





Dynamic Prompt Learning: Addressing Cross-Attention Leakage for Text-Based Image Editing

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Learning and Machine Perception Team (LAMP)



Text-to-Image (T2I) advancing at revolutionary pace



DALL-E, Imagen, Stable Diffusion, Mid-Journey, and many others ...

Current Problems

Deep Generative Learning

- Requires huge computational resources to train
- > Does not have image editing ability

Text-guided Image Editing

- > Allows users to easily manipulate an image using text prompts
- > Not able to deal with complex scenarios

Limitation in Existing Text-guided Image Editing

Lacks the capability to control specific regions of given image



Average Cross-Attention maps





cat mask

Dynamic Prompt Learning (DPL)



Feature visualization and background estimation



Addressing Cross Attention Leakage Loss Functions

• Disjoint Object Attention Loss

$$\mathcal{L}_{dj} = \sum_{i=1}^{K} \sum_{\substack{j=1 \ i
eq j}}^{K} ext{cos}(\mathcal{A}_t^{v_t^i}, \mathcal{A}_t^{v_t^j})$$

• Background Leakage Loss

$$\mathcal{L}_{bg} = \sum_{i=1}^{K} \cos(\mathcal{A}_t^{v_t^i}, \mathcal{B})$$

• Attention Balancing Loss

$$\mathcal{L}_{at} = \max_{v_t^k \in \mathcal{V}_t} \mathcal{L}_{v_t^k}$$
 where $\mathcal{L}_{v_t^k} = 1 - \max[\mathcal{F}(\mathcal{A}_t^{v_t^k})]$

• Updating all token

 $\underset{\mathcal{V}_{t}}{\operatorname{arg\,min}} \mathcal{L} \quad \text{where} \quad \mathcal{L} = \lambda_{at} \cdot \mathcal{L}_{at} + \lambda_{dj} \cdot \mathcal{L}_{dj} + \lambda_{bg} \cdot \mathcal{L}_{bg}$

Cross-attention Maps Comparison





Attention Refinement and Reweighting



Some Qualitative Results



Some Qualitative Results



Some Qualitative Results (Generated Images)



Thanks for your attention!

Code, Arxiv, Neurips 2023