Diffusion-NPO: Negative Preference Optimization for Better Preference Aligned Generation of Diffusion Models



Motivation

- ▷ Diffusion models excel in image generation, but those trained on vast, uncurated datasets often produce results that diverge from human preferences. Various fine-tuning techniques have improved alignment with human expectations.
- ▷ We contend that current alignment methods overlook the importance of managing negative-conditional outputs, reducing their ability to prevent unwanted results. To address this, we introduce Diffusion-NPO, a simple yet highly effective solution.

Effectiveness of Diffusion-NPO



Diffusion-NPO enhances high-frequency details, color and lighting, and lowfrequency structures in images by aligning human's negative preference.

Effectiveness on Video Generation.

Prompt: "A person playing a guitar by a campfire under a starry sky."



VideoCrafter2



VADER



VADER + NPO (HPSv2)



VADER + NPO (PickScore)

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Compatibility of Diffusion-NPO and User Study



Stable Diffusion v1-5



Methodology

- ▷ Our crucial insight is that training such a negative preference aligned model requires no new training strategies or datasets, only minor modifications to existing methods.
- ▷ **Training of Diffusion-NPO.** In essence, all strategies can be perceived as reversing the order of image pairs in the collected preference data by adapting the same training procedure.



Hongsheng Li¹

Inference of Diffusion-NPO: Leveraging classifier-free guidance, we apply a preferencealigned model for conditional outputs and a negatively aligned model for negativeconditional outputs to maximize preference alignment.

Generation







w/o NPO





More Generation Results



w/NPO

w/o NPO

w/ NPO