Imagic: Text-Based Real Image Editing with Diffusion Models

Bahjat Kawar* [1,2] Shiran Zada* [1] Oran Lang[1] Omer Tov[1]
Huiwen Chang[1] Tali Dekel[1,3] Inbar Mosseri[1] Michal Irani[1,3]
[1]Google Research [2]Technion [3]Weizmann Institute of Science

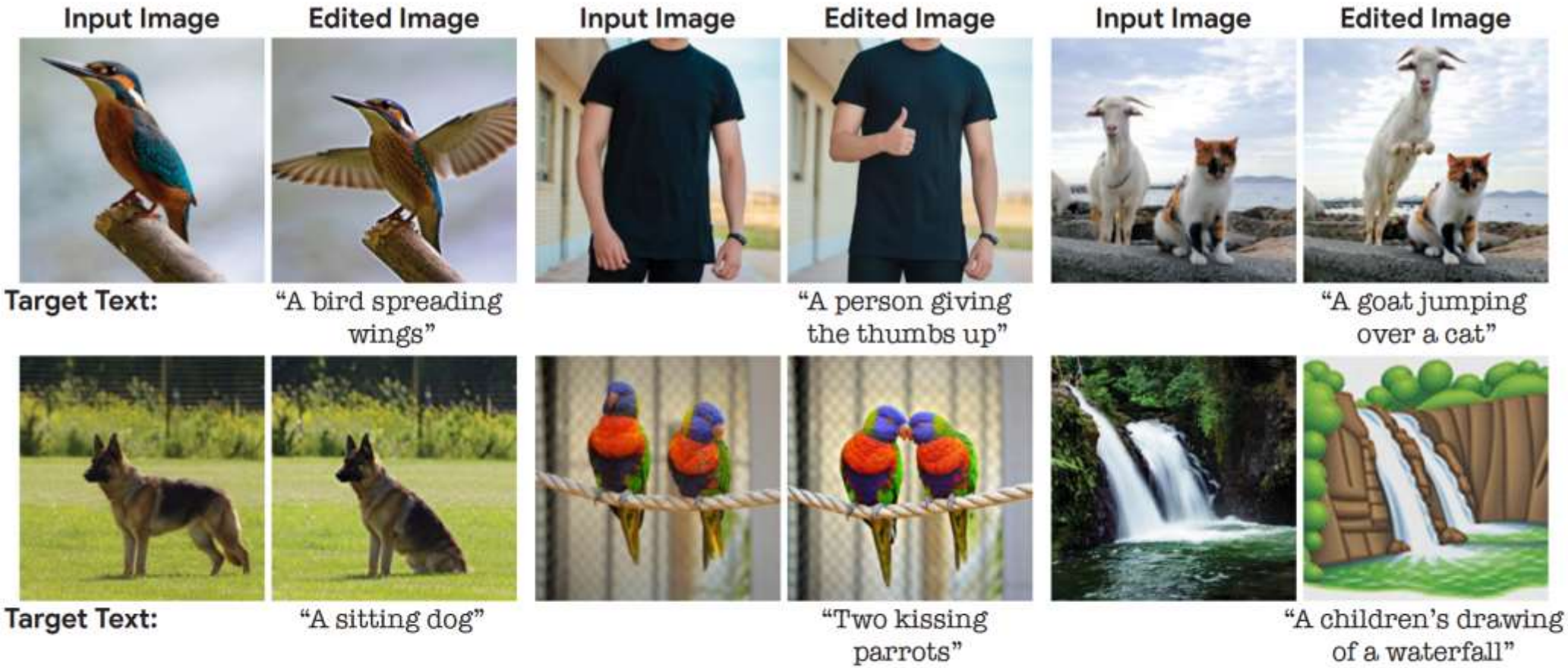
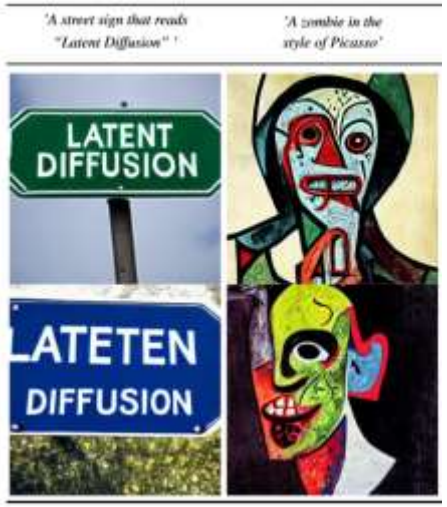
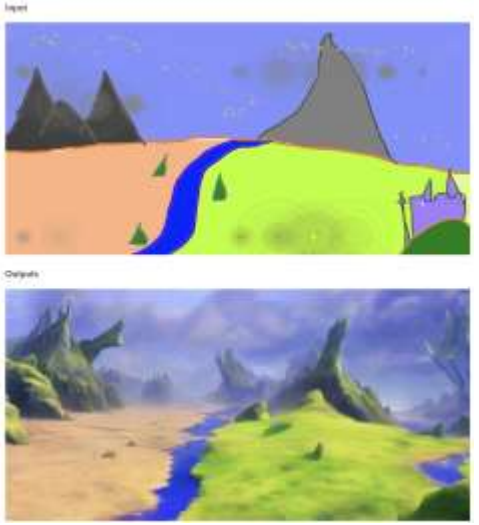


Figure 1. ***Imagic* – Editing a single real image.** *Our method can perform various text-based semantic edits on a single real input image, including highly complex non-rigid changes such as posture changes and editing multiple objects. Here, we show pairs of* 1024×1024 *input (real) images, and edited outputs with their respective target texts.*

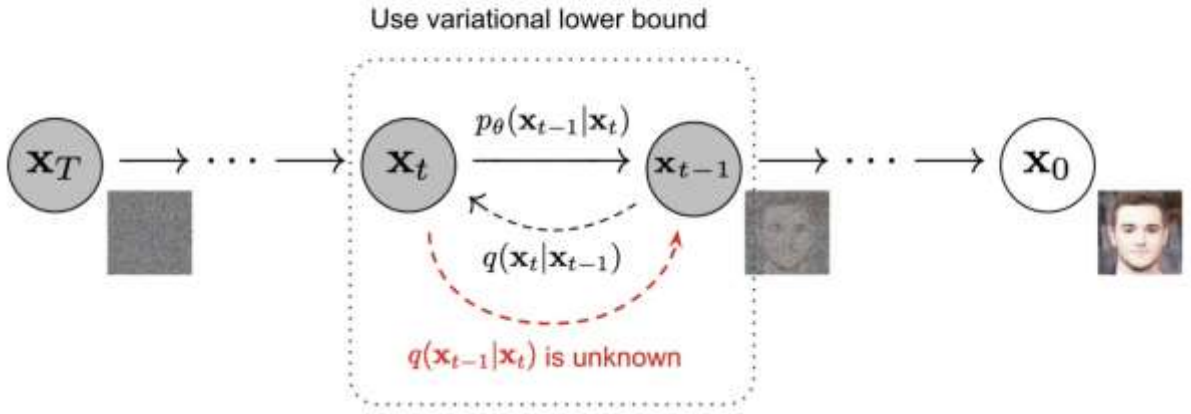
Backgrounds

- Diffusion Models
  - Diffusion model for image generation
    - Text-to-Image
    - Image-to-Image





  - Diffusion Process
    - Forward process
      - Used for training
      - Parameters free
    - Reverse process

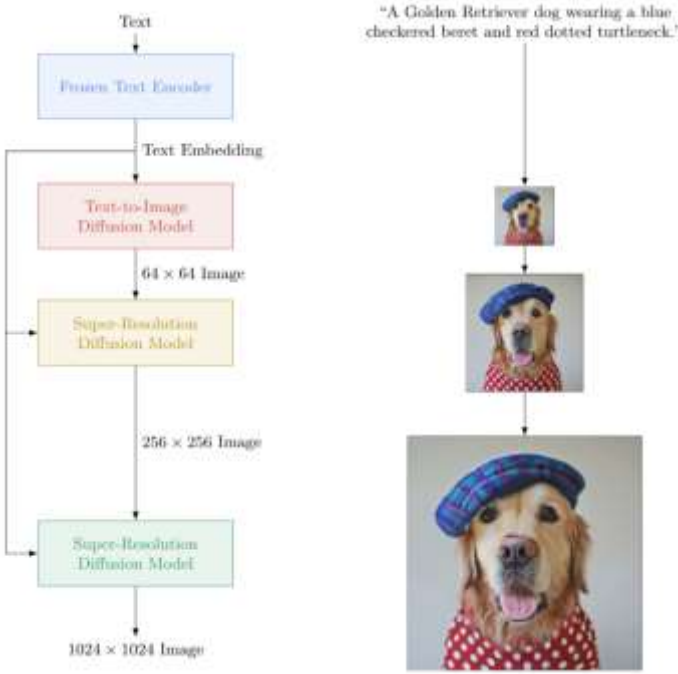


Backgrounds

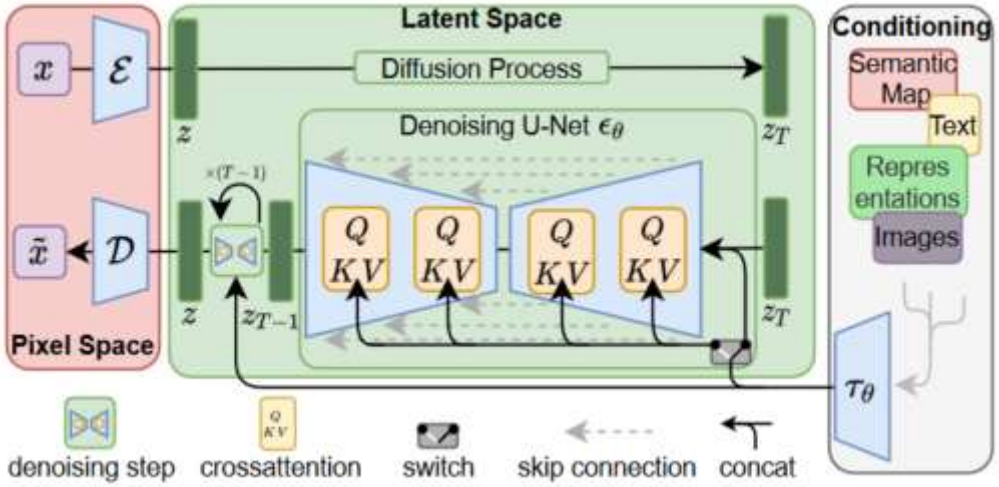
- Diffusion Models
  - Noise prediction
    - U-Net
    - $L_{DM} = \mathbb{E}_{x,\epsilon\sim\mathcal{N}(0,1),t}\left[\|\epsilon - \epsilon_\theta(x_t, t)\|_2^2\right]$
  - Modeling conditional distribution
    - U-Net: Res-block + Attention module
    - Condition encoder(Text encoder)

Backgrounds

- Diffusion Models
  - Image-level diffusion
    - Imagen



  - Latent space diffusion
    - Stable Diffusion



Introduction

- Settings
  - Input a source image and a prompt which describe the wanted changes on source image
  - Output target images

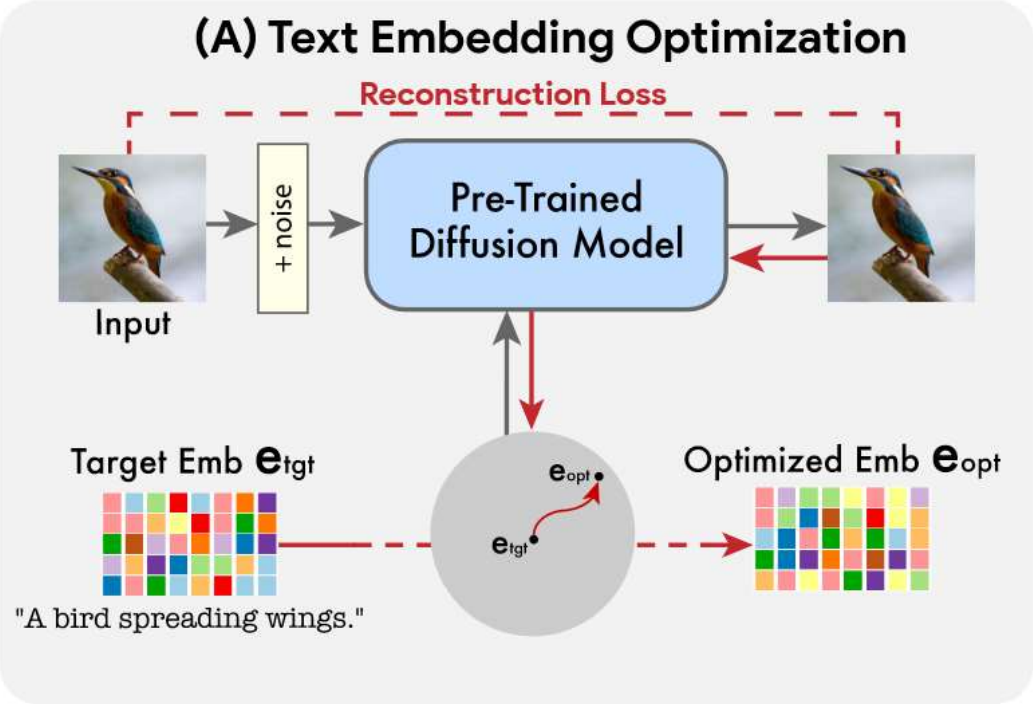
Introduction

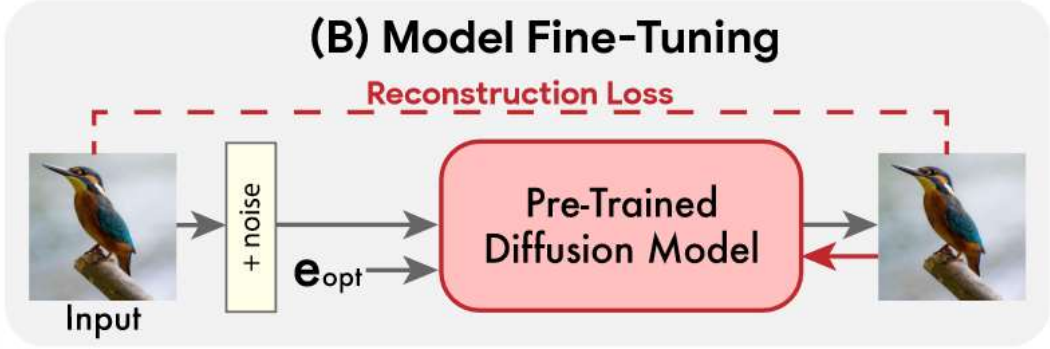
- Fast, cheap(relatively) **single image-text pair finetuning** methodology for Generative Image Editing
  - Two versions: Imagen \ Stable Diffusion (v1)
  - Time and resources for finetuning a single image
    - Imagen: 8 minutes on two TPU V4
    - Stable Diffusion: 7 minutes on one A100

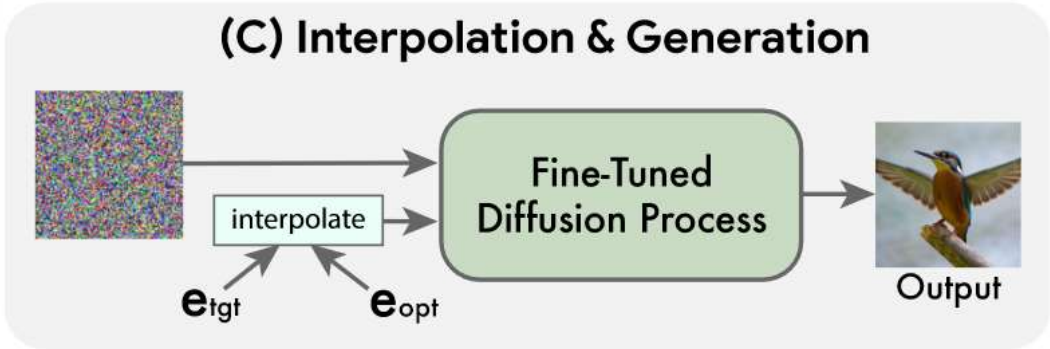
- Balance text alignment with fidelity
  - Maintaining foreground and background contexts
  - Achieve purpose modification

Methodology

- Three procedures for image editing
  - Maintain fidelity
    - (A) Text Embedding Optimization
    - (B) Model Fine-Tuning
  - Balance text alignment with fidelity
    - (C) Interpolation and Generation





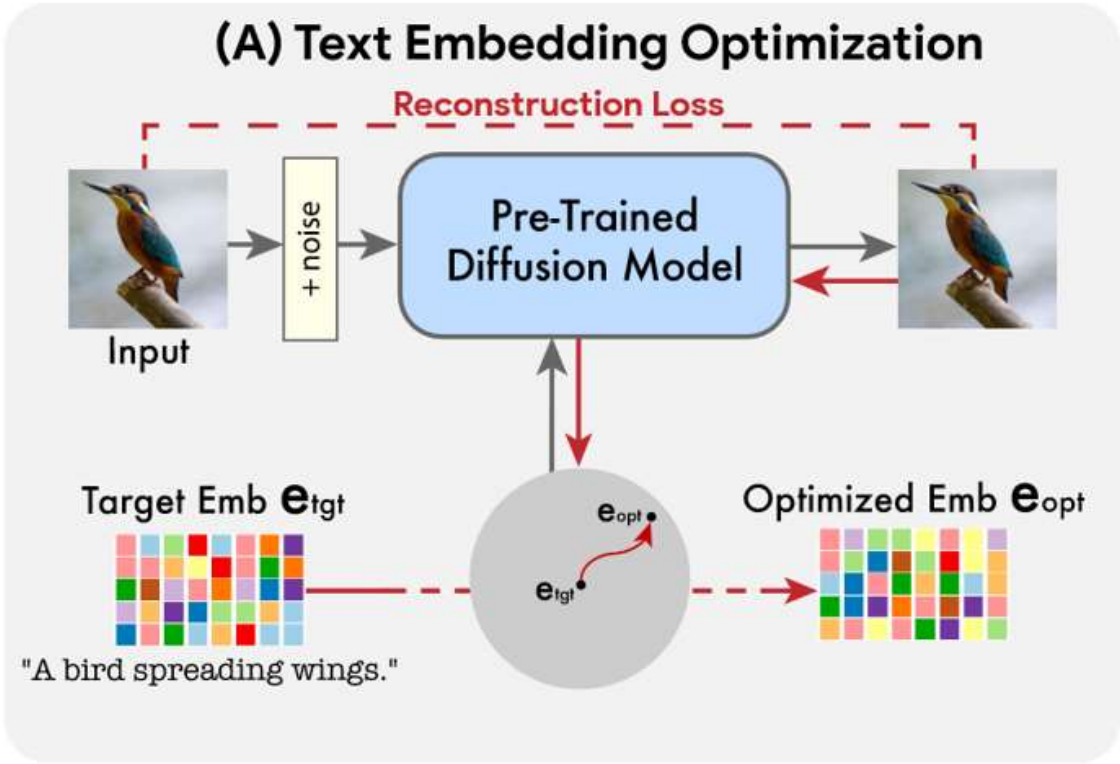


Methodology

- Text Embedding Optimization
  - Introduced T5[1] text encoder to get **target** text embedding $\mathbf{e}_{tgt} \in \mathbb{R}^{T \times d}$
  - Diffusion model is frozen
  - Using reconstruction objective to optimize text embedding

$$\mathcal{L}(\mathbf{x}, \mathbf{e}, \theta) = \mathbb{E}_{t,\boldsymbol{\epsilon}} \left[\|\boldsymbol{\epsilon} - f_\theta(\mathbf{x}_t, t, \mathbf{e})\|_2^2 \right]$$

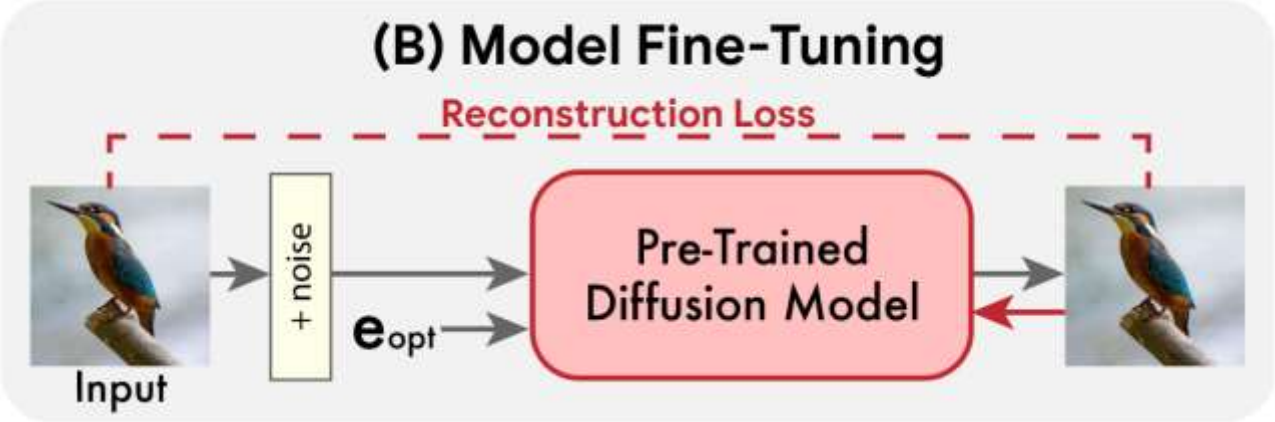
  - Produces optimized embedding $\mathbf{e}_{opt}$



Methodology

- Model Fine-Tuning
  - Further help the model generate high fidelity editing results
  - Using $\mathbf{e}_{opt}$ as text embedding to finetune Diffusion Model with the objective of:

$$\mathcal{L}(\mathbf{x}, \mathbf{e}, \theta) = \mathbb{E}_{t,\boldsymbol{\epsilon}}\left[\|\boldsymbol{\epsilon} - f_\theta(\mathbf{x}_t, t, \mathbf{e})\|_2^2\right]$$

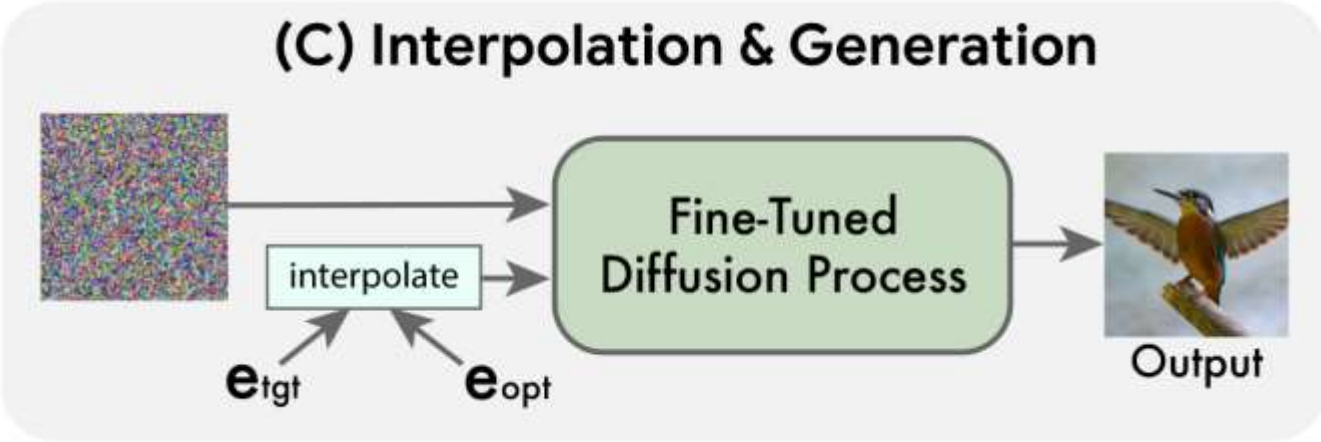


Methodology

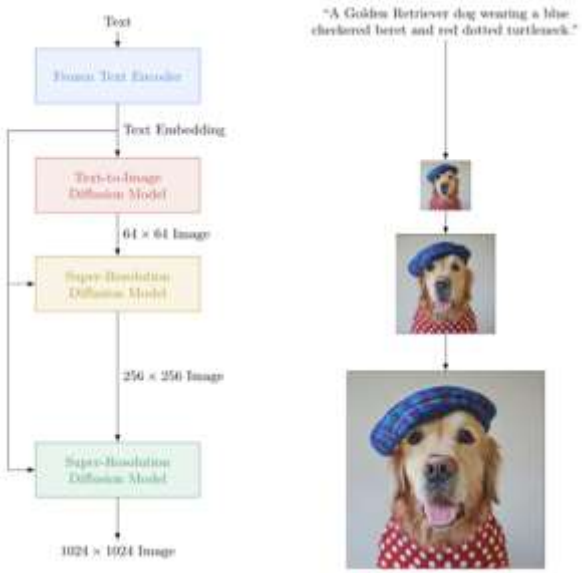
- Interpolation and Generation
  - Simple linear interpolation between a and b can achieve a result that takes into account fidelity and text alignment

$$\bar{\mathbf{e}} = \eta \cdot \mathbf{e}_{tgt} + (1 - \eta) \cdot \mathbf{e}_{opt}$$

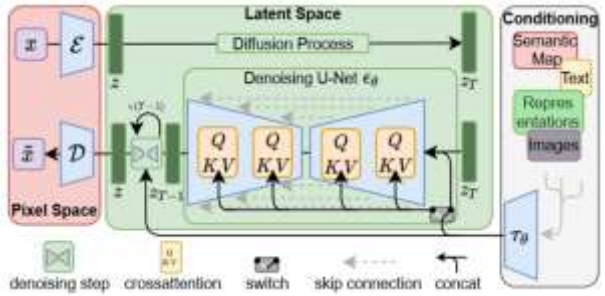
  - Generation process follow normal txt2img pipeline, using fine-tuned diffusion model.



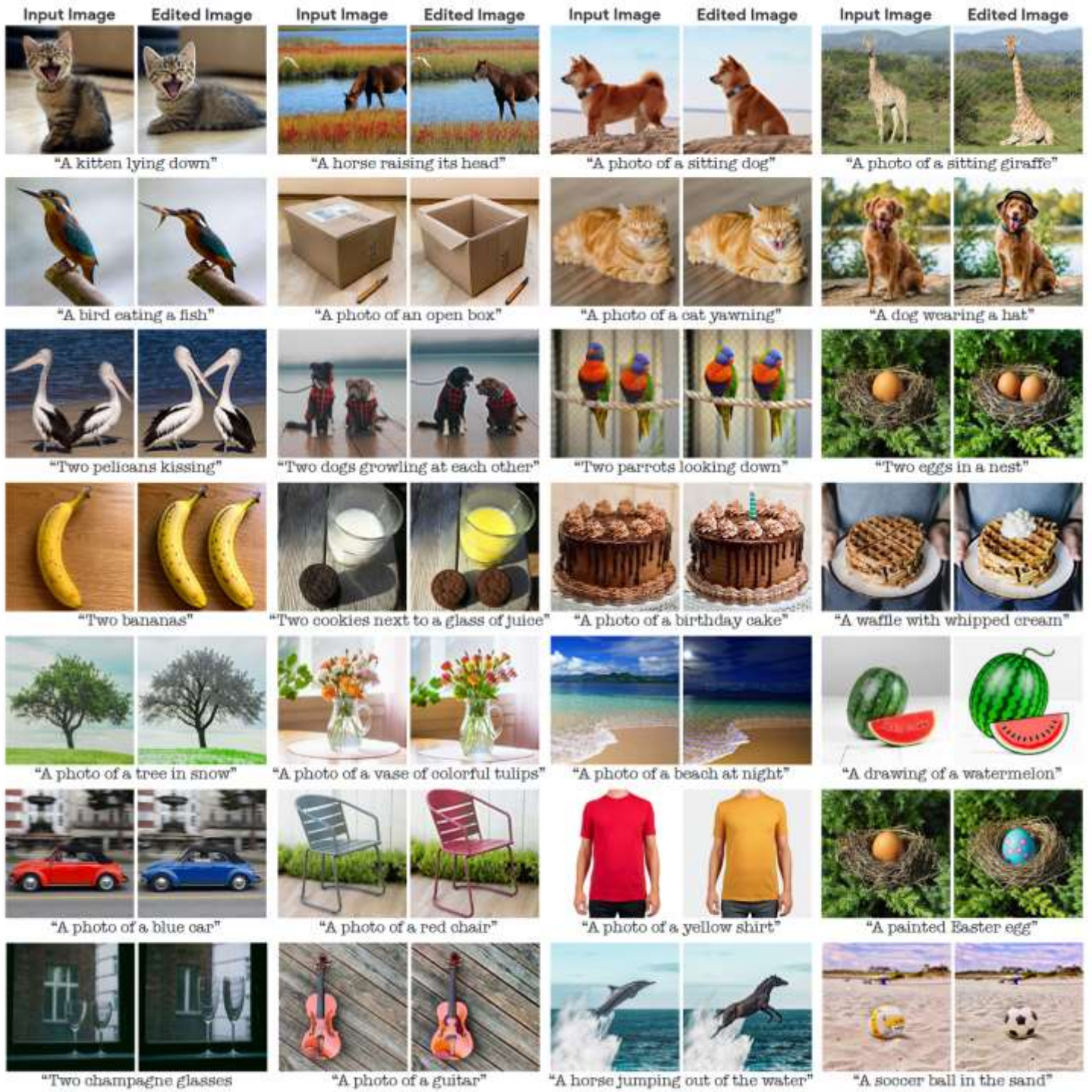
Methodology



- Implementation Details
  - Imagen
    - Optimize text embedding on 64x64 for 100 steps (Adam 1e-3)
    - Finetuning diffusion model on 64x64 for 1500 steps
    - Finetuning on 64x64 → 256x256 SR diffusion for 1500 steps
    - Finetuning on 64x64 → 256x256 adds little effect, thus directly use pretrained model
  - Stable Diffusion
    - Optimize text embedding on latent space diffusion for 1000 steps (Adam 2e-3)
    - Finetuning for 1500 steps (Adam 5e-7)



Experiments



Experiments

- User study
  - TEdBench
    - a novel collection of 100 pairs of input images and target texts describing a desired complex non-rigid edit.

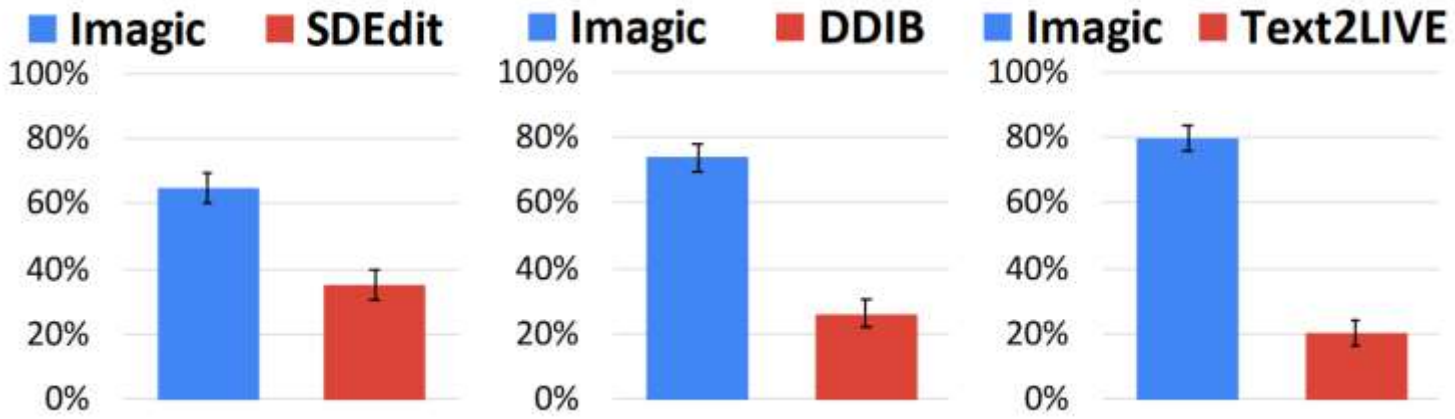


Figure 8. **User study results.** *Preference rates (with 95% confidence intervals) for image editing quality of Imagic over SDEdit [35], DDIB [59], and Text2LIVE [7].*

Ablation Study

- Text Embedding Optimization

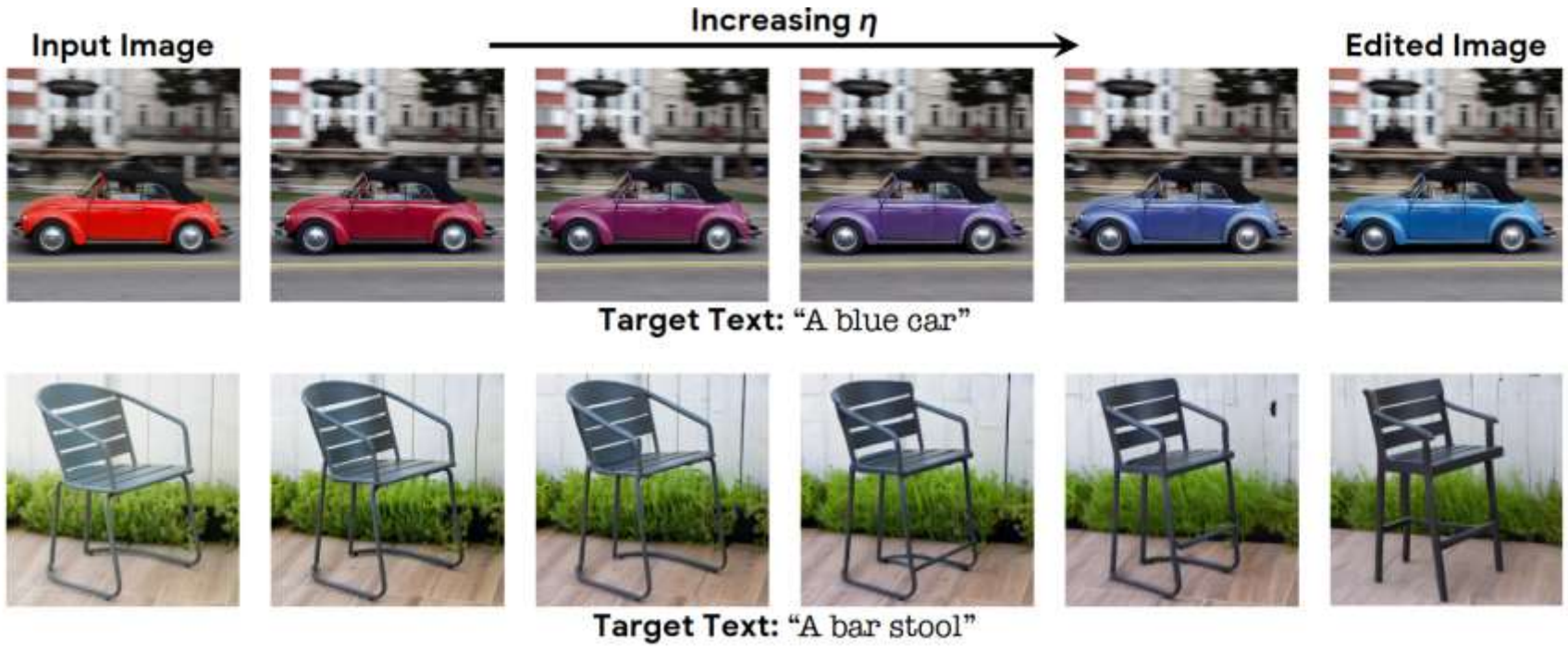
Ablation Study

- Model Fine-Tuning

Figure 7. **Embedding interpolation.** *Varying η with the same seed, using the pre-trained (top) and fine-tuned (bottom) models.*

Ablation Study

- Interpolation and Generation



Ablation Study

- Interpolation and Generation
  - When using different random seeds and different samples, users need to make small adjustments to the value of η to get the best results
  - Select the value range of η by two evaluation indicators

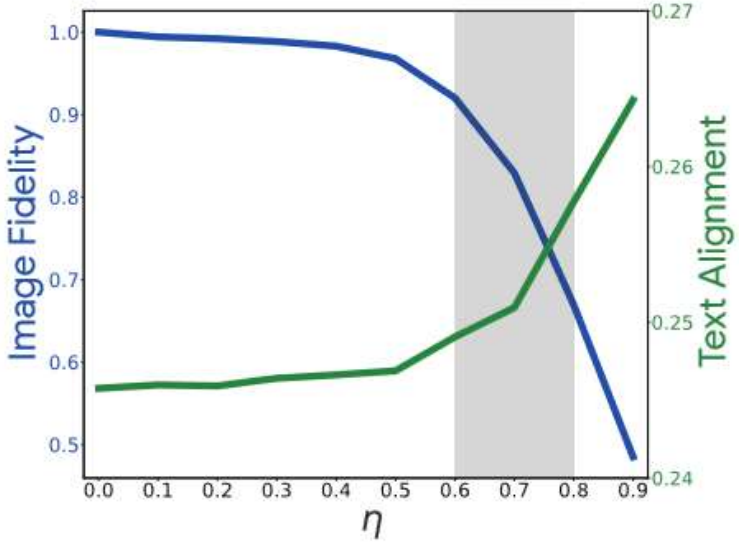


Figure 9. **Editability–fidelity tradeoff.** *CLIP score (target text alignment) and 1−LPIPS (input image fidelity) as functions of η, averaged over 150 inputs. Edited images tend to match both the input image and text in the highlighted area.*

  - η in [0.6, 0.8]

Limitations

- Subtle cases
- Affects extrinsic image details

Figure 10. **Failure cases.** *Insufficient consistency with the target text (top), or changes in camera viewing angle (bottom).*