Distilling Diffusion Models into Conditional GANs

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Motivation: "Diffusion + GAN for one-step generation"

Denoising inference is time-consuming and expansive.

Model distillation

One-step image generation

We propose one-step Diffusion2GAN generator!

a) Fast inference

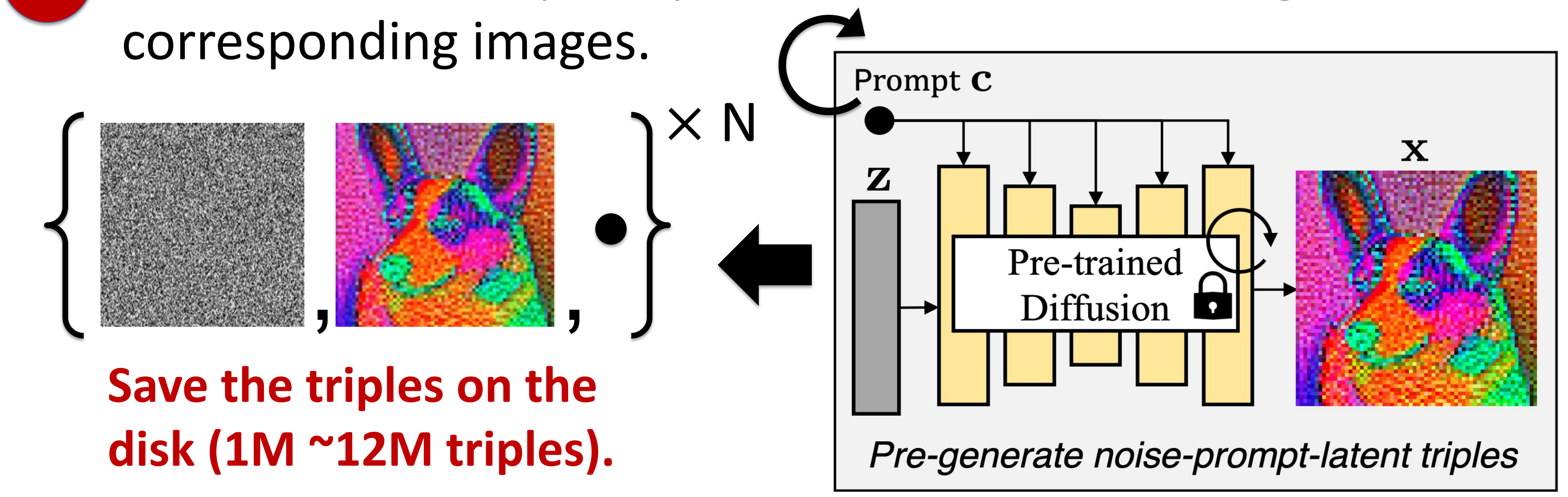
b) High-quality

c) ODE preserving distillation

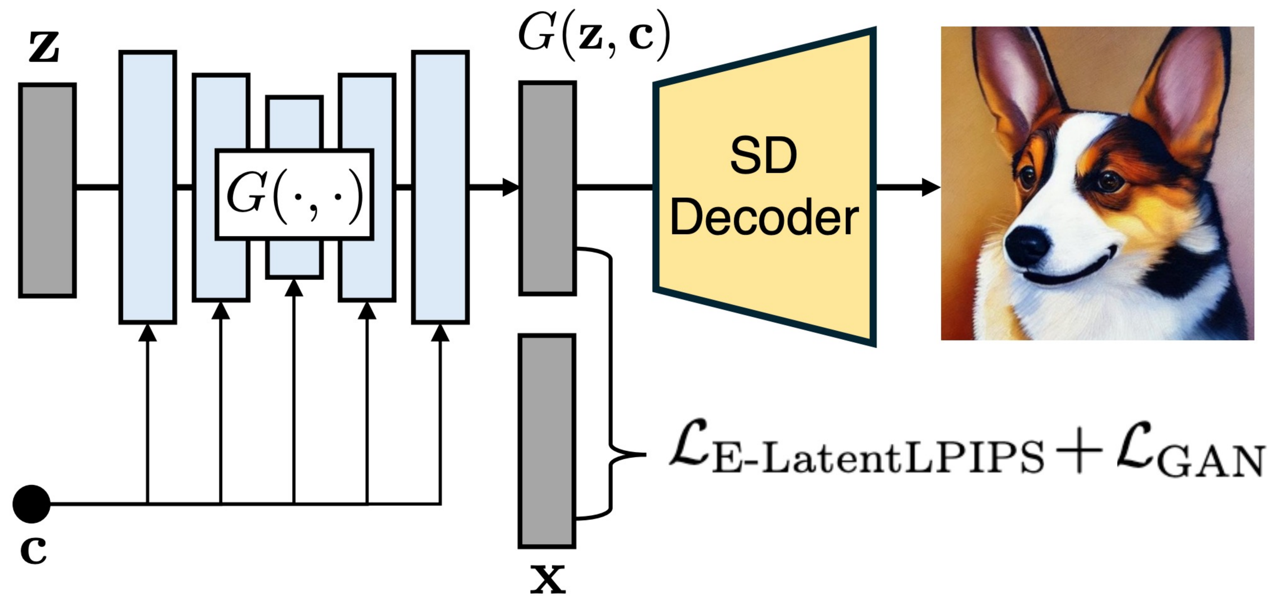
d) Diverse image generation

Distillation procedure: "Training a conditional GAN"

1 Simulate randomly sampled Gaussian noises and get their corresponding images.

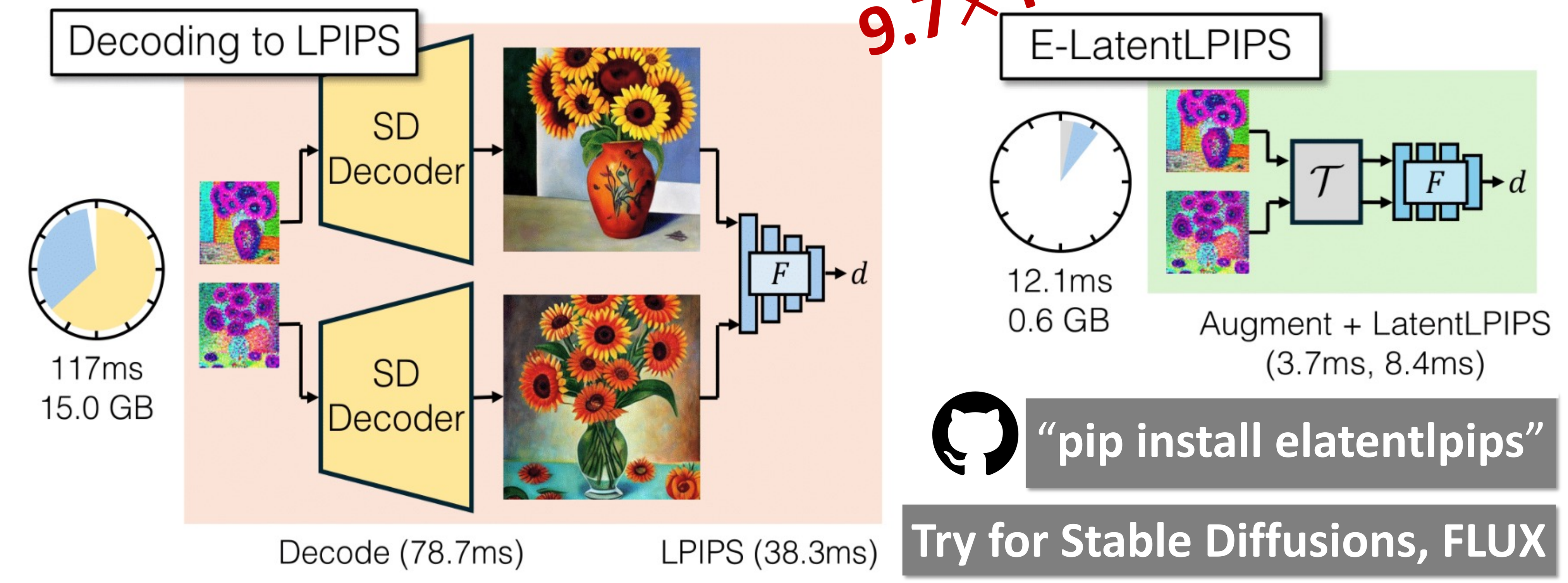


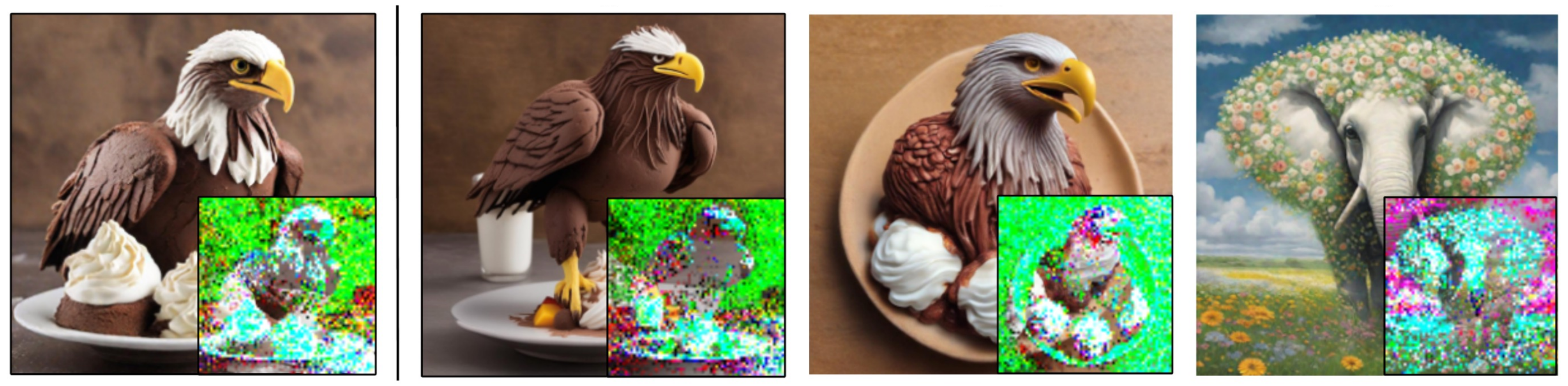
2 Train a conditional GAN where the inputs are noise and prompts, and the targets are their ODE solutions.



Latent space training: "Everything in latent space"

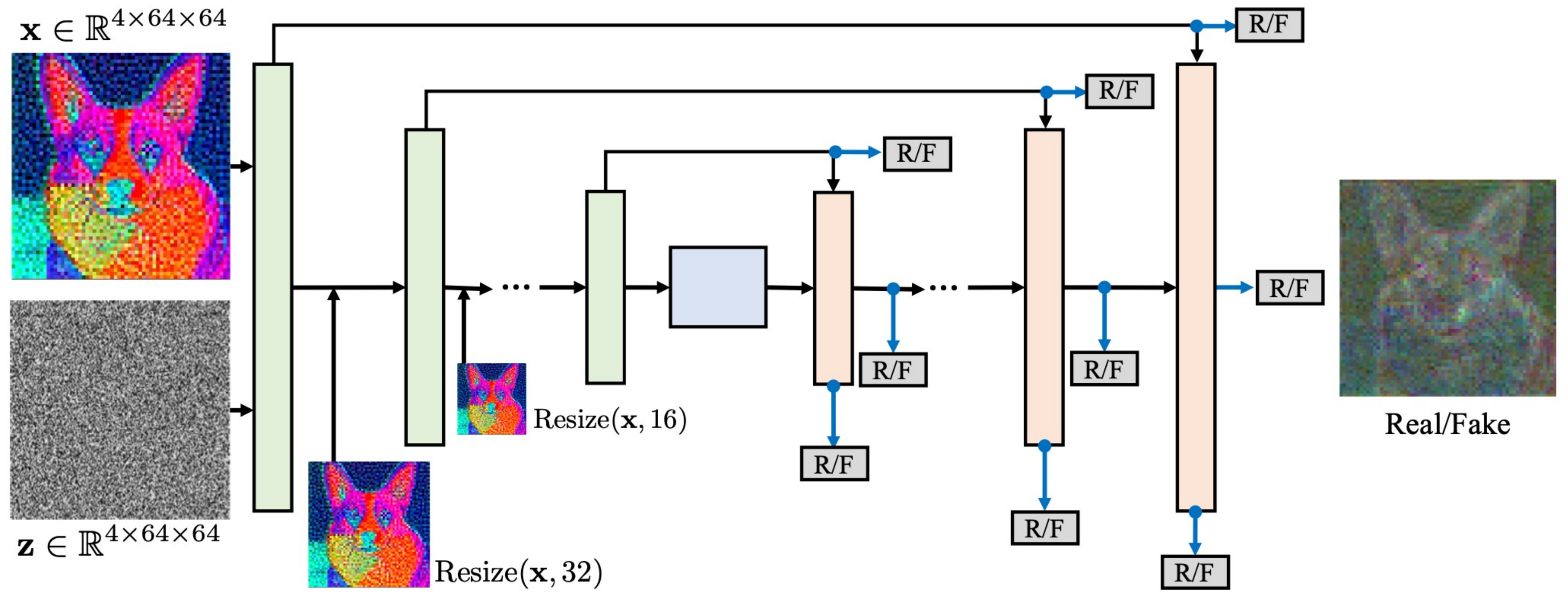
G Perceptual loss for LDM





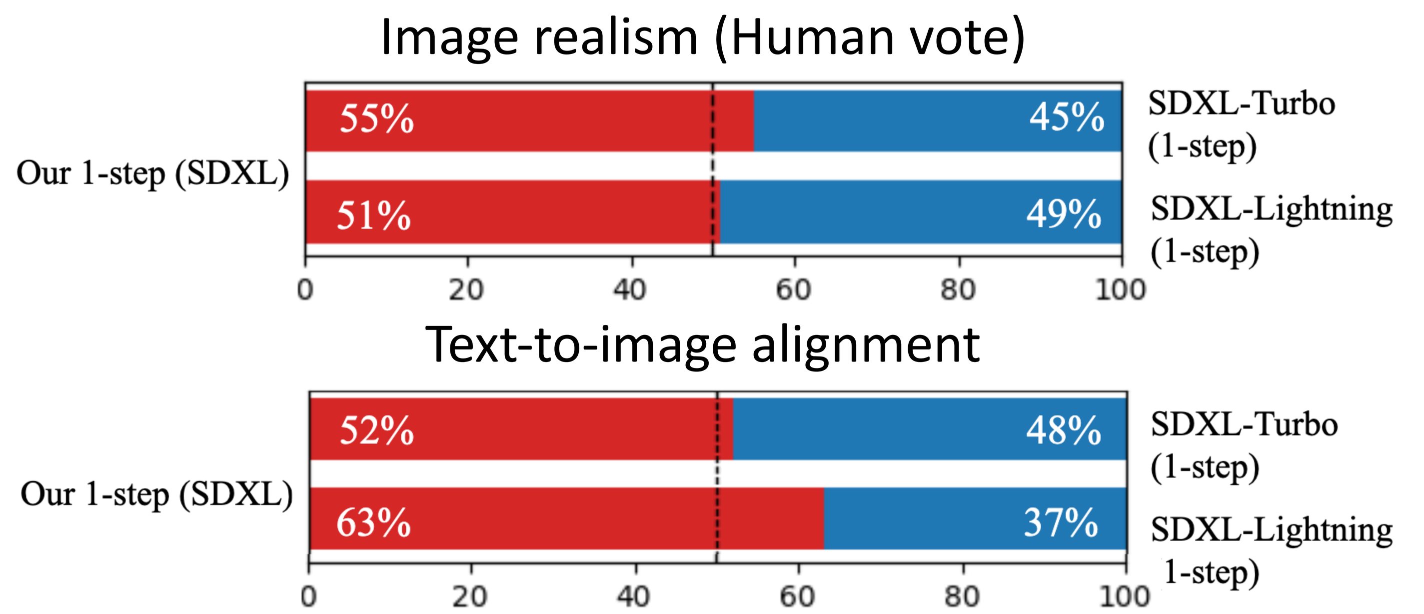
Reference | LatentLPIPS= 0.125 | 0.139 | 0.207

D Multi-scale I/O conditional discriminator



Evaluation: "Comparable to the latest distillation work"

ODE preserving distillation: "Mimic teacher diffusion."



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