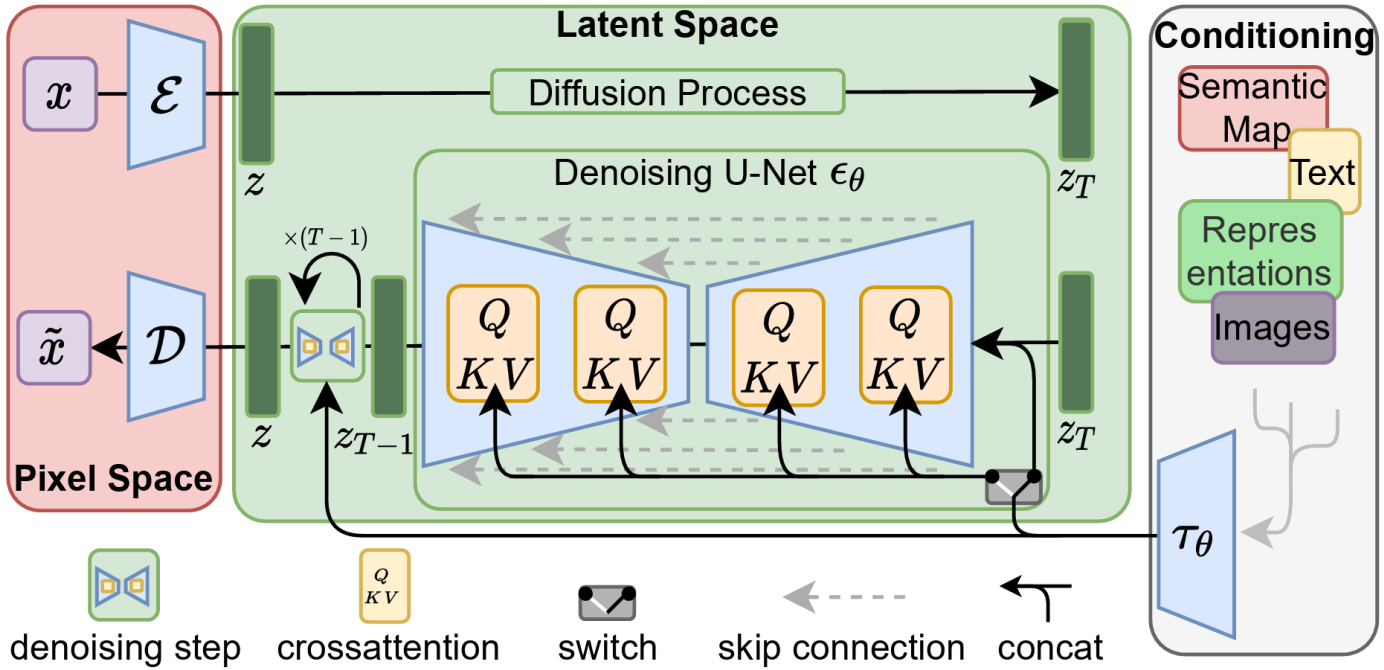



Rombach et al., “High-Resolution Image Synthesis with Latent Diffusion Models.” CVPR, 2022.

# The “Bright Ending” (BE) Phenomenon

- We derive the cross-attention maps for text-to-image generations:

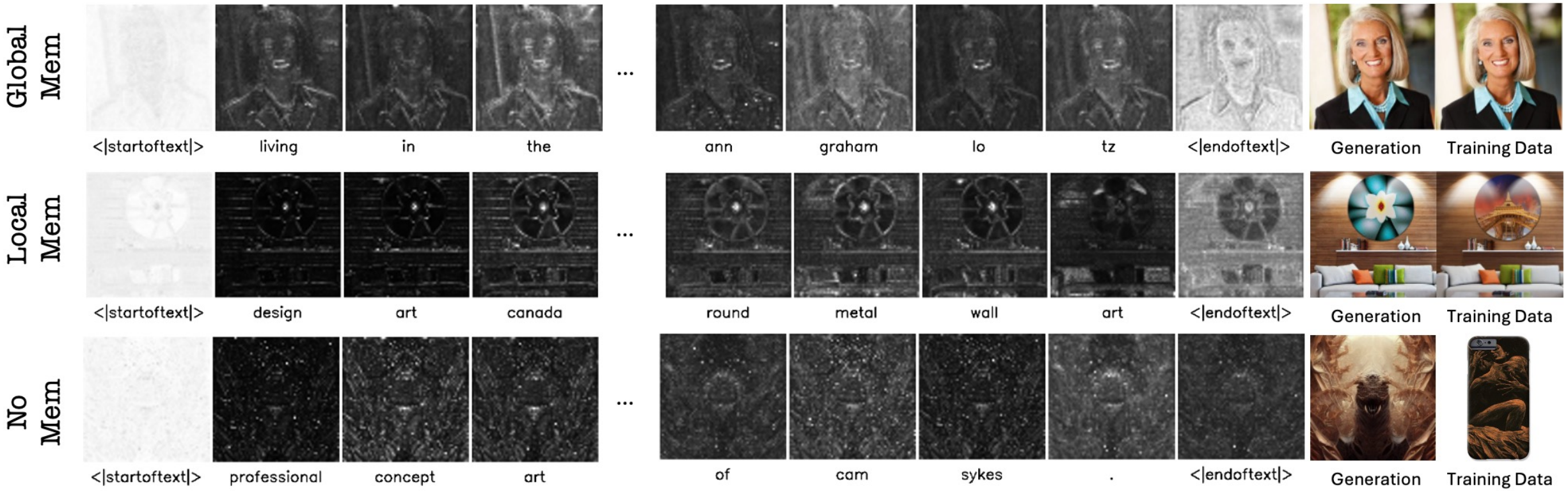
$$AttentionMap(Q,K) = SoftMax\left(\frac{QK^T}{\sqrt{d}}\right)$$




Rombach et al., “High-Resolution Image Synthesis with Latent Diffusion Models.” CVPR, 2022.

# The “Bright Ending” (BE) Phenomenon

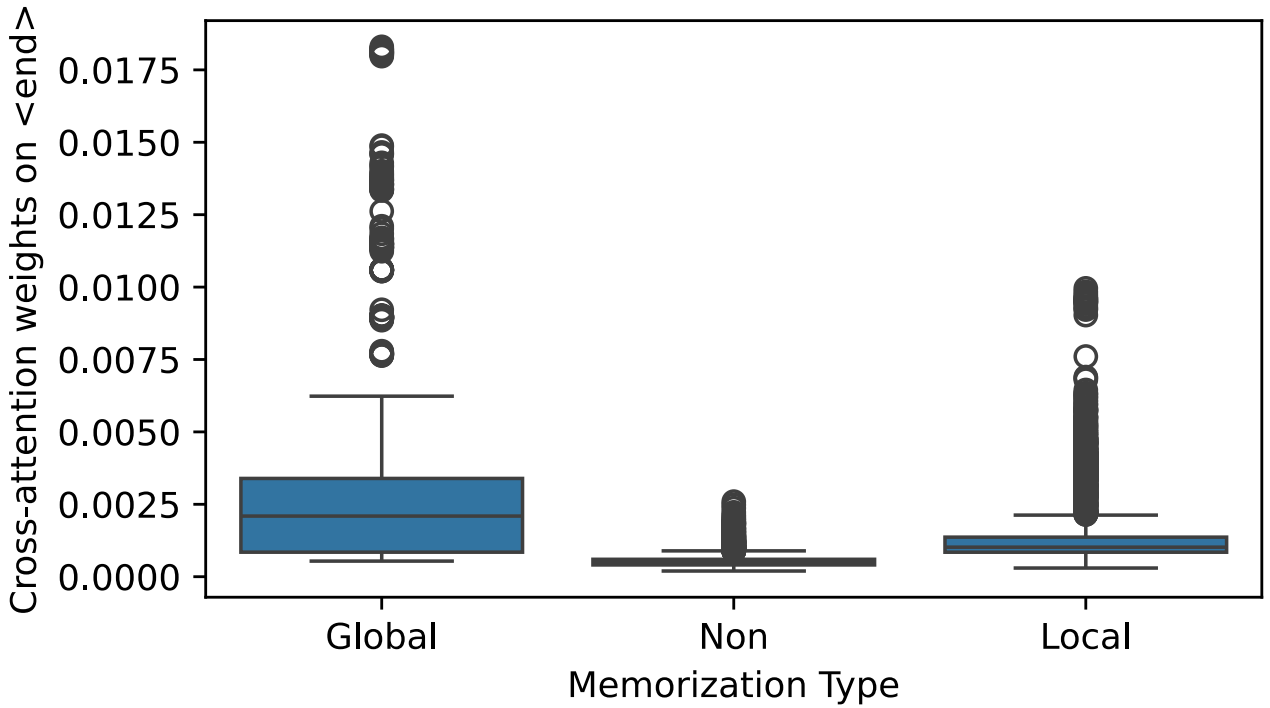
- We then average and visualize such maps from the first two downsampling U-Net layers.
- **Observing the “bright ending” anomaly for memorized Diffusion Models.**




Chen et al., “Exploring Local Memorization in Diffusion Models via Bright Ending Attention.” ICLR, 2025.

# The “Bright Ending” (BE) Phenomenon

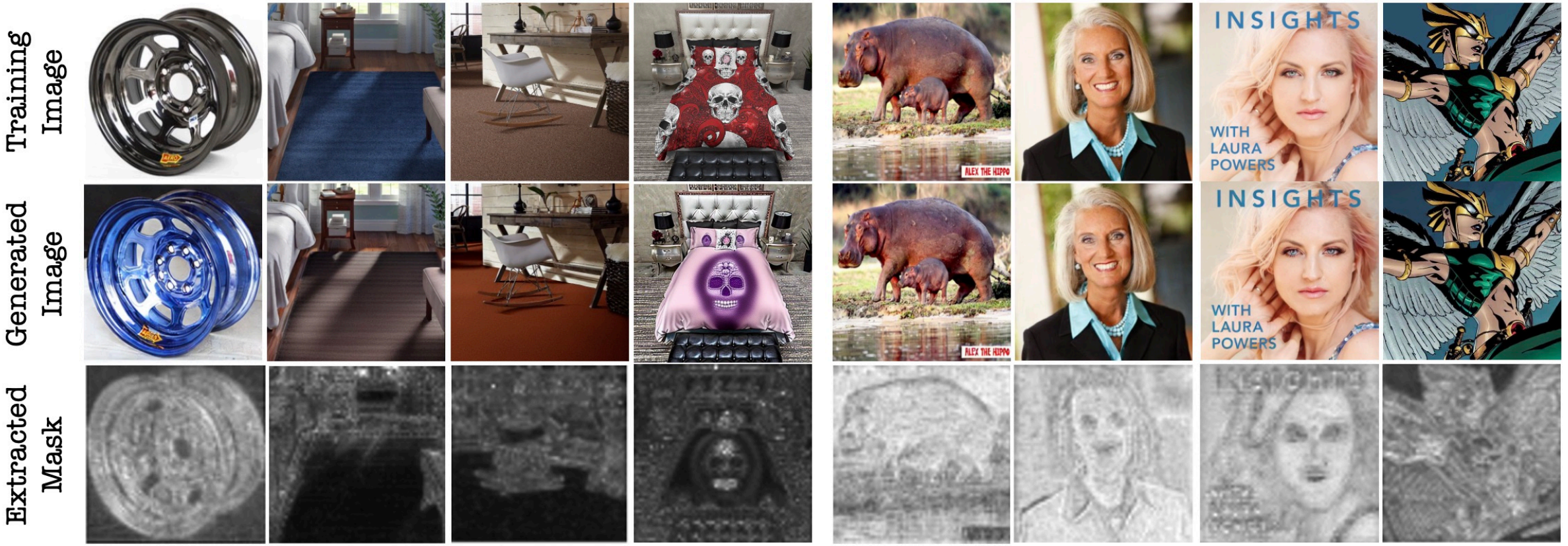
- Distributions of the attention scores of the <EOS> token at the final inference step for global, local, and non-memorization scenarios can further validate our observation:




Chen et al., “Exploring Local Memorization in Diffusion Models via Bright Ending Attention.” ICLR, 2025.

# The “Bright Ending” (BE) Phenomenon

- More examples:




Chen et al., “Exploring Local Memorization in Diffusion Models via Bright Ending Attention.” ICLR, 2025.

# Localized Memorization Detection Strategy

- The cost function of the denoiser network (without text-conditioning):

$$L = \mathbb{E}_{t\in[1,T],\varepsilon\sim\mathcal{N}(0,\boldsymbol{I})}\left[\left\|\varepsilon_t - \varepsilon_\theta\left(x_t, e_\phi\right)\right\|_2^2\right]$$

- The cost function of the denoiser network (with text-conditioning):

$$L = \mathbb{E}_{t\in[1,T],\varepsilon\sim\mathcal{N}(0,\boldsymbol{I})}\left[\left\|\varepsilon_t - \varepsilon_\theta\left(x_t, e_p\right)\right\|_2^2\right]$$

- Computing the Bright Ending (BE) mask:

$$\boldsymbol{m} = SoftMax\left(\frac{QK^T}{\sqrt{d}}\right)$$

- Localized detection strategy by incorporating the BE mask:

$$LD = \frac{1}{T}\sum_{t=1}^{T}\left\|\left(\varepsilon_\theta\left(x_t, e_p\right) - \varepsilon_\theta\left(x_t, e_\phi\right)\right)\circ\boldsymbol{m}\right\|_2 \Big/ \left(\frac{1}{N}\sum_{i=1}^{N} m_i\right)$$

Chen et al., “Exploring Local Memorization in Diffusion Models via Bright Ending Attention.” ICLR, 2025.

# Localized Memorization Mitigation Strategy

- The corresponding mitigation strategy relies on the magnitude-based detection strategy:

$$LD = \frac{1}{T}\sum_{t=1}^{T} \left\| \left( \varepsilon_\theta(x_t, e_p) - \varepsilon_\theta(x_t, e_\phi) \right) \circ \boldsymbol{m} \right\|_2 \Big/ \left( \frac{1}{N}\sum_{i=1}^{N} m_i \right)$$

- Localized mitigation strategy by incorporating the BE mask:
  - Improved loss function ($LD$) that allows more effective prompt optimization.
  - More accurate trigger signal ($LD$) based on the localized detection strategy.

Chen et al., “Exploring Local Memorization in Diffusion Models via Bright Ending Attention.” ICLR, 2025.

# Localized Memorization Evaluation Strategy

- Global evaluation strategies:

$$SSCD(\hat{x}, x) = 1_{SSCD>0.5}$$

$$S(\hat{x}, x) = -1_{SSCD<0.5} \cdot \|\hat{x} - x\|_2$$

- Computing the Bright Ending (BE) mask:

$$\boldsymbol{m} = SoftMax\left(\frac{QK^T}{\sqrt{d}}\right)$$

- Localized evaluation strategy by incorporating the BE mask :

$$LS(\hat{x}, x) = -1_{SSCD<0.5} \cdot \|(\hat{x} - x) \circ \boldsymbol{m}\|_2$$

Chen et al., “Exploring Local Memorization in Diffusion Models via Bright Ending Attention.” ICLR, 2025.

# Results – Detecting Memorization

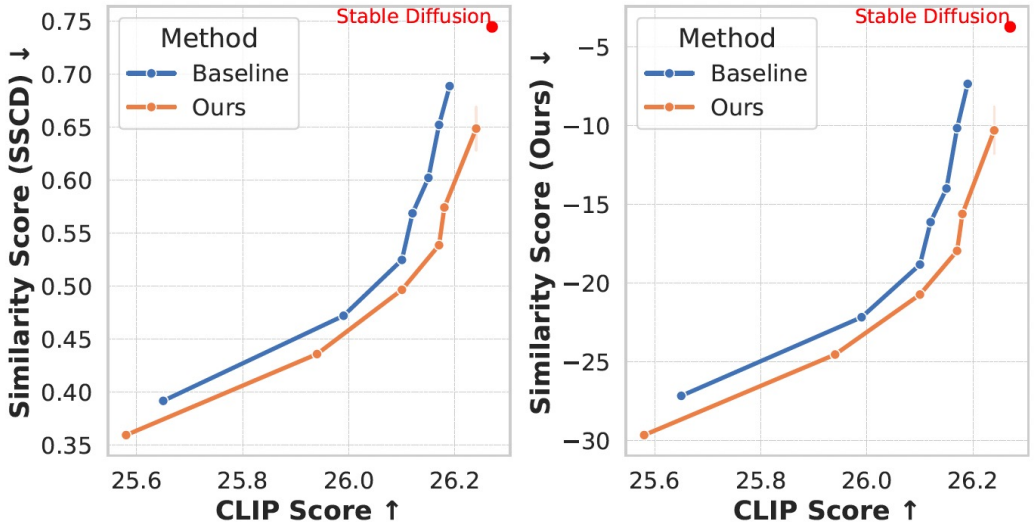
- Results show the incorporation of localization, and “bright ending” insights can improve existing state-of-the-art **detection** strategy’s performance on local memorization cases:

| | First Step | | | First 10 Steps | | | All Steps | | |
|---|---|---|---|---|---|---|---|---|---|
| | AUC | F1 | T@1%F | AUC | F1 | T@1%F | AUC | F1 | T@1%F |
| Baseline - Local | 0.918 | 0.864 | 0.629 | 0.989 | 0.982 | 0.953 | 0.990 | 0.983 | 0.560 |
| Ours - Local | **0.943** | **0.893** | **0.731** | **0.995** | **0.987** | **0.985** | **0.996** | **0.988** | **0.926** |
| Baseline - Global | 0.979 | 0.944 | 0.934 | **1.000** | **0.987** | **1.000** | **0.999** | 0.976 | **1.000** |
| Ours - Global | **0.981** | **0.948** | **0.940** | **1.000** | **0.987** | **1.000** | **0.999** | **0.977** | **1.000** |

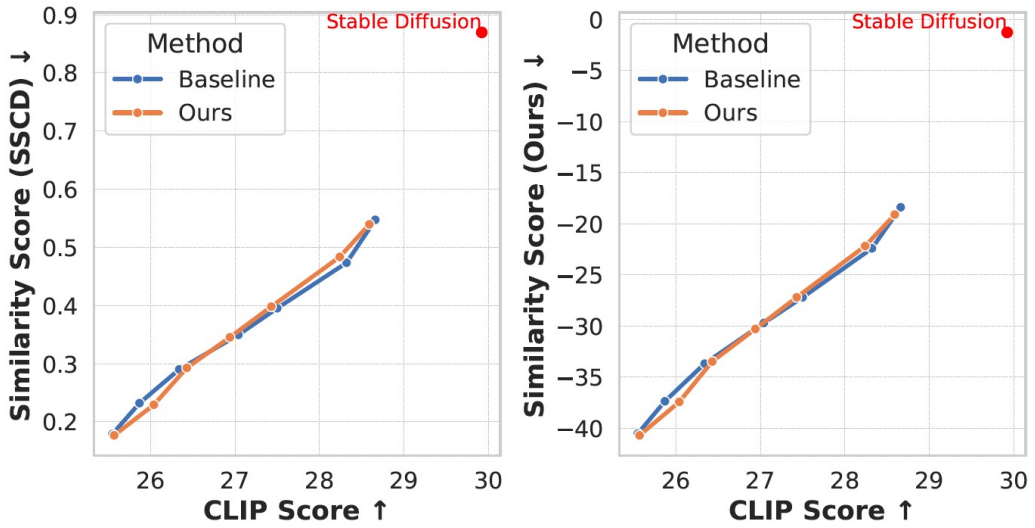
Chen et al., “Exploring Local Memorization in Diffusion Models via Bright Ending Attention.” ICLR, 2025.

# Results – Mitigating Memorization

- Results show the incorporation of localization, and “bright ending” insights can improve existing state-of-the-art **mitigation** strategy’s performance on local memorization cases:




Local memorization’s mitigation




Global memorization’s mitigation

Chen et al., “Exploring Local Memorization in Diffusion Models via Bright Ending Attention.” ICLR, 2025.

# Results – Evaluating Memorization

- Results show the incorporation of localization, and “bright ending” insights can improve existing state-of-the-art **evaluation** strategy’s performance on local memorization cases:

| | Local | Global |
|---|---|---|
| SSCD | 0.940 | 1.000 |
| S | 0.991 | 1.000 |
| LS (Ours) | **0.995** | 1.000 |

Chen et al., “Exploring Local Memorization in Diffusion Models via Bright Ending Attention.” ICLR, 2025.

# Results – Summary

- Our localization insight can help improve the existing memorization detection, mitigation, and evaluation strategies.

- Bright Ending (BE) is effective in automatically extracting local memorization masks.

Chen et al., “Exploring Local Memorization in Diffusion Models via Bright Ending Attention.” ICLR, 2025.