



# TACA: Rethinking Cross-Modal Interaction in Multimodal Diffusion Transformer

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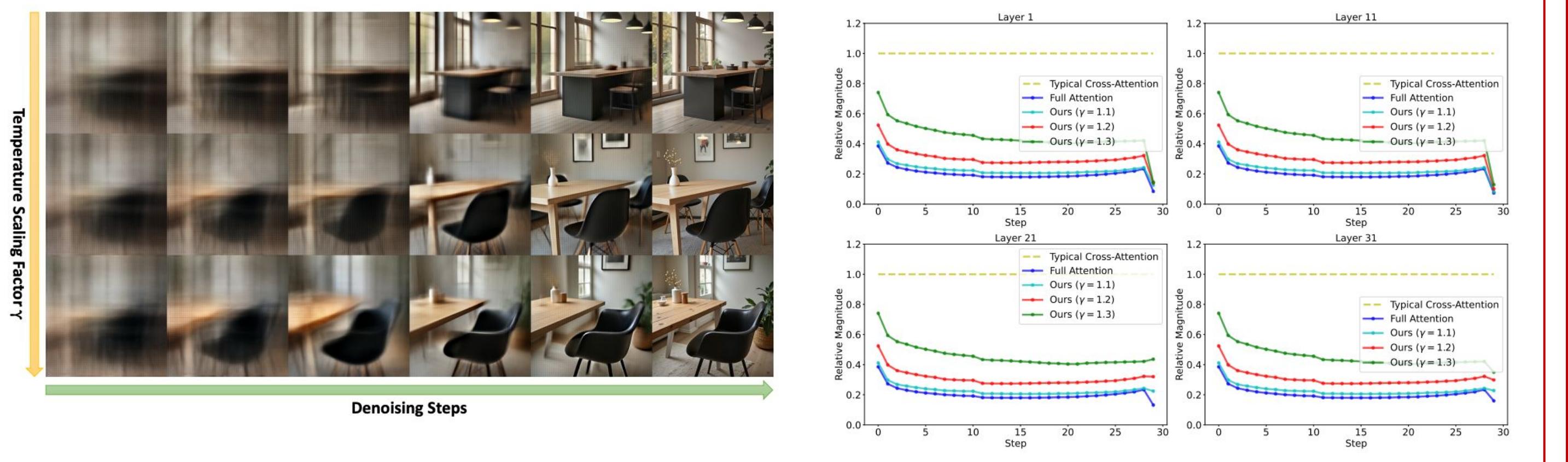
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## Motivation

Task: We propose **TACA**, a parameter-efficient method that dynamically rebalances cross-modal attention in multimodal diffusion transformers to **improve text-image alignment**.

### Motivation:

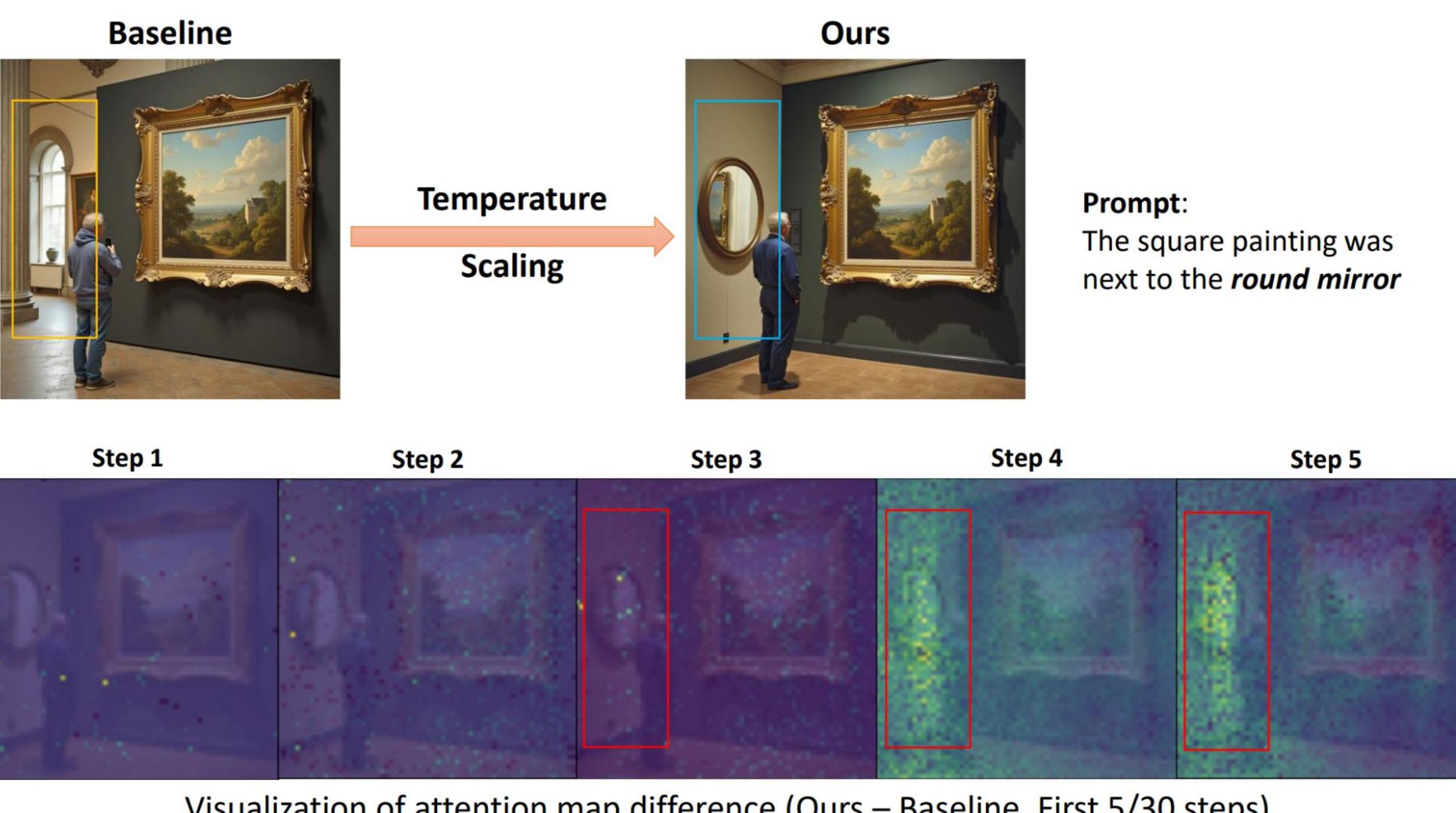
- In **MM-DiT**, the cross-modal attention between visual and text tokens is suppressed **due to the significant imbalance in their numbers**
- The attention weighting in DiT **does not adapt to the varying needs** of the denoising process across different timesteps.



## Investigation

### Temperature scaling helps visual-text alignment.

To mitigate the suppression of cross-attention caused by the dominance of visual tokens ( $N_{\text{vis}} \gg N_{\text{txt}}$ ), we **amplify the logits of visual-text interactions through a temperature coefficient gamma**



## Method

### Temperature-Adjusted Cross-modal Attention (TACA)

In MM-DiT:  $\text{Attention}(\mathbf{Q}, \mathbf{K}, \mathbf{V}) = \text{softmax} \left( \frac{\mathbf{Q}\mathbf{K}^T}{\sqrt{D}} \right) \mathbf{V}$ ,

where the  $\mathbf{Q}\mathbf{K}^T$  term can be expanded to

$$\begin{aligned} \mathbf{Q}\mathbf{K}^T &= \begin{pmatrix} \mathbf{W}_c^Q \mathbf{c} (\mathbf{W}_c^K \mathbf{c})^T & \mathbf{W}_c^Q \mathbf{c} (\mathbf{W}_x^K \mathbf{x})^T \\ \mathbf{W}_x^Q \mathbf{x} (\mathbf{W}_c^K \mathbf{c})^T & \mathbf{W}_x^Q \mathbf{x} (\mathbf{W}_x^K \mathbf{x})^T \end{pmatrix} \\ &= \begin{pmatrix} \mathbf{Q}_{\text{txt}} \mathbf{K}_{\text{txt}}^T & \mathbf{Q}_{\text{txt}} \mathbf{K}_{\text{vis}}^T \\ \mathbf{Q}_{\text{vis}} \mathbf{K}_{\text{txt}}^T & \mathbf{Q}_{\text{vis}} \mathbf{K}_{\text{vis}}^T \end{pmatrix}. \end{aligned}$$

After Softmax:

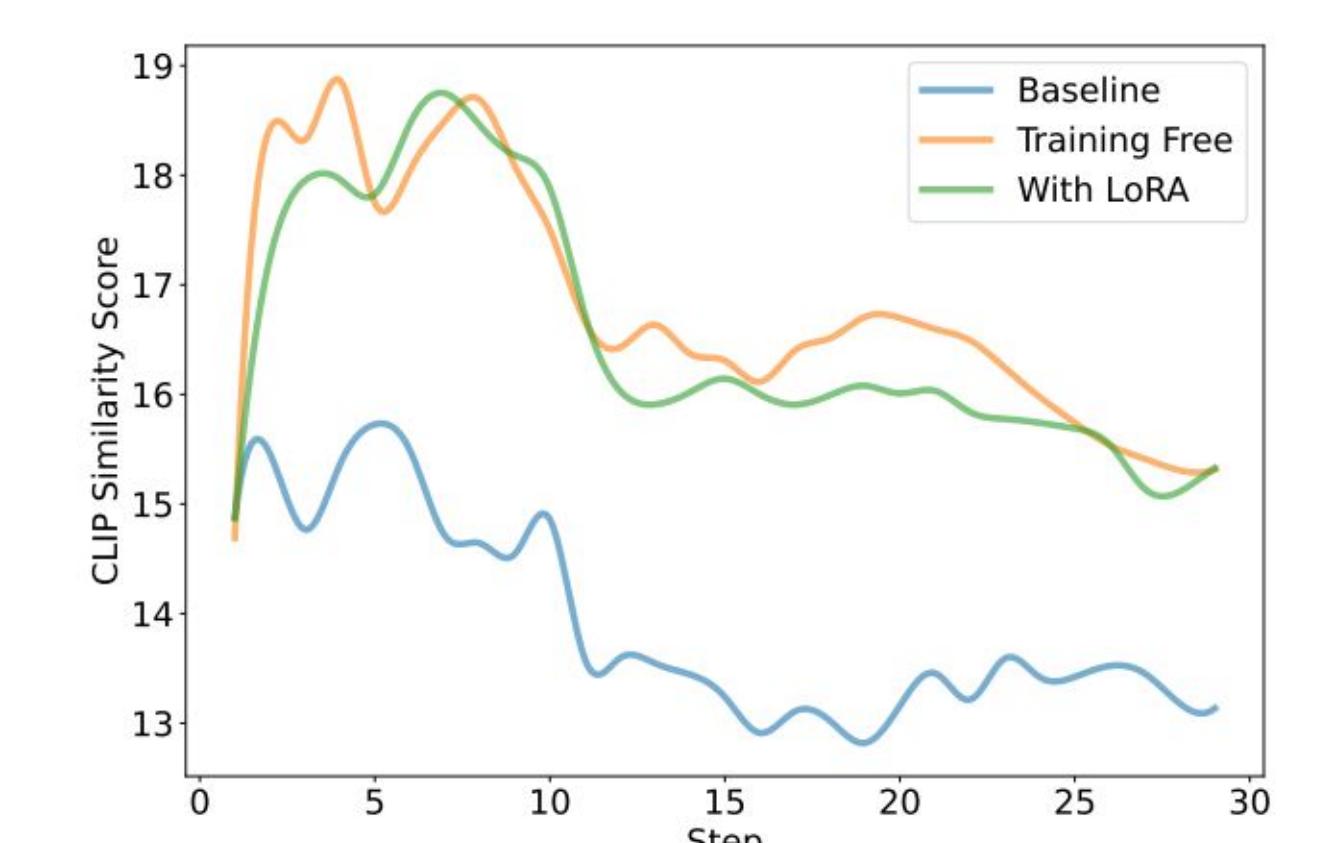
$$P_{\text{vis-txt}}^{(i,j)} = \frac{e^{\gamma s_{ij}^{\text{vt}} / \tau}}{\sum_{k=1}^{N_{\text{txt}}} e^{\gamma s_{ik}^{\text{vt}} / \tau} + \sum_{k=1}^{N_{\text{vis}}} e^{s_{ik}^{\text{vv}} / \tau}},$$

where  $s_{ik}^{\text{vt}} = \mathbf{Q}_{\text{vis}}^{(i)} \mathbf{K}_{\text{txt}}^{T(k)} / \sqrt{D}$  and  $s_{ik}^{\text{vv}} = \mathbf{Q}_{\text{vis}}^{(i)} \mathbf{K}_{\text{vis}}^{T(k)} / \sqrt{D}$

Only enhance the early timesteps:

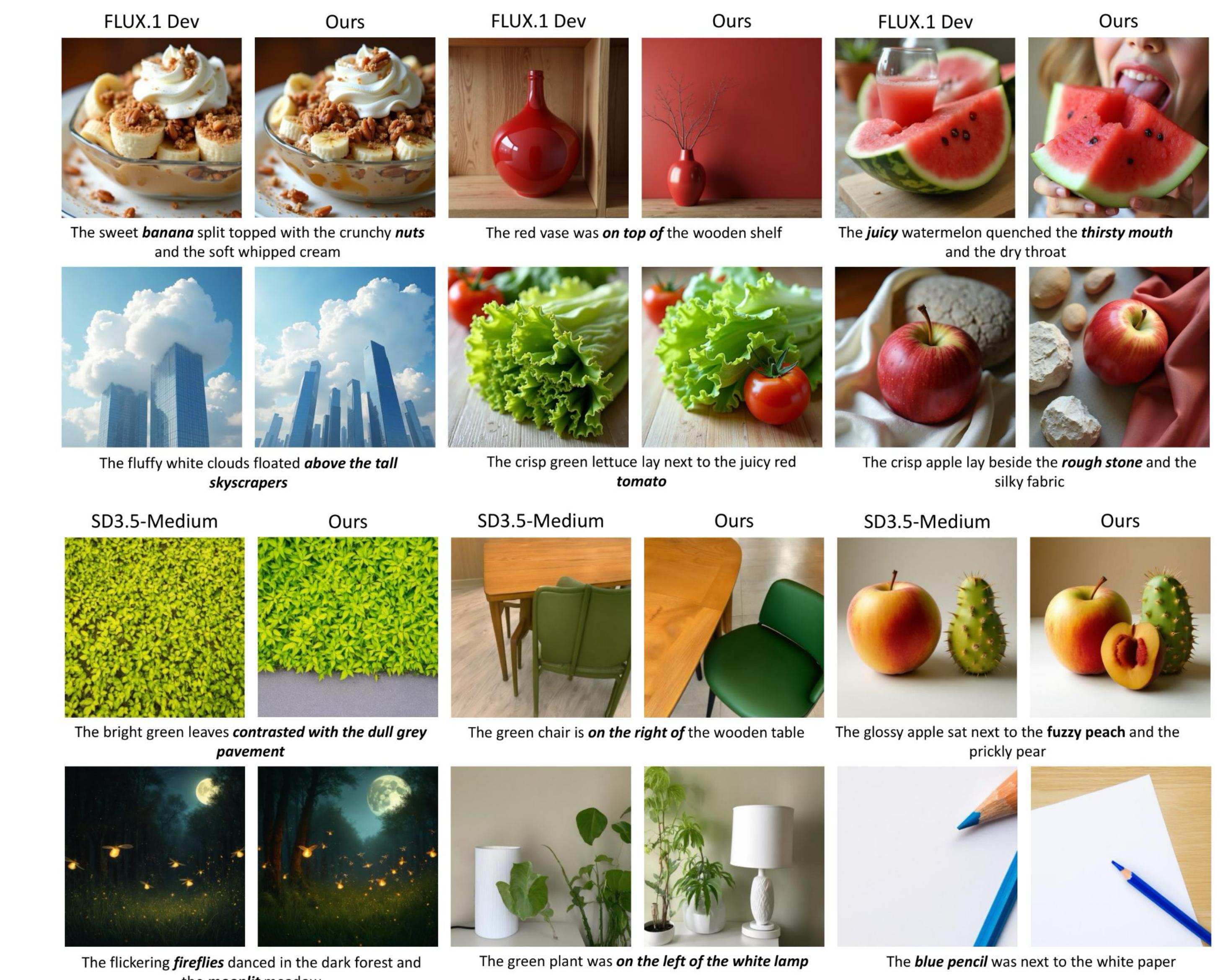
$$\gamma(t) = \begin{cases} \gamma_0 & t \geq t_{\text{thresh}} \\ 1 & t < t_{\text{thresh}} \end{cases}$$

We trained a LoRA to mitigate artifacts caused by the shift in the output distribution of each attention layer



## Results

Model	Attribute Binding		Object Relationship		Complex ↑
	Color ↑	Shape ↑	Texture ↑	Spatial ↑	
FLUX.1-Dev	0.7678	0.5064	0.6756	0.2066	0.3035
FLUX.1-Dev + TACA ( $r = 64$ )	<b>0.7843</b>	<b>0.5362</b>	<b>0.6872</b>	<b>0.2405</b>	0.3041
FLUX.1-Dev + TACA ( $r = 16$ )	0.7842	0.5347	0.6814	0.2321	<b>0.4494</b>
SD3.5-Medium	0.7890	0.5770	0.7328	0.2087	0.3104
SD3.5-Medium + TACA ( $r = 64$ )	<b>0.8074</b>	<b>0.5938</b>	<b>0.7522</b>	<b>0.2678</b>	0.3106
SD3.5-Medium + TACA ( $r = 16$ )	0.7984	0.5834	0.7467	0.2374	<b>0.4470</b>
					<b>0.4505</b>



Project  
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Paper