Training-free approaches for image inversion and editing using latent diffusion and flow models

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Based on joint work with: Litu Rout, Yujia Chen, Nataniel Ruiz, Abhishek Kumar*, Constantine Caramanis, and Wen-Sheng Chu

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Google
Google DeepMind
IFML
AI EDGE Institute
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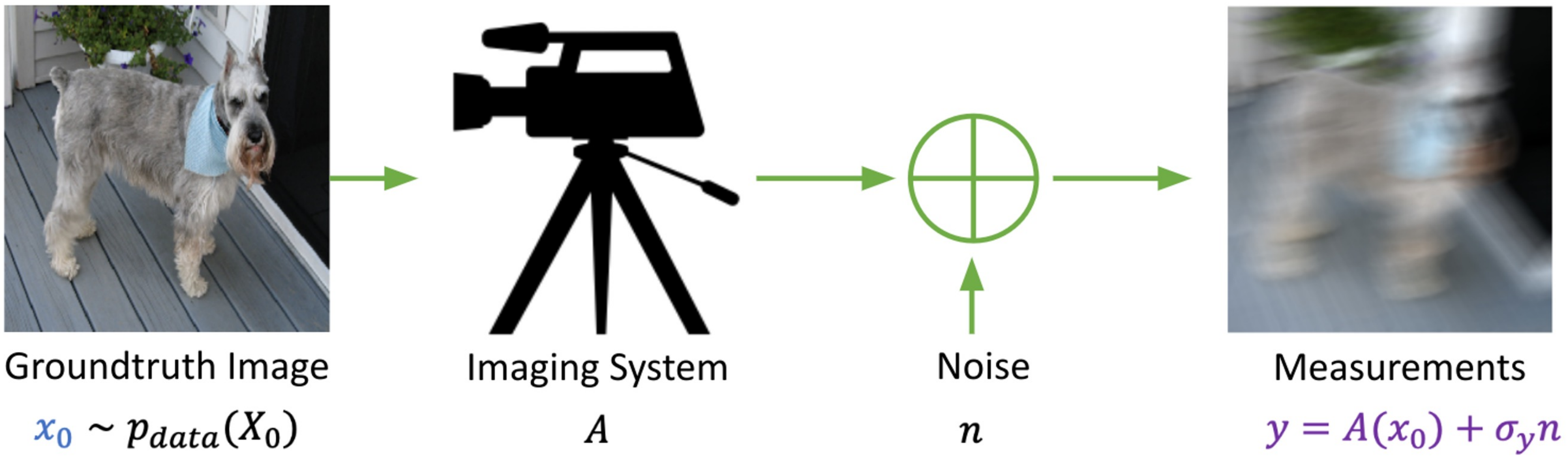
Inverse Problems Setting

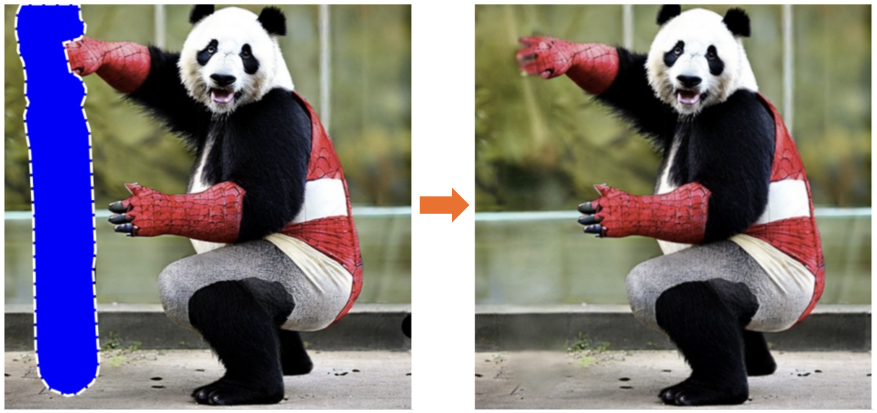


Problem: Reconstruct ground truth image x_0 from noisy measurements y

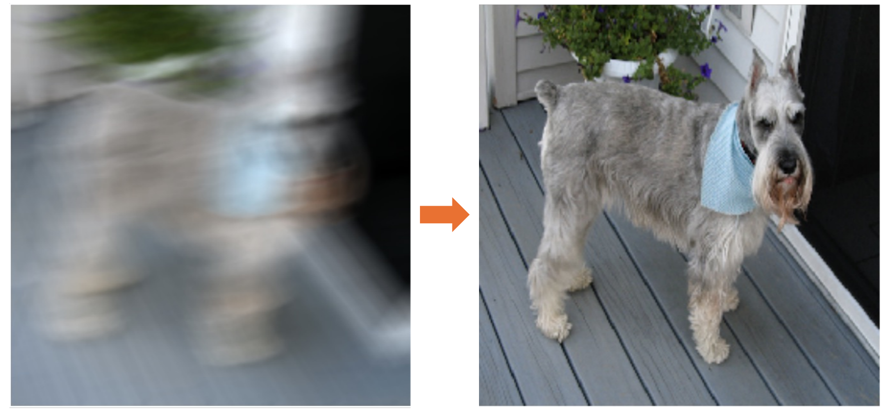
Challenge: Problem is ill-posed, that is infinitely many solutions x_0 exist

Approach: Use prior knowledge $p(x_0)$ of how the image should look like

Examples of Inverse Problems

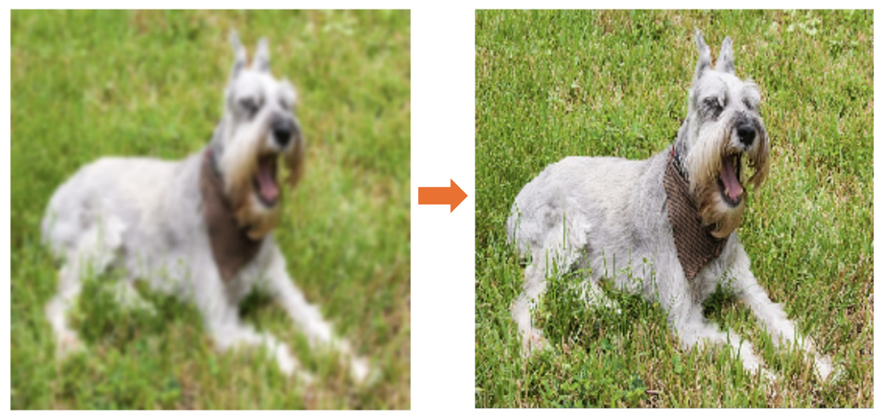


Free-form inpainting



Motion Deblur

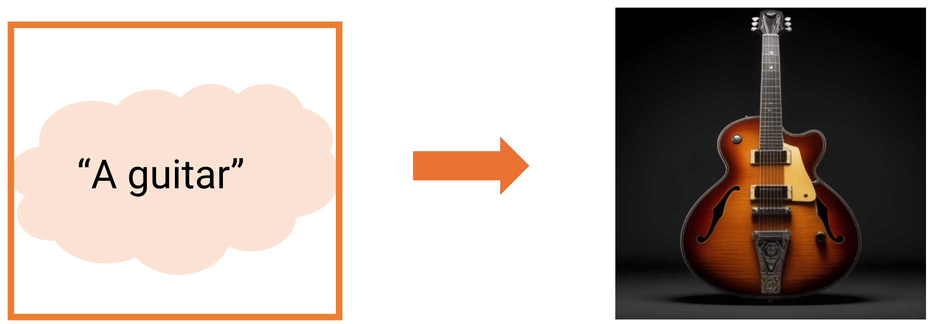
Super-resolution (4X)



Gaussian Deblur

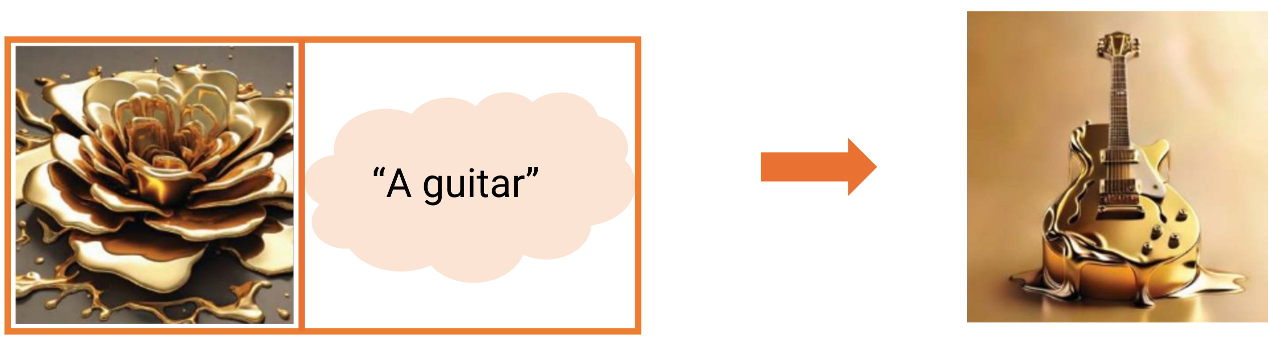
Stylization using Text and Image Prompts

Text-to-image generation



Input Output

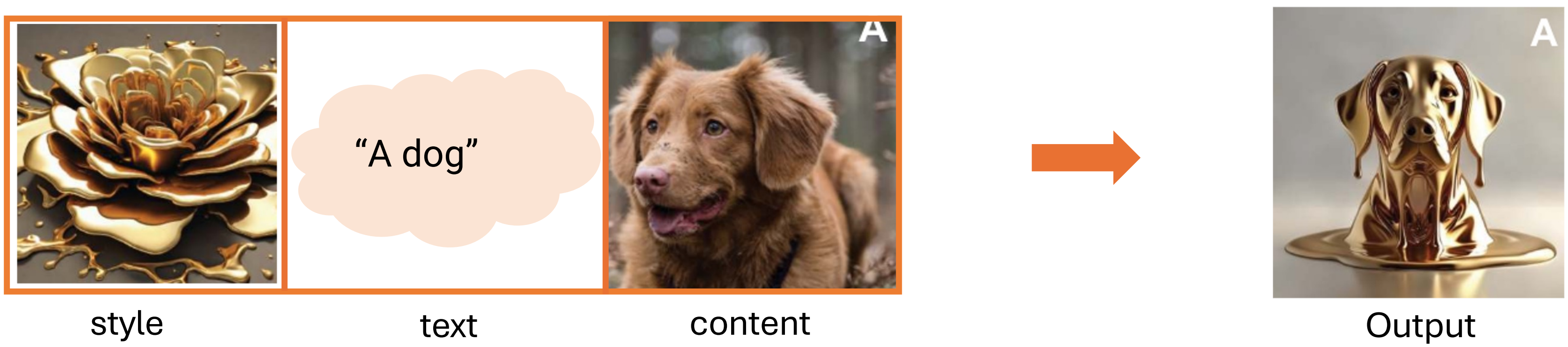
Personalized text-to-image generation: stylization



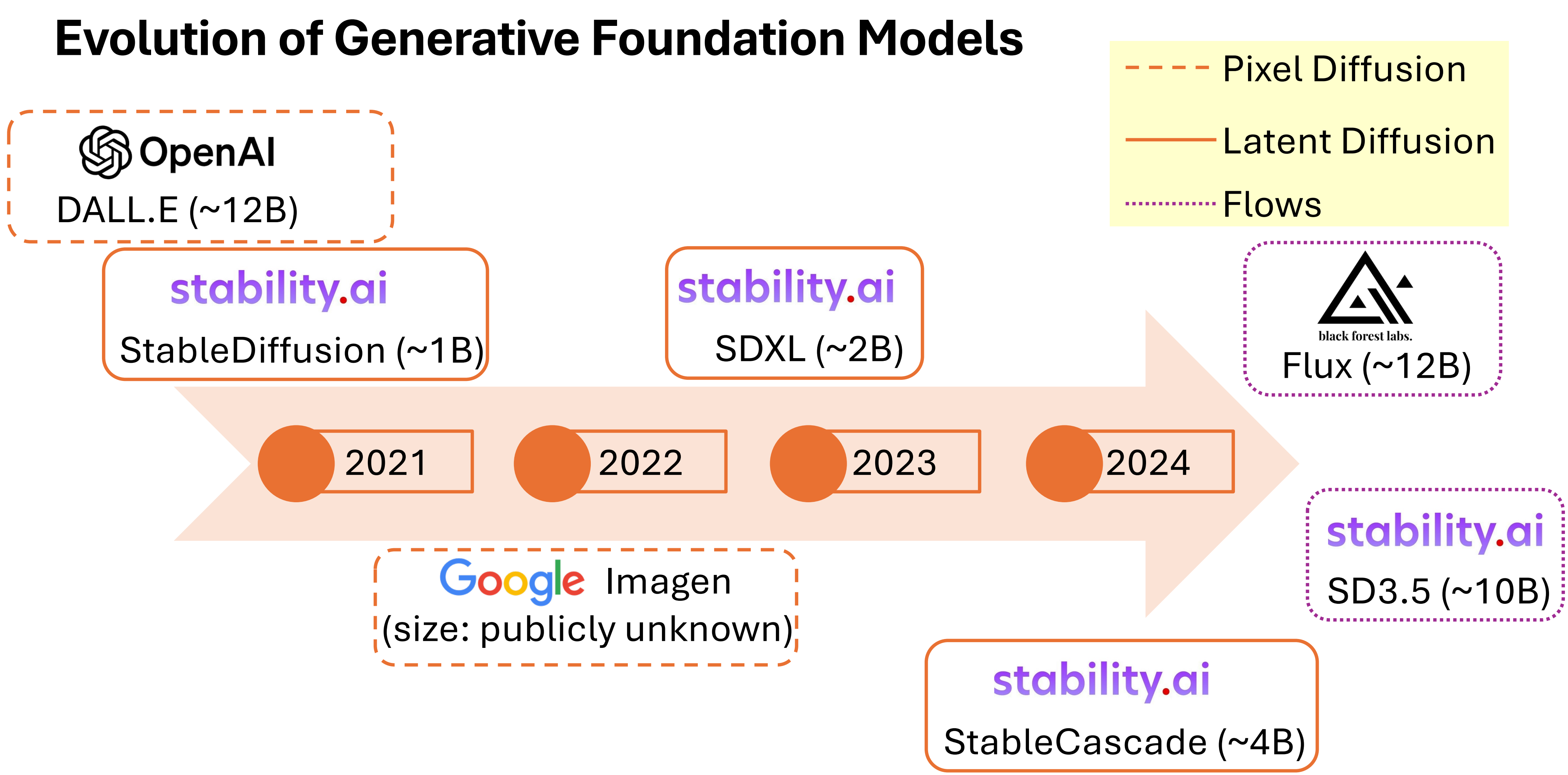
style text Output

Content-Style Composition Using Text and Image Prompts

Personalized text-to-image generation: content-style composition



Diffusion models have recently emerged as powerful foundation models for solving such generalized inverse / composition problems

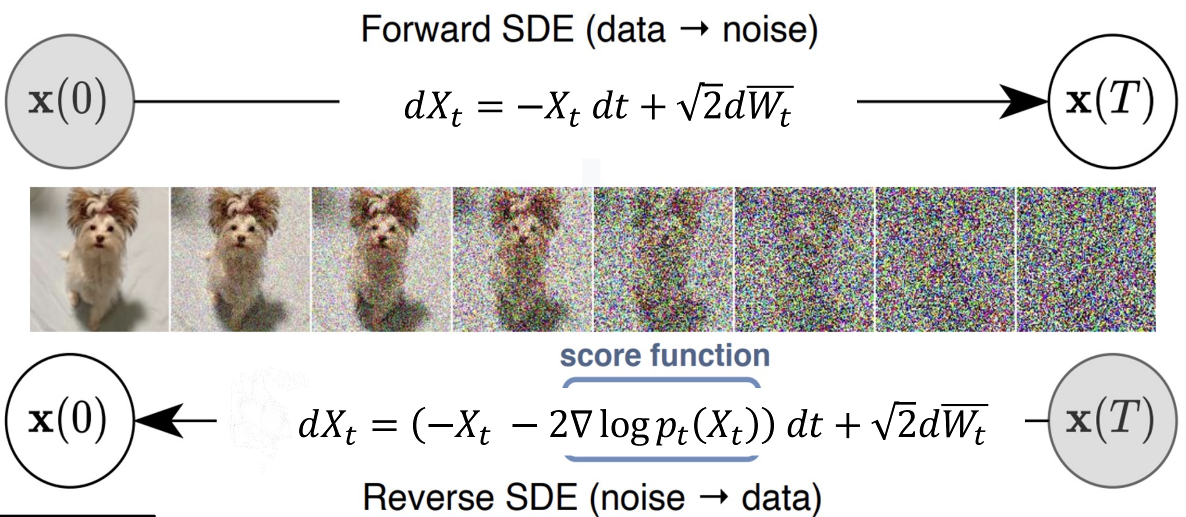

Evolution of Generative Foundation Models
Pixel Diffusion
Latent Diffusion
Flows
OpenAI
DALL.E (~12B)
stability.ai
StableDiffusion (~1B)
stability.ai
SDXL (~2B)
black forest labs.
Flux (~12B)
2021
2022
2023
2024
Google Imagen
(size: publicly unknown)
stability.ai
SD3.5 (~10B)
stability.ai
StableCascade (~4B)

Our Work on Inverse Problems and Editing using Latent Diffusion Models and Rectified Flows

- PSLD – First algorithm for solving inverse problems in latent space of diffusion models (NeurIPS 2023)
- STSL – Algorithm for inverse problems and image editing through efficient second-order methods (CVPR 2024)
- RB-Modulation – Algorithm for stylization and editing via Test-time Optimization using proximal methods (ICLR 2025, Oral)
  - Avoids backpropagation through score network
- RF-Inversion – First Algorithm for Inversion and Editing with Rectified Flow (ICLR 2025)

Focus of today's talk

Background on Diffusion Models



512 ×512 image ≈ 800K dim. vector

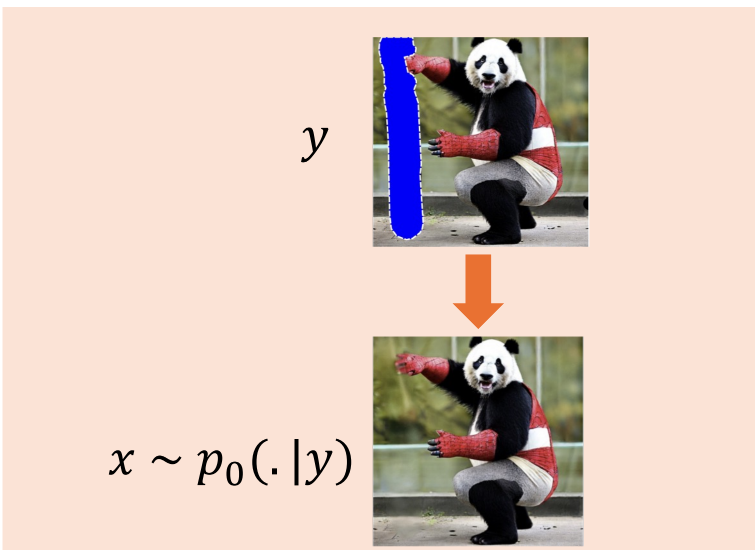
Image Credit: Song *et al.*, https://arxiv.org/pdf/2011.13456.pdf, ICLR'21

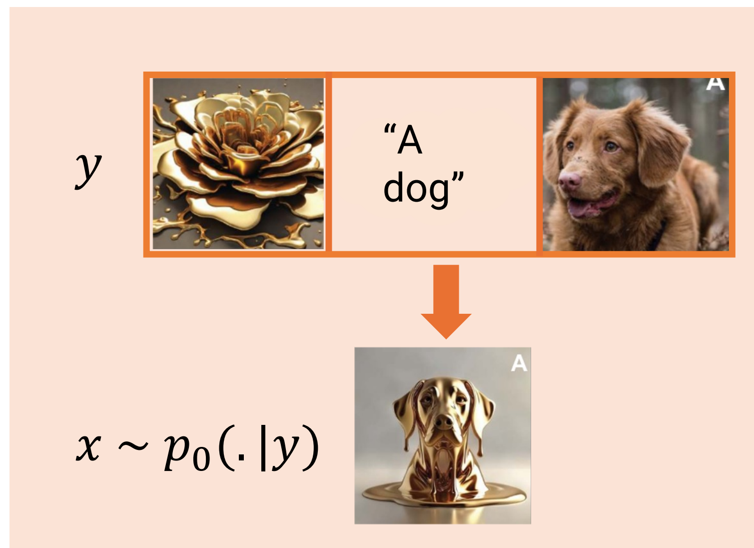
- Goal: Design a Markov process-based sampler (a transition kernel) such that stationary distribution samples images
- Approach: Learn annealed score that is affine in the conditional expectation of $X(0)$ (clean image) given $X(t)$ (noisy image) by Tweedie's Formula

References: Deep Unsupervised Learning using Diffusion (Sohl-Dickstein et al.' 2015); Score-based Generative Models (Song & Ermon' 2019); Diffusion Probabilistic Models (Ho et al.'2020); Score-based Generative Models through SDEs (Song et al.' 2021)

Posterior Sampling with Diffusion

- Inverse problems such as infilling, super resolution, denoising, editing, stylization, etc. are all examples of posterior sampling
- Goal: Given “measurement / context” y, generate a sample x, where $x \sim p_0(.\,|y)$





Posterior Sampling with Diffusion

Problem: Sample from $p_0(x_0|y)$ instead of $p(x_0)$

$$dX_t = (-X_t - 2\nabla \log p_t(X_t|y))\, dt + \sqrt{2}d\bar{W}_t, \qquad t = T, \cdots, 0$$

Unknown

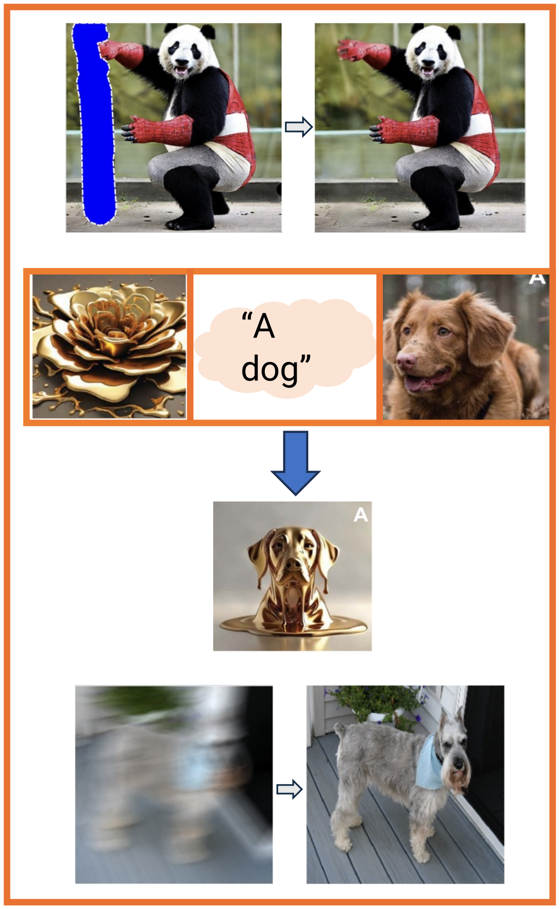
Bayes rule: $\log p_t(x_t|y) = \log p_t(y|x_t) + \log p_t(x_t) - \log p_t(y)$

$$dX_t = (-X_t - 2\nabla \log p_t(y|X_t) - 2\nabla \log p_t(X_t))\, dt + \sqrt{2}d\bar{W}_t, \qquad t = T, \cdots, 0$$

Unknown

Known: $\nabla \log p_t(X_t) \approx s_\theta(X_t, t)$

How well can we approximate $\nabla \log p_t(y|x_t)$?



DDRM: Kawar et al. https://arxiv.org/pdf/2201.11793.pdf , NeurIPS'21; DPS: Chung *et al.*, https://arxiv.org/pdf/2209.14687.pdf, ICLR'23
See also Delbracio & Milanfar, https://openreview.net/pdf?id=VmyFF5lL3F, TMLR'23 for an alternate formulation of supervised inverse problems.

PSLD: Posterior Sampling using Latent Diffusion

- First algorithm for solving inverse problems in latent diffusion (NeurIPS 2023)

- Generalizes prior work DPS (Chung et' al, ICLR 2023) that holds for pixel space diffusion

- $\nabla \log p_{T-t}(y|Z_t)$ ensures consistency w.r.t. the measurement y
  - Approximated using a Test Time Optimization (aka training-free) step
  - Requires a gradient computation with respect to the input to score $s_\theta(.,t)$ at each denoising step

PSLD (Rout et al.,NeurIPS'23):

$$\nabla \log p_{T-t}(y|Z_t) \approx \nabla \log p_0(y|Dec(\bar{Z}_T)) \;+\; \gamma_t \nabla \left|\left|\bar{Z}_T - Enc\left(A^T y + (I - A^T A)Dec(\bar{Z}_T)\right)\right|\right|^2$$

where $\bar{Z}_T = E_{Z_T \sim p_{T-t}(Z_T|Z_t)}[Z_T] = c_1(t) + c_2(t)s_\theta(Z_t, t)$

"Solving Linear Inverse Problems Provably using Posterior Sampling with Latent Diffusion Models", Litu Rout, Negin Raoof, Giannis Daras, Constantine Caramanis, Alexandros G. Dimakis, and Sanjay Shakkottai, *NeurIPS 2023*

Experimental Results with PSLD

(a) Input (b) Groundtruth (c) Comm. Serv. 1 (d) Comm. Serv. 2 (e) PSLD (Ours)

(a) Input (b) Groundtruth (c) DPS [11] (d) PSLD (Ours)

- Scalable to higher resolution images
    - Gradients computed in latent space
- One foundation model (SD1.5) many tasks
    - FFHQ (human faces) and ImageNet

- Convenient for real-world deployment
    - Images from the web, OOD samples
- No additional training or finetuning needed
    - Faster than pixel space diffusion

STSL: Second-order Tweedie from Surrogate Loss

- Algorithm for inverse problems and image editing through efficient second-order methods (CVPR 2024)
- Decreases bias of DPS or PSLD through a second order drift correction
- Requires only trace (a scalar quantity), leading to lighter computations
  - Estimate using an inner-loop stochastic approximation

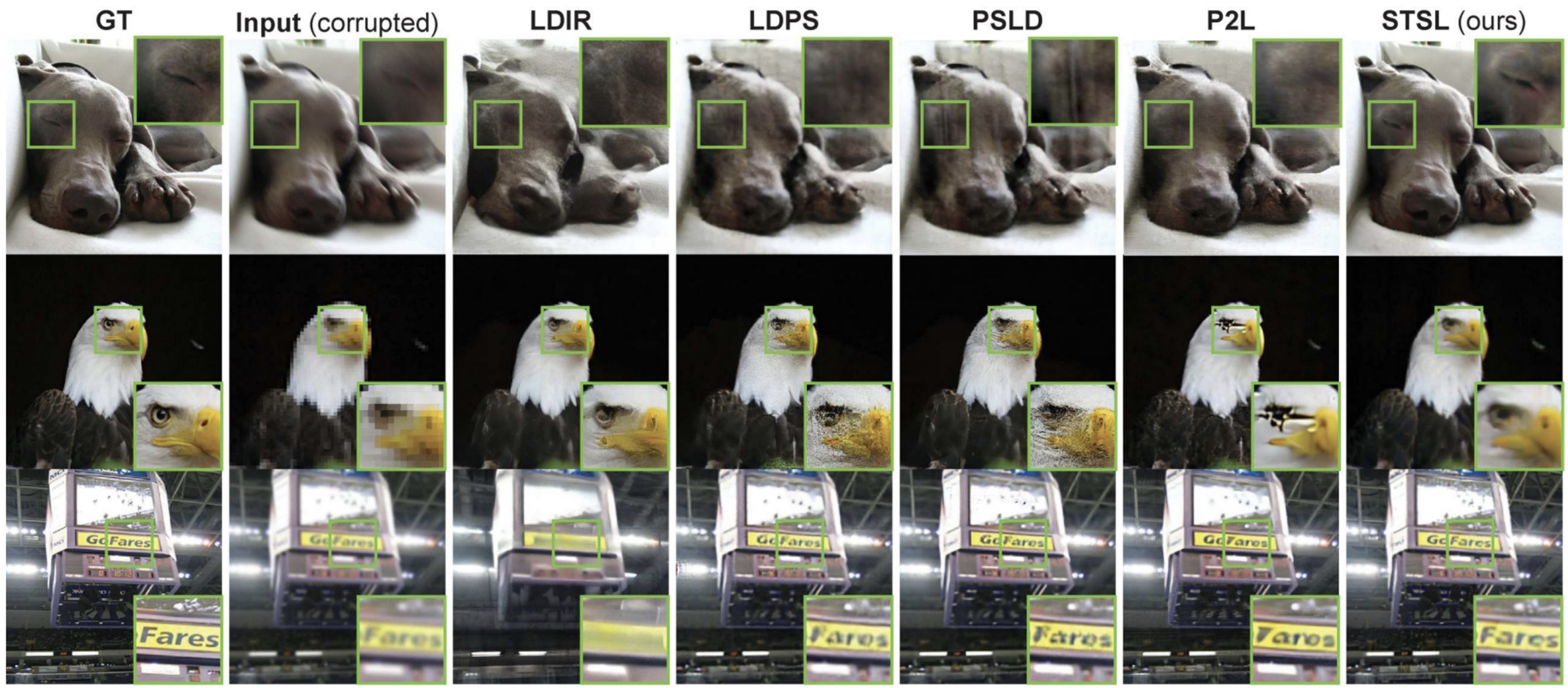
STSL (Rout et al., CVPR'2024):

$$\nabla \hat{L}(y, Z_t) = \nabla \log p_{T-t}(y|Dec(\bar{Z}_T)) - \gamma \nabla \, \mathrm{Trace}(\nabla^2 \log p_{T-t} \, (Z_t))$$

where $\bar{Z}_T = E_{Z_T \sim p_{T-t}(Z_T|Z_t)}[Z_T]$

"Beyond First-Order Tweedie: Solving Inverse Problems using Latent Diffusion", Litu Rout, Yujia Chen, Abhishek Kumar, Constantine Caramanis, Sanjay Shakkottai, Wen-Sheng Chu, CVPR 2024

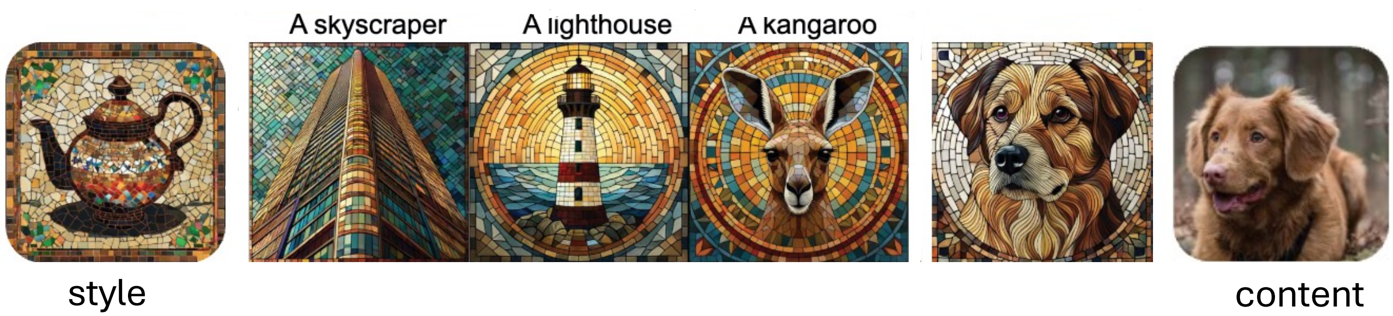
Experimental Results with STSL: ImageNet



First row: Motion Deblur, **Second row:** Super-resolution, **Third row:** Gaussian Deblur.

RB-Modulation for Content-Style Composition

- Algorithm for stylization and editing via Test-time Optimization using proximal methods (ICLR 2025, Oral)
  - Training-free approach
  - Avoids backpropagation through score network
  - All previous training-free algorithms (e.g., DPS, PSLD, STSL) require backpropagating through the score network to address inverse problems



"RB-Modulation: Training-Free Stylization using Reference-Based Modulation", Litu Rout, Yujia Chen, Nataniel Ruiz, Abhishek Kumar, Constantine Caramanis, Sanjay Shakkottai, Wen-Sheng Chu, *ICLR 2025 (Oral)*

Training vs Test-time Optimization

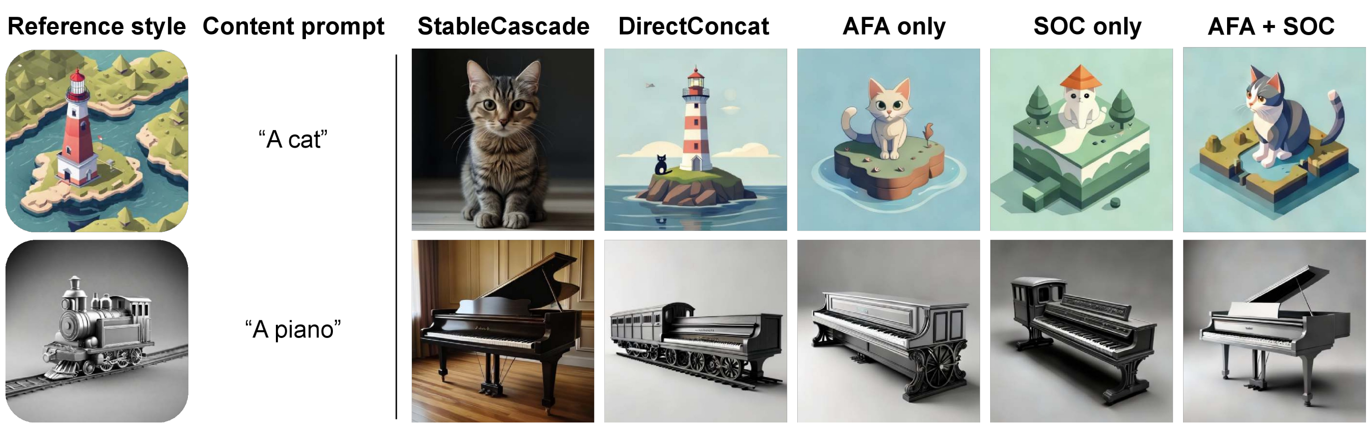
- Training-time optimization (DreamBooth, LoRA, IP-Adapter)
  - Approximately 10s of samples per conditioning (style/content)
    - Single sample leads to catastrophic forgetting
  - Gradient computed with respect to weights of base model
  - LoRA finetuning takes ~20 min per style (40 min for content-style)
  - Full finetuning takes hours

- Test-time optimization (DPS, PSLD, P2L, STSL)
  - Single sample suffices (no catastrophic forgetting)
  - Gradient computed with respect to input to base model
  - Takes ~10 min for PSLD (1B), ~20 min for P2L(1B) (longer for Flux-12B)

- Proximal test-time optimization (RB-Modulation)
  - Takes 40 sec using StableCascade (4B)

RB-Modulation: SOC and AFA

- RB Modulation has two key elements
  - Stochastic Optimal Controller (SOC) and Attention Feature Aggregation (AFA)
  - SOC: An optimal control formulation-based sampler, implemented as a test-time proximal optimizer
  - SOC: Incorporate desired attributes (e.g., style) in controller's terminal cost
  - AFA: Personalize the score and disentangle content-style from the reference images through an alternate cross-attention processor



Posterior Sampling using Diffusion and Optimal Control

Goal: Interpret posterior sampling as a control problem

Recall: Sample $p_X(\cdot\,|y)$ instead of $p_X(\cdot)$ using conditional reverse SDE

$$dX_t = (-X_t - 2\nabla \log p_t(X_t|y))\, dt + \sqrt{2} d\overline{W}_t, \qquad t = T, \cdots, 0$$

Approach: (i) Using Bayes rule, $\log p_t(x_t|y) = \log p_t(y|x_t) + \log p_t(x_t) - \log p_t(y)$

$$dX_t = (-X_t - 2\nabla \log p_t(y|X_t) - 2\nabla \log p_t(X_t))\, dt + \sqrt{2} d\overline{W}_t\,, \qquad t = T, \cdots, 0$$

(ii) Stochastic optimal control problem with terminal cost

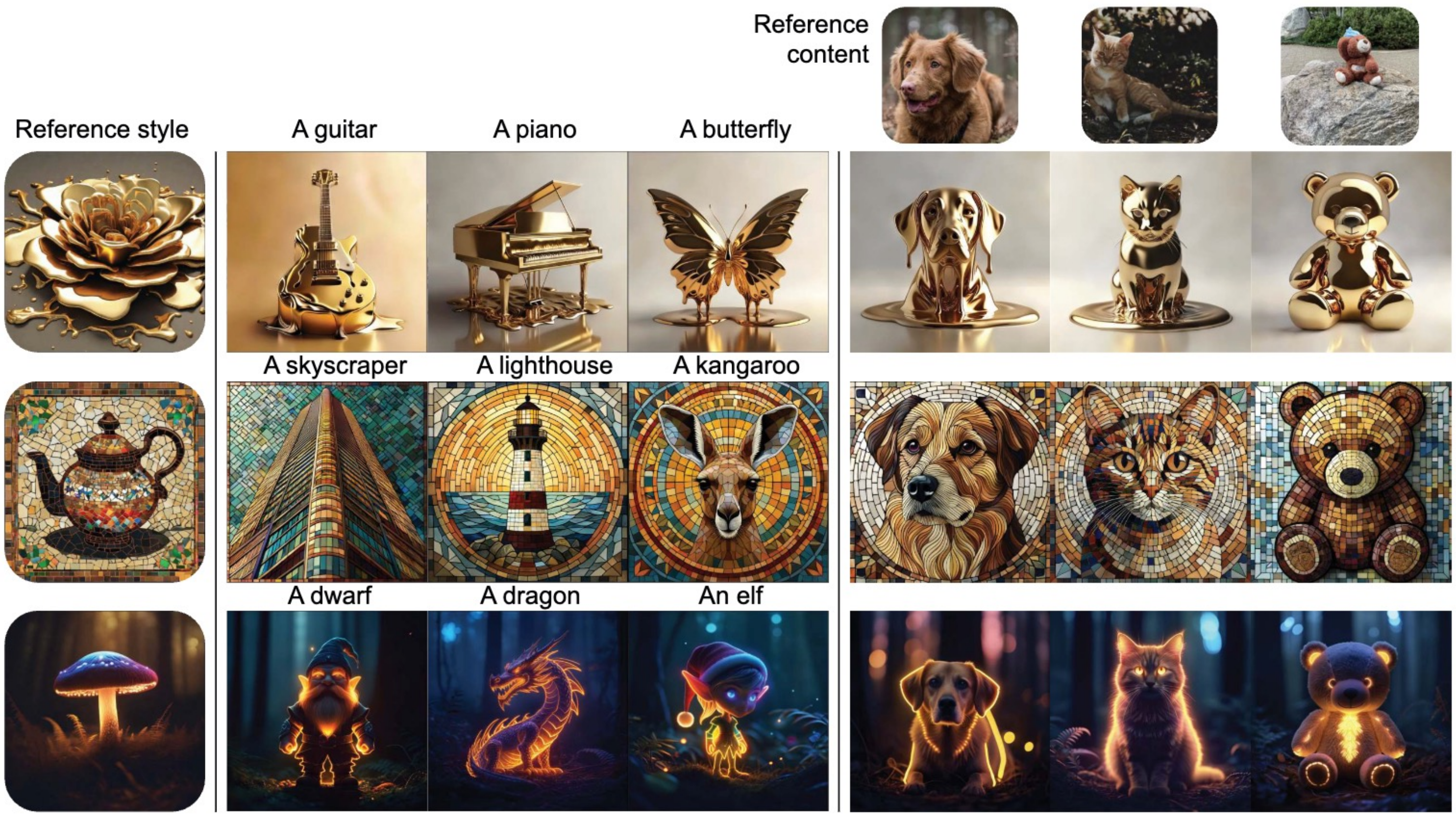
Terminal Cost

$$\min_{u \in U} E\left[\int_0^1 [\|u(X_t^u, t)\|^2]\, dt + g(X_1^u, y)\right]$$

Style Features

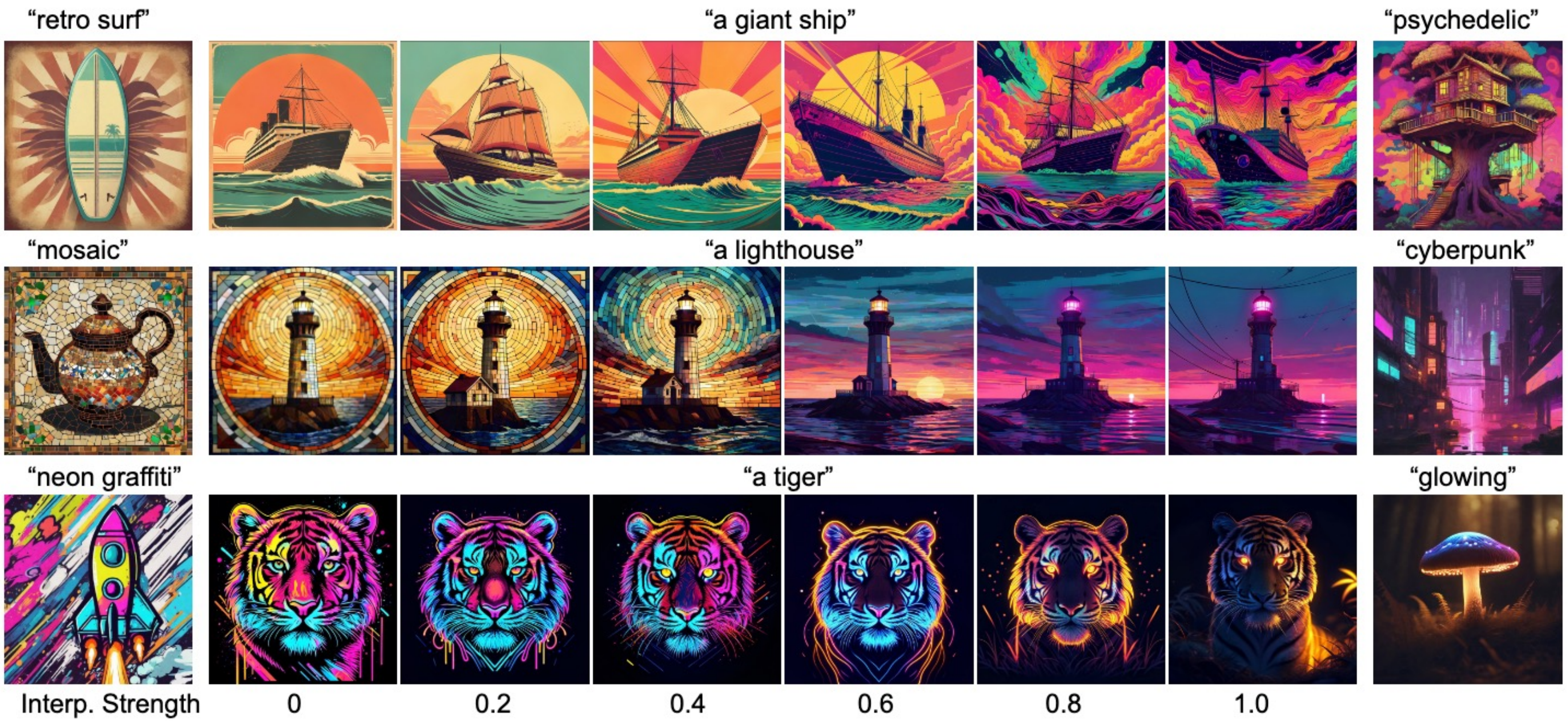
$$dX_t^u = (-X_t + u(X_t^u, t) - 2\nabla \log p_t(X_t))dt + \sigma(t) dW_t\,, \qquad X_0^u \sim p_0.$$

Personalization using RB-Modulation



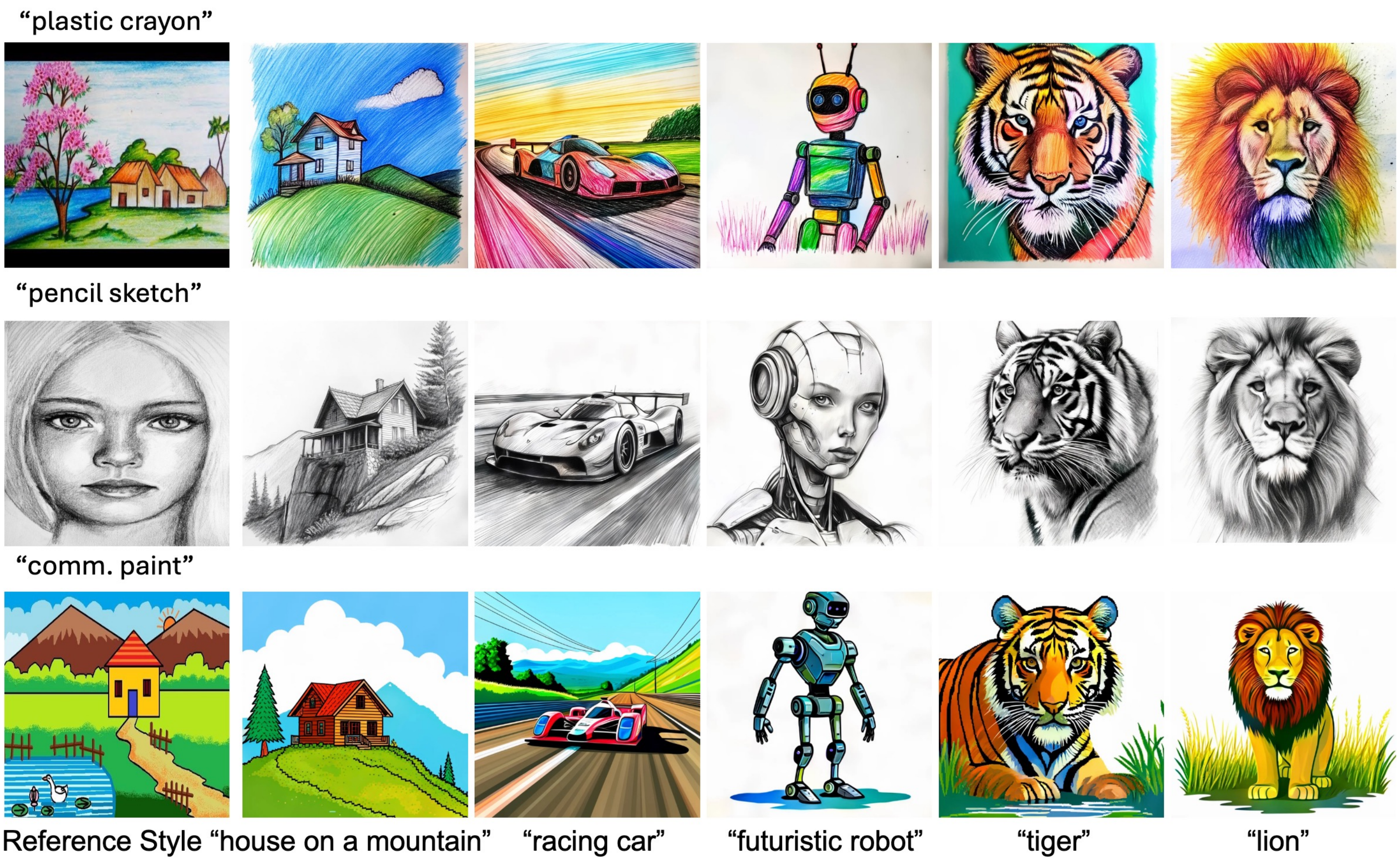
RB-Modulation as a plug-and-play solution for (a) stylization (b) content-style composition

Novel Style Synthesis: Interpolating Reference Styles



Training based methods cannot interpolate novel styles due to lack of prior examples

Stylization: Hand Drawn Reference Images



Please see: https://openreview.net/forum?id=bnINPG5A32 for reference image credits

RB-Modulation: Production Status

- Collaboration with Google and Google DeepMind researchers
  - Code available on github: https://rb-modulation.github.io
- Teams at Google are currently productionizing RB Modulation into several devices and production pipelines
  - Pixel, Chromebook, Tablet, and YouTube
  - Several application settings (e.g., on device personalization)
- Demo became #1 on HuggingFace in the week of its release

Reference Style "mountain" "pillow" "building" "bottle" "turtle"

Emerging Foundation Models: Rectified Flows

RF-Inversion

- First Algorithm for Inversion and Editing with Rectified Flow (ICLR 2025)
  - Rectified Flow models are current SOTA (Flux, SD3.5)
  - RF-Inversion avoids any test-time optimization
  - Can implement on edge device such as Pixel

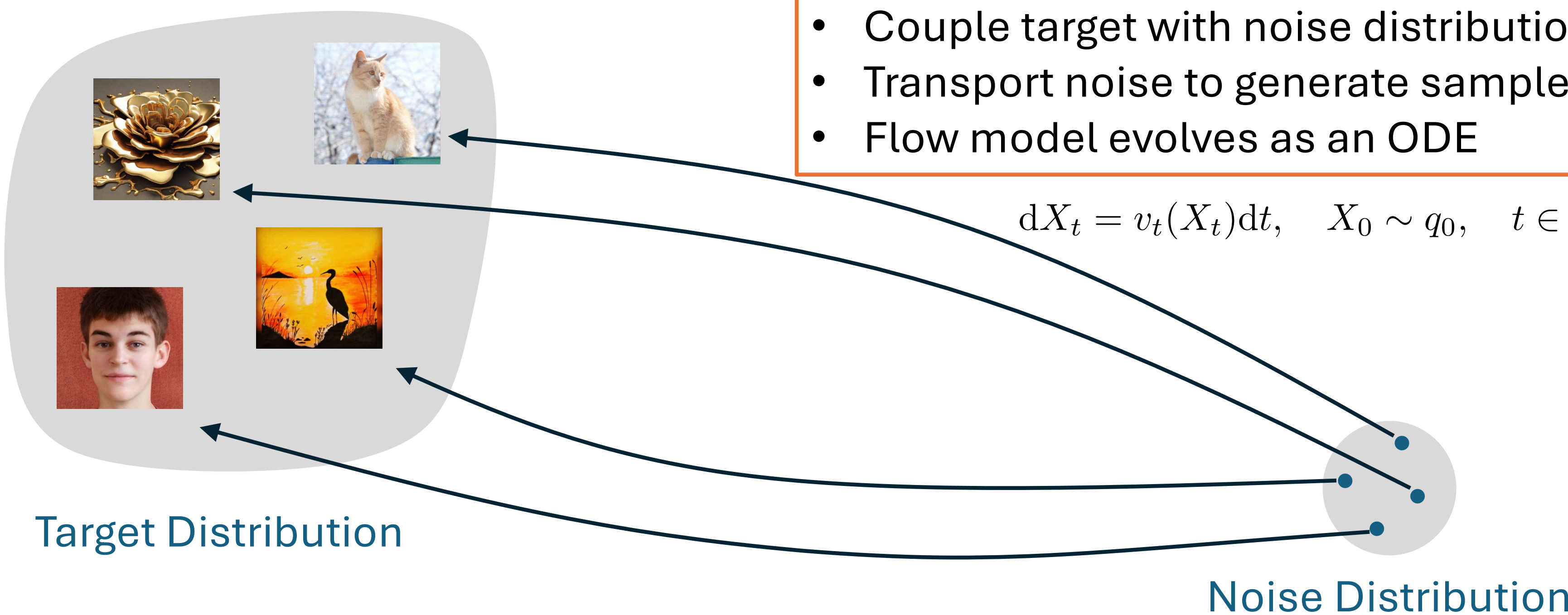
"Semantic Image Inversion and Editing using Stochastic Rectified Differential Equations", Litu Rout, Yujia Chen, Nataniel Ruiz, Constantine Caramanis, Sanjay Shakkottai, Wen-Sheng Chu, *ICLR 2025*

Goal of Rectified Flows

Generate samples from a target distribution given a (large) finite number of samples from that distribution

- Couple target with noise distribution
- Transport noise to generate samples
- Flow model evolves as an ODE

$$\mathrm{d}X_t = v_t(X_t)\mathrm{d}t, \quad X_0 \sim q_0, \quad t \in [0,1]$$

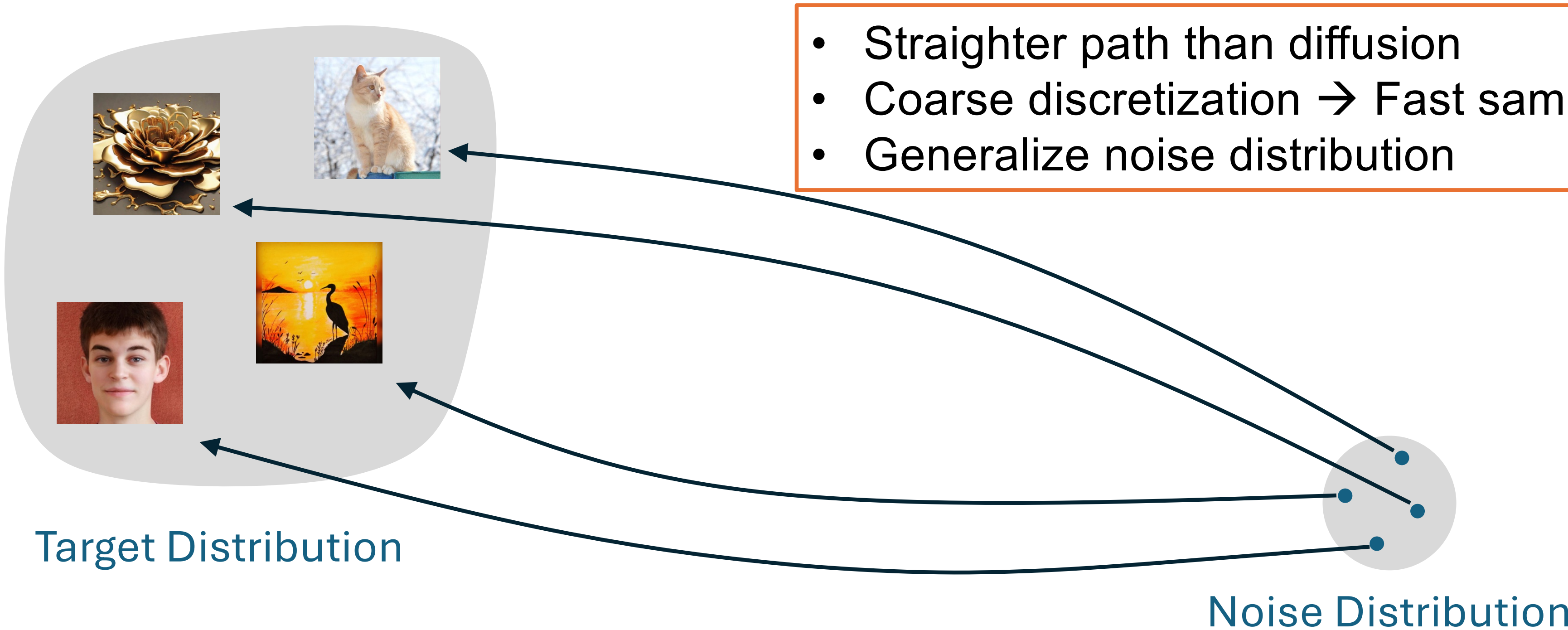


RF: Liu et. al., Flow straight and fast: Learning to generate and transfer data with rectified flow, ICLR 2022; Lipman et. al. Flow matching for generative modeling, 2022; Albergo and Vanden-Eijnden, Building normalizing flows with stochastic interpolants; ICLR 2023.

Benefit of Rectified Flows

Generate samples from a target distribution given a (large) finite number of samples from that distribution

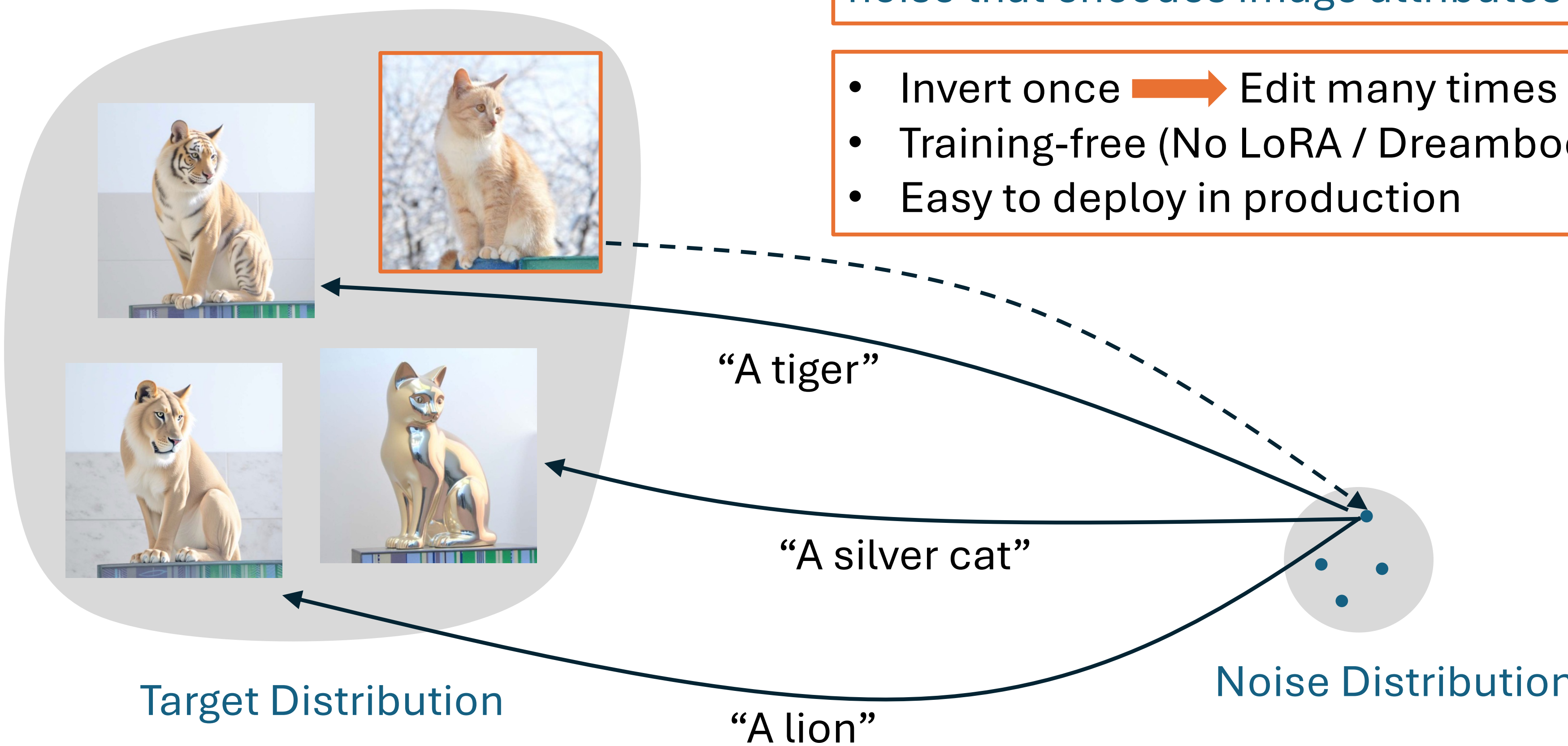
- Straighter path than diffusion
- Coarse discretization → Fast sampling
- Generalize noise distribution



Inversion with RF (1/2)

Inversion: Transform image into structured noise that encodes image attributes

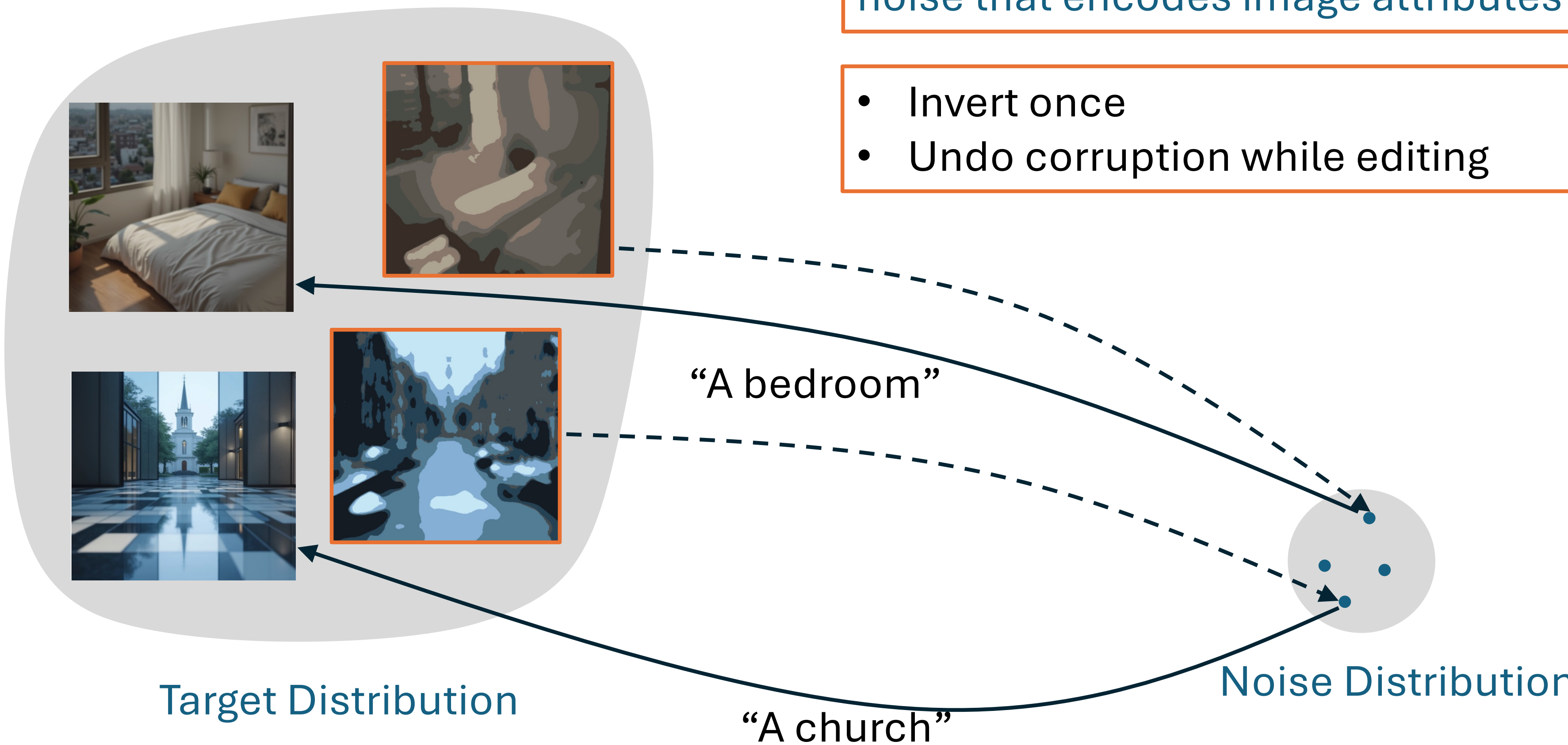
- Invert once ➡ Edit many times
- Training-free (No LoRA / Dreambooth)
- Easy to deploy in production



Inversion with RF (2/2)

Inversion: Transform image into structured noise that encodes image attributes

- Invert once
- Undo corruption while editing



State-of-the-art Inversion

- No algorithm to directly invert and edit using rectified flows
- Other approaches available for diffusion models
  - Inversion possible through SDEdit and DDIM inversion (for diffusions) but ...
    - They lead to inconsistencies (preservation of conditioning structure/layout) due to highly non-linear sample paths
  - Alternate methods maintain consistency through expensive training (e.g., DreamBooth, LoRA), test-time optimization (RB Modulation), or complex attention processors (NTI, P2P)

Related Works: Inversion and Editing using Diffusion Models

Method	**Training**	**Optimization**	**Attention Manipulation**
SDEdit [MHS+22]	✗	✗	✗
DDIM [SME21]	✗	✗	✗
NTI [MHA+23]	✗	✓	✗
NTI+P2P [HMT+22]	✗	✓	✓
LEDIT++ [BFK+24]	✗	✗	✓
InstructPix2Pix [BHE23]	✓	✗	✗
Ours	✗	✗	✗

- Diffusion models are the mainstream approach for inversion and editing
- SoTA methods require training, optimization, or attention manipulation
- SDEdit, DDIM, NTI, NTI+P2P are leading training-free methods
- NTI and P2P require test-time optimization or complex attention processors

Goal: Inversion and Editing using Rectified Flows

- Diffusion models (DMs) traditionally outperformed Rectified Flows (RFs)
- SD3.5 and Flux show RFs can beat DMs

- RF-Inversion or editing remain unexplored

- DM inversion techniques face challenges in RFs
    - Training of additional parameters (DreamBooth, StyleDrop)
    - Optimization of latent variables (RB-Modulation)
    - No null conditioning in distilled Flux (NTI)
    - Complex cross-attention processors (P2P)

First efficient inversion and editing using rectified flows without training, optimization, complex attention processors

Introduction to Rectified Flows

Goal: Generate samples from a target distribution given a finite number of samples from that distribution

Approach: Simulate an ODE to generate samples

$$\mathrm{d}X_t = v_t(X_t)\mathrm{d}t, \quad X_0 \sim q_0, \quad t \in [0,1]$$

vector field / drift

initialization

Normalized time

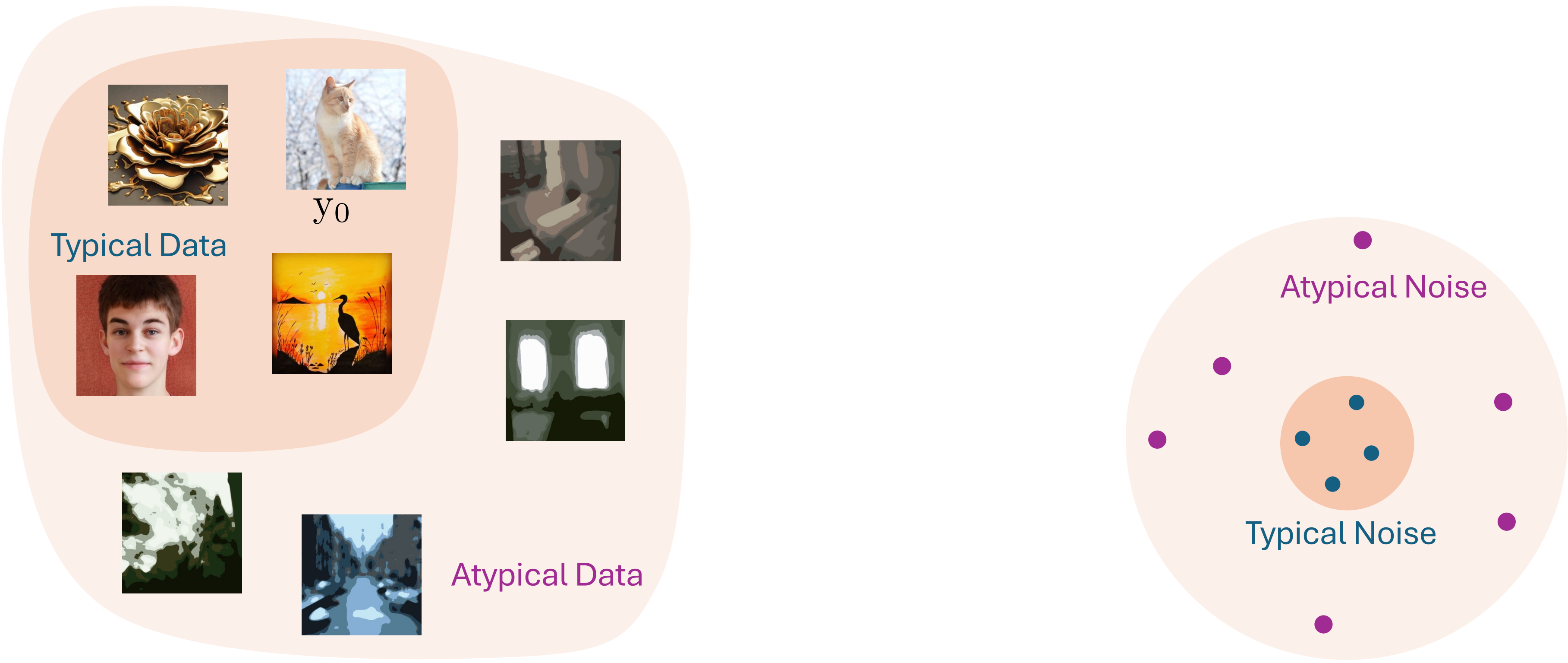
A common choice: $X_0 \sim \mathcal{N}(0, I)$ and $v_t(\cdot) = -u(\cdot, 1-t; \phi)$

$u(\cdot, \cdot; \phi)$ is a Neural Network (NN) trained using Conditional Flow Matching (CFM)

RF: Liu et. al., Flow straight and fast: Learning to generate and transfer data with rectified flow, ICLR 2022; Lipman et. al. Flow matching for generative modeling, 2022; Albergo and Vanden-Eijnden, Building normalizing flows with stochastic interpolants; ICLR 2023.

Our Approach: RF-Inversion

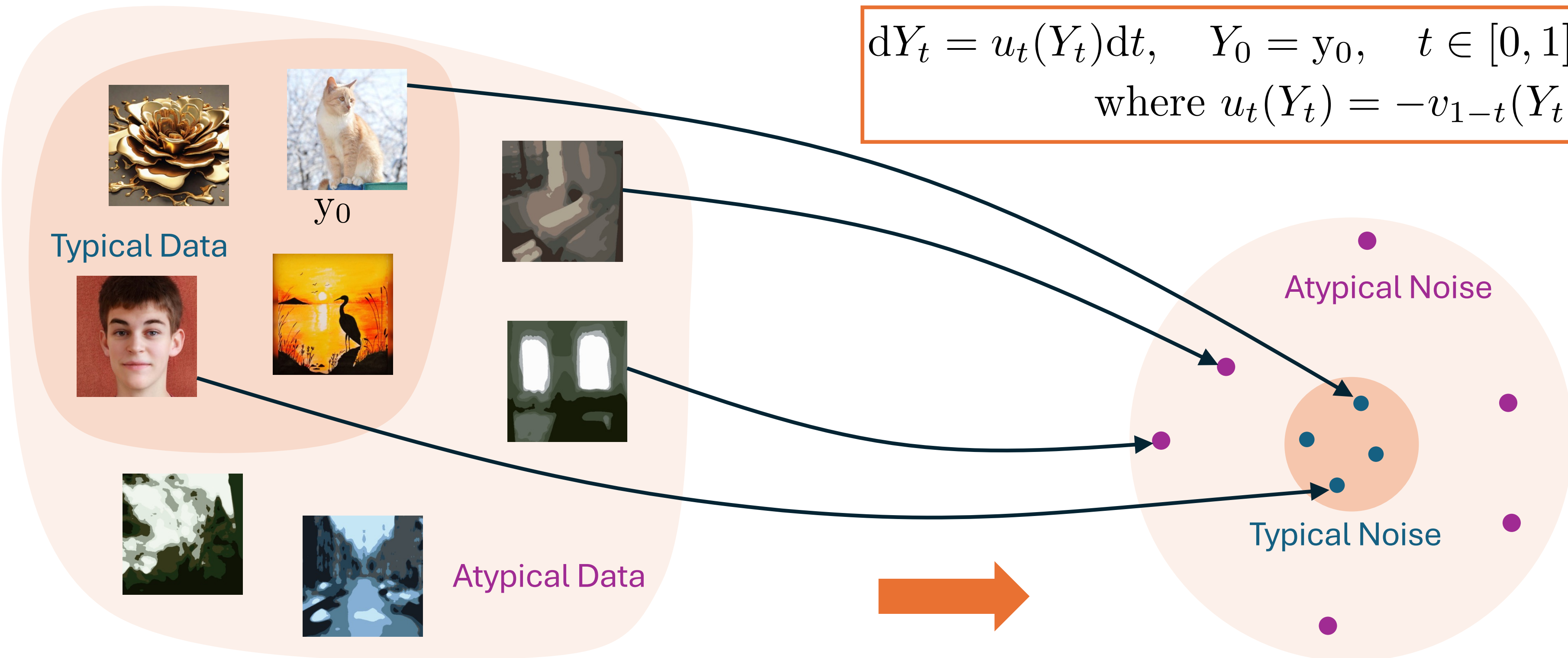
Inversion using Rectified Flows



Distributions can be (roughly) grouped into two types: typical and atypical

Inversion using Rectified Flows

$$\mathrm{d}Y_t = u_t(Y_t)\mathrm{d}t, \quad Y_0 = \mathrm{y}_0, \quad t \in [0,1],$$
$$\text{where } u_t(Y_t) = -v_{1-t}(Y_t)$$

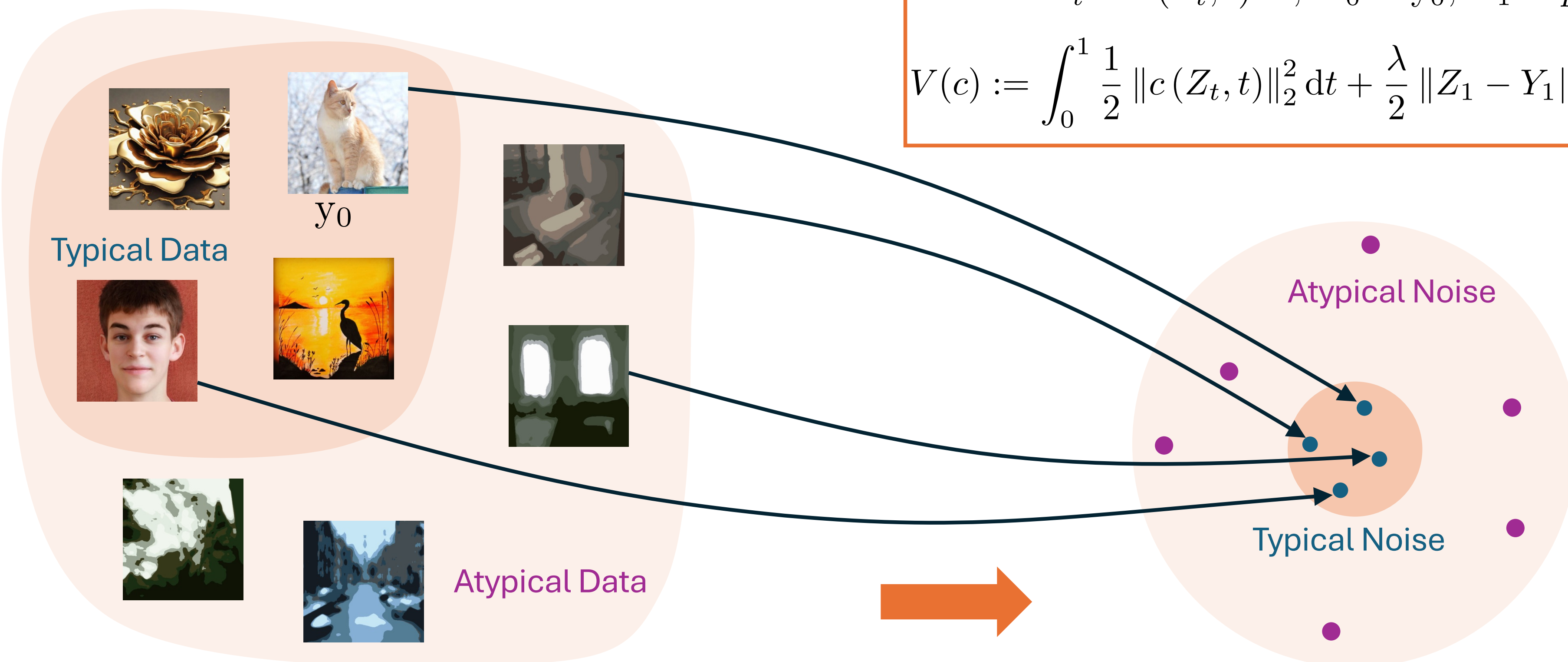


RF transforms typical image to typical noise; atypical image to atypical noise

Inversion using Optimal Control

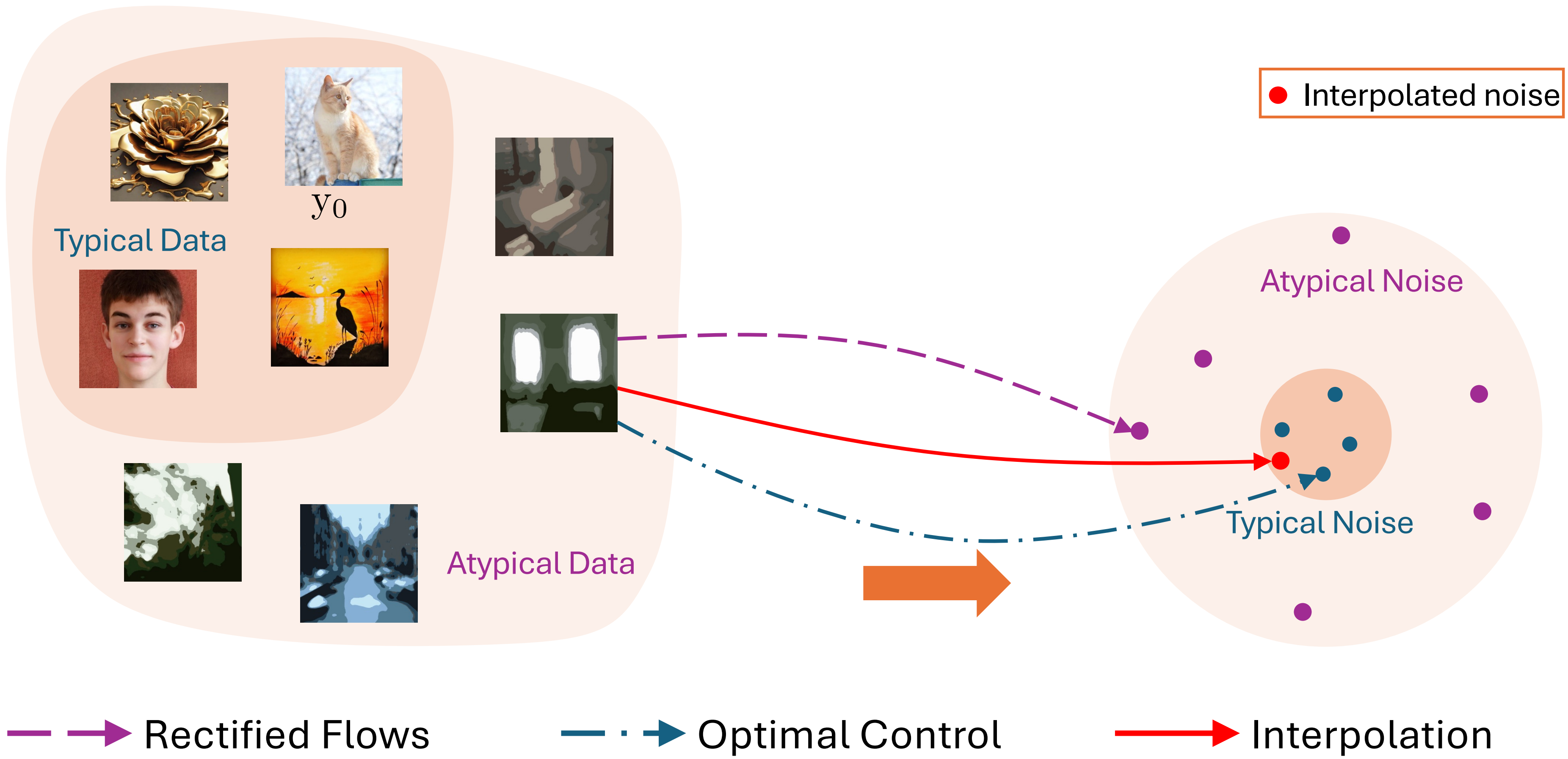
$$\mathrm{d}Z_t = c\,(Z_t, t)\,\mathrm{d}t,\;\; Z_0 = \mathrm{y}_0,\;\; Y_1 \sim p_1$$

$$V(c) := \int_0^1 \frac{1}{2}\,\|c\,(Z_t, t)\|_2^2\,\mathrm{d}t + \frac{\lambda}{2}\,\|Z_1 - Y_1\|_2^2$$

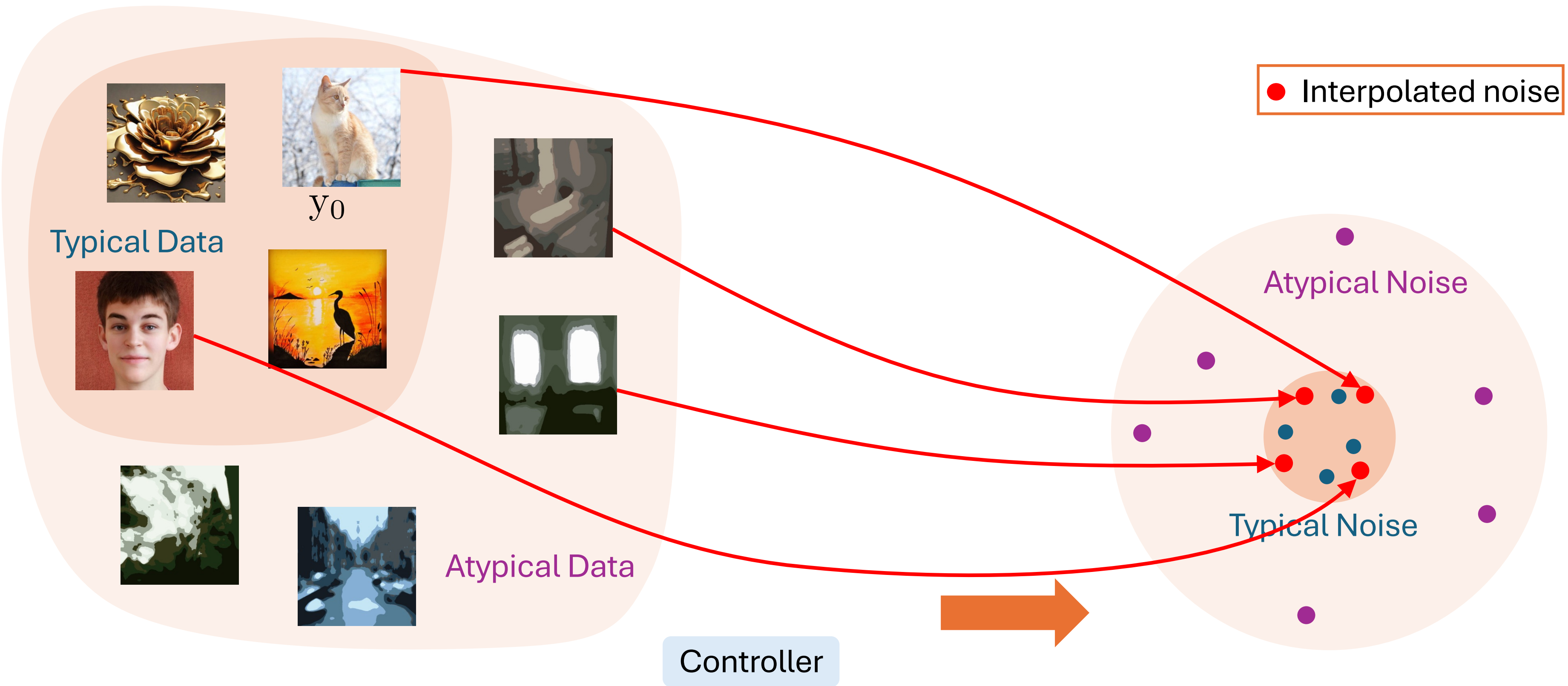


Optimal controller transforms any image to typical noise

Interpolation of the Two Fields

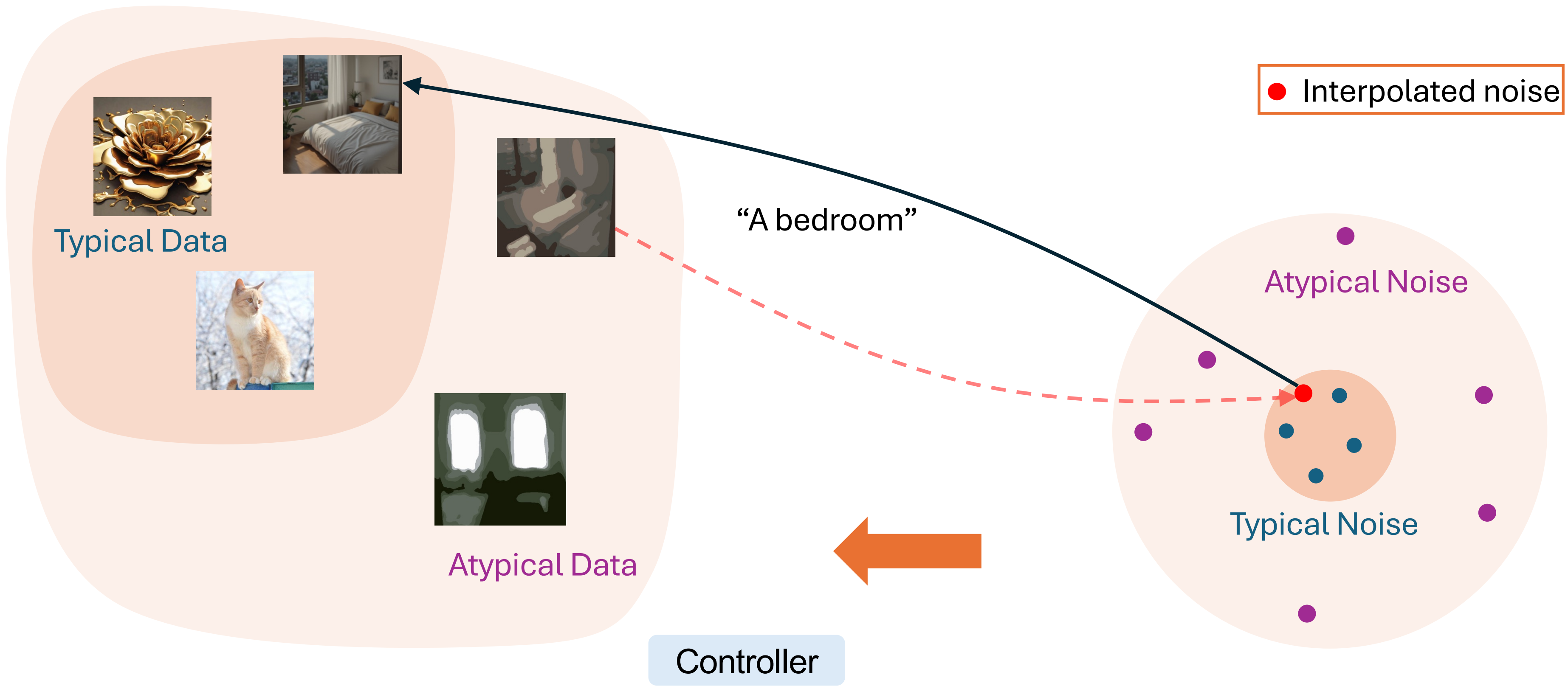


Inversion using Optimally Controlled Rectified Flow



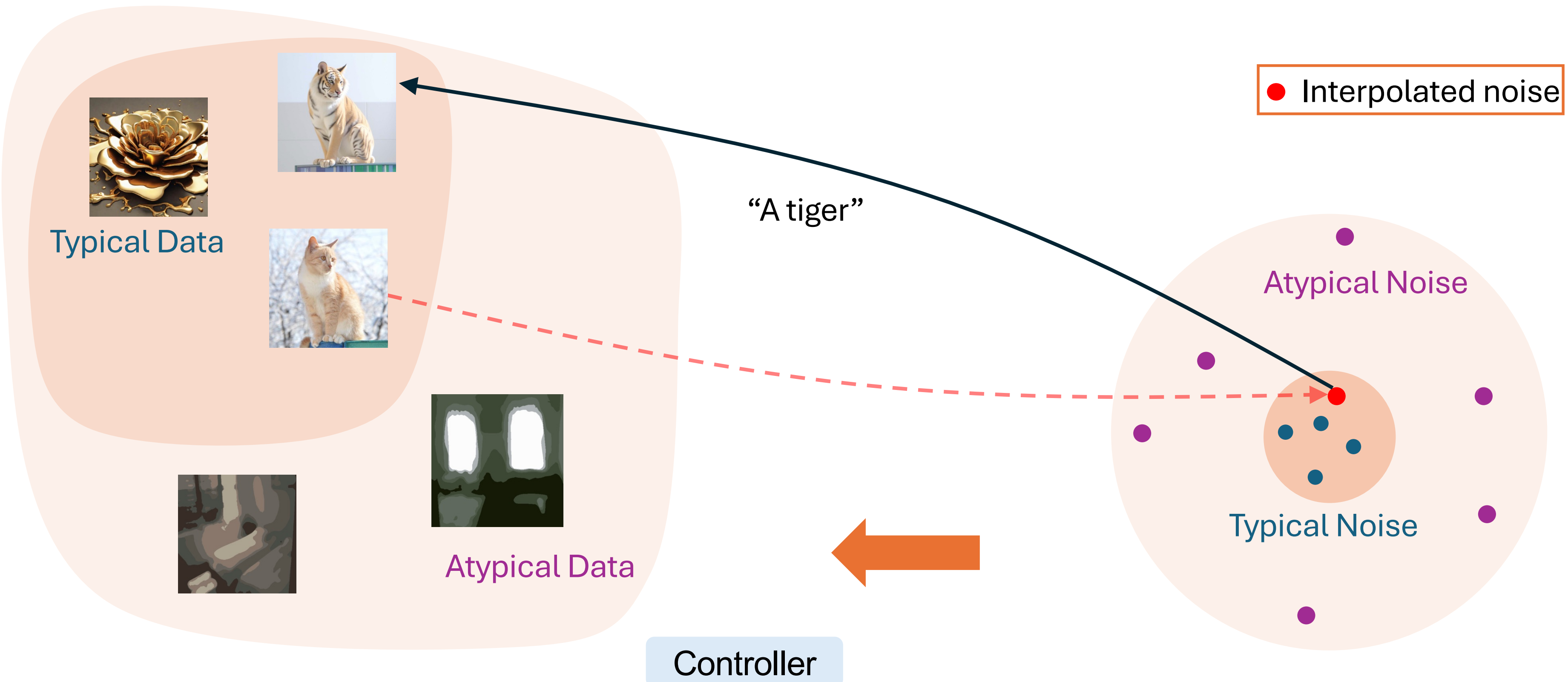
$$\mathrm{d}Y_t = \Big[u_t(Y_t) + \gamma\left(u_t(Y_t|\mathrm{y}_1) - u_t(Y_t)\right)\Big]\mathrm{d}t, \quad Y_0 = \mathrm{y}_0$$

Generation using Optimally Controlled Rectified Flows



$$\mathrm{d}X_t = \Big[v_t(X_t, \mathrm{prompt}) + \eta\,\big(v_t(X_t|\mathrm{y}_0) - v_t(X_t, \mathrm{prompt})\big)\Big]\mathrm{d}t, \quad X_0 = \mathrm{y}_1$$

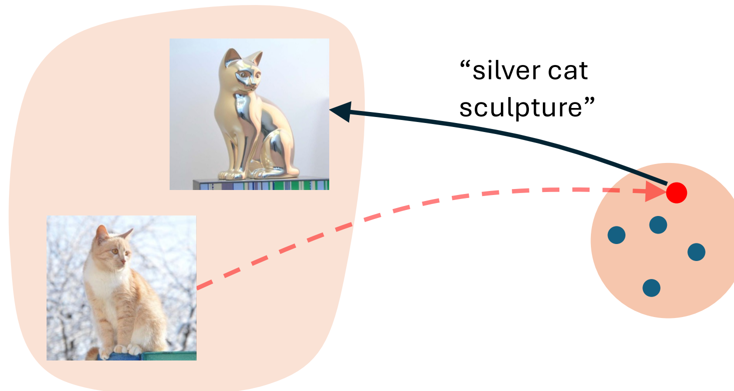
Generation using Optimally Controlled Rectified Flows



$$\mathrm{d}X_t = \Big[v_t(X_t, \mathrm{prompt}) + \eta \left(v_t(X_t | \mathrm{y}_0) - v_t(X_t, \mathrm{prompt}) \right) \Big] \mathrm{d}t, \quad X_0 = \mathrm{y}_1$$

Counterfactual Sampling (1/2)

- The counterfactual question: "Imagine if this cat was a silver sculpture"
- Three step approach for counterfactual reasoning with an SCM (Pearl et. al. 2016)
  - Noise abduction
  - Action ('do')
  - Prediction
- RF-Inversion intuition
  - Going back to noise through Inversion ⇔ Noise abduction
  - Doing through text conditioning ⇔ Action
  - Generating through reverse controlled flow ⇔ Prediction



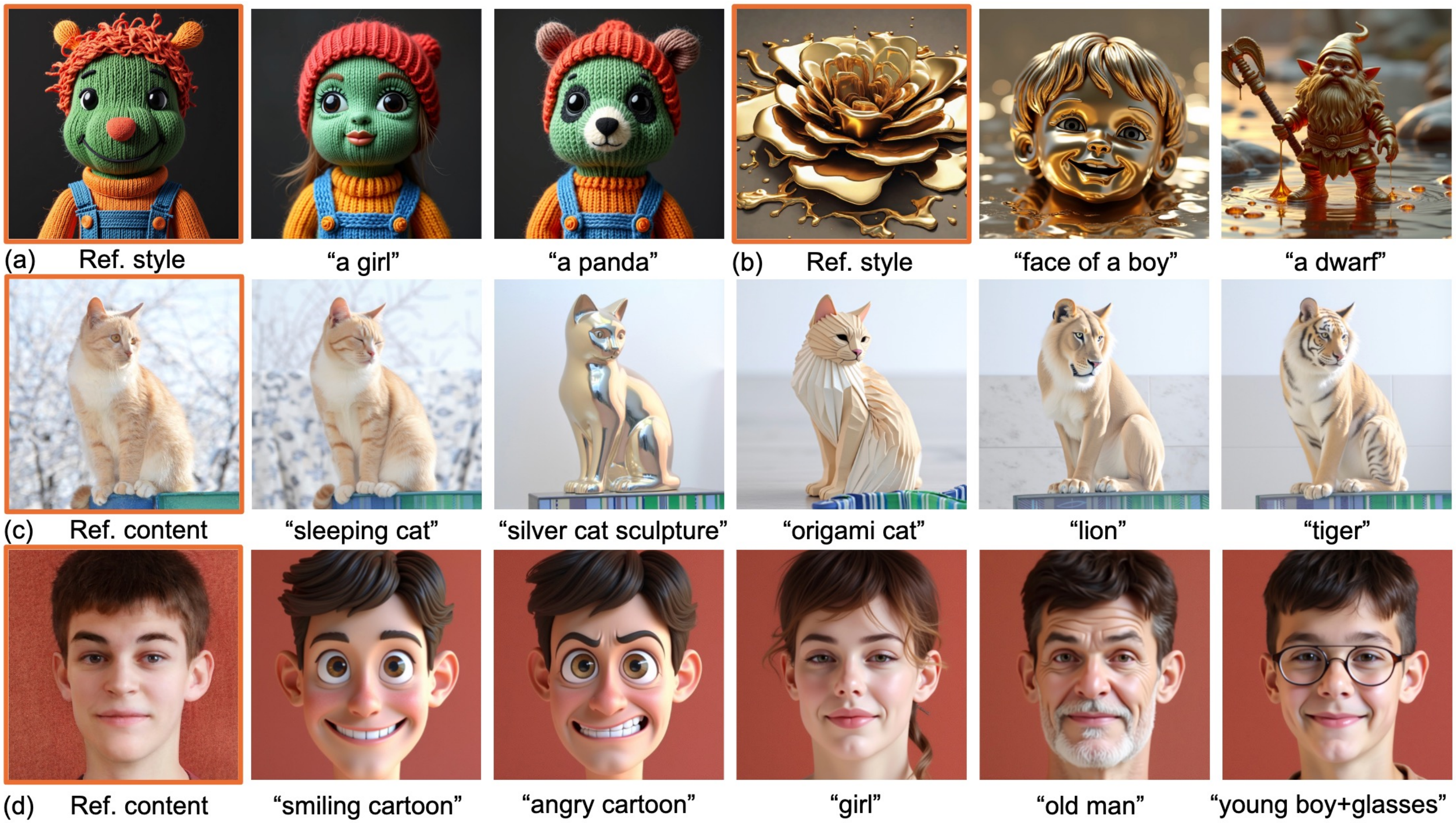
RF-Inversion interpreted as a prototype of a counterfactual sampler

Counterfactual Sampling (2/2)

Ref. Image | w/o controller + null-text (“”) | w/ controller + null-text (“”) | w/ controller + “silver sculpture” | w/ controller + “tiger”

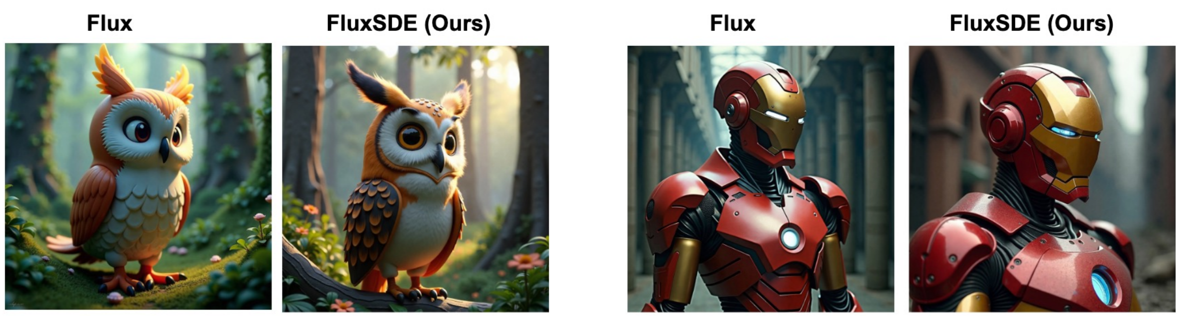
- Reference image
- (Reference image ➞ noise ➞ generated image) without our controller
- (Reference image ➞ noise ➞ generated image) with our controller
  - Conditional vector field is grounded to the reference image
- Using text prompts of: ‘A silver cat sculpture’ and ‘A tiger’

Image Inversion and Editing using Rectified Flows



A Stochastic Sampler for RF

- Benefits of a Stochastic Sampler for Rectified Flows
  - Many diffusion-based inversion and editing approaches rely on stochastic nature of the diffusion sampler
  - Higher-order solvers benefit from SDE interpretation of diffusion samplers
  - With finer discretization, SDE samplers outperform deterministic samplers in generative modeling, measured by Frechet Inception Distance (FID)
  - SDE samplers show robustness to corruption in the initial distribution, i.e., their invariant measure remains the same



Our Approach: Deterministic to Stochastic Sampler

- Closed-form expression for vector field with RF (using Tweedie's Formula):

$$u_t(\mathrm{y}_t) = \mathbb{E}_{(Y_0,Y_1)\sim p_1 \times p_0}\left[Y_1 - Y_0 | Y_t = \mathrm{y}_t\right] \; = \left[-\frac{1}{1-t}\mathrm{y}_t - \frac{t}{1-t}\nabla \log p_t(\mathrm{y}_t)\right]$$

- Closed form expression for optimal controller (using minimum principle):

$$u_t(\mathrm{y}_t | Y_1) = \frac{Y_1 - \mathrm{y}_t}{1-t}$$

- Interpolate between these drift fields to get structured noise:

$$\boxed{\mathrm{d}Y_t = u_t(Y_t) + \gamma(u_t(Y_1|\mathrm{y}_1) - u_t(Y_t))\mathrm{d}t, \quad Y_0 = \mathrm{y}_0, \quad t \in [0,1]}$$

Our Approach: Deterministic to Stochastic Sampler

- Controlled Rectified Flow ODE:

$$\mathrm{d}Y_t = u_t(Y_t) + \gamma(u_t(Y_1|\mathrm{y}_1) - u_t(Y_t))\mathrm{d}t, \quad Y_0 = \mathrm{y}_0, \quad t \in [0,1]$$

- Density evolution by continuity equation:

$$\frac{\partial p_t(Y_t)}{\partial t} = \nabla \cdot \left[\left(\frac{1}{1-t} \left(Y_t - \gamma \mathrm{y}_1 \right) + \frac{(1-\gamma)t}{1-t} \nabla \log p_t(Y_t) \right) p_t(Y_t) \right]$$

- Controlled SDE using Fokker-Planck equation:

$$\mathrm{d}Y_t = -\frac{1}{1-t} \left(Y_t - \gamma \mathrm{y}_1 \right) \mathrm{d}t + \sqrt{\frac{2(1-\gamma)t}{1-t}} \mathrm{d}W_t, \quad Y_0 \sim p_0$$

Analogous approach for deriving SDE for Generation

Experiments

Experiments: Identity Preservation in Face Editing

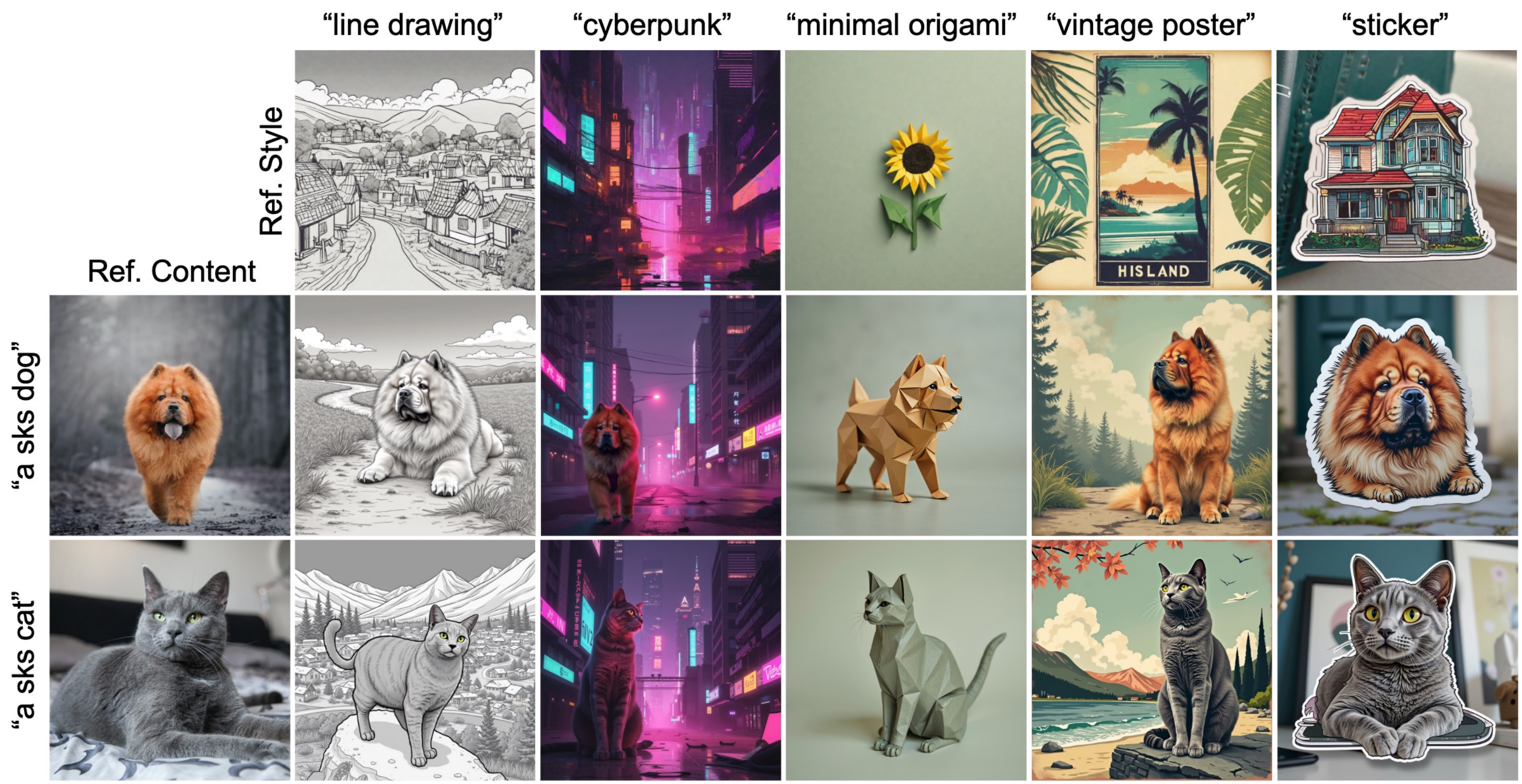
Original | SDEdit | DDIM Inversion | NTI | NTI+P2P | Ours

Prompt: “… + wearing glasses”

Experiments: Semantic Image Editing

Editing (a) stylized expression, (b) age, (c) gender, and (d) object insert

Experiments: Content-style composition



Experiments: Generalization to another flow model SD3.5

(a,b) Generated reference style (c,d) Hand drawn reference style

Please see: https://openreview.net/forum?id=bnINPG5A32 for reference image credits

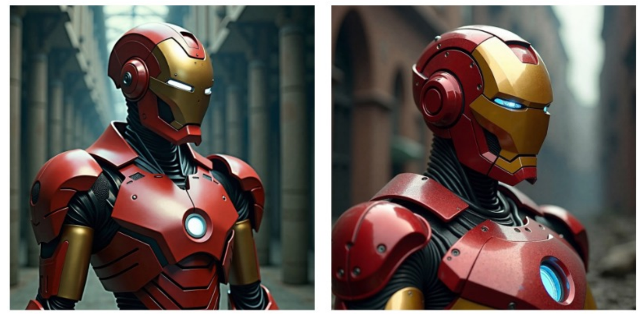
Experiments: Generative modeling using rectified flow SDE

Flux **FluxSDE (Ours)**

Prompt: “portrait, looking to one side of frame, lucid dream-like 3d model of an owl, video game character, forest, wonderland, photorealism, cinematic artistic style.”

Prompt: “a dragon soaring through the sky, battle ground, people fighting on the ground.”

Flux **FluxSDE (Ours)**



Prompt: “a robot with a reflective helmet, iron armor, photorealistic, in shades of red and golden brown, dark gloomy environment, epic scene.”

Prompt: “a genius scientist, in his 60s, standing, writing on the black board, white hair, white beard, round spectacles.”

Community Developments

Day 1
(Oct 14)

- Paper released on ArXiv: https://arxiv.org/pdf/2410.10792
- Project page: https://rf-inversion.github.io/
- ComfyUI code reproduced results from RF-Inversion (<24hrs)
  https://tinyurl.com/xwv24wbp

Week 1-2

- 8 Steps Style and Face Transfer with Unsampling and RF Inversion
- YouTube Tutorial: https://www.youtube.com/watch?v=H_G2AaLWN2o
- Endless creative possibilities: https://tinyurl.com/57b72ks4
- Test of RF-Inversion on style transfer: https://tinyurl.com/bdhs4vy3
- Podcasts: https://tinyurl.com/3x496jkv, https://tinyurl.com/3djmevef

Week 3-4

- Animate movies using RF-Inversion: https://tinyurl.com/xwv24wbp
- Mochi Video Editing with RF-Inversion: https://tinyurl.com/yeyej7x8
- Integration in diffusers from HuggingFace: https://tinyurl.com/2avrfzh5
- Follow up works: ReCapture (Zhang et al.), RF-Edit (Wang et al.), AnimateAnything (Lei et al.), EditAway (wang et al.), MyTimeMachine (Qi et al.), HeadRouter (Xu et al.)

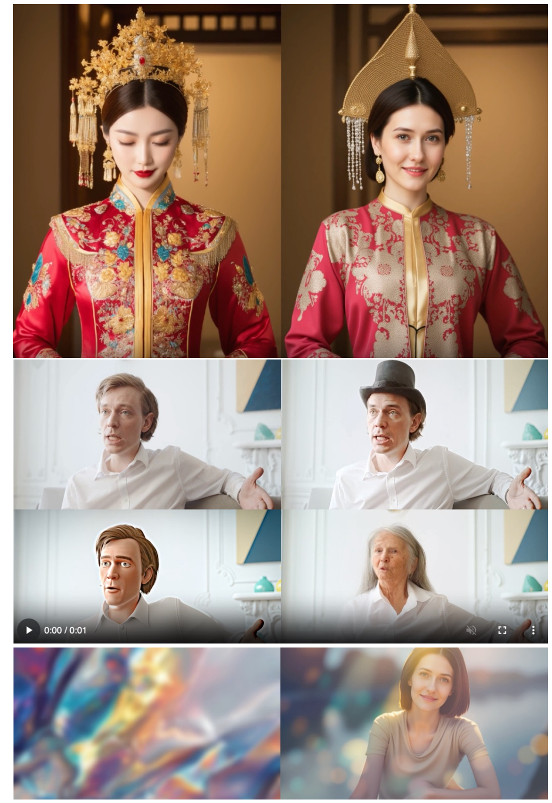


Image Credit: https://tinyurl.com/57b72ks4, https://tinyurl.com/xwv24wbp

Summary

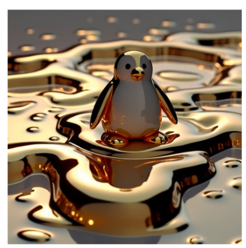
- First efficient inversion and editing for rectified flows
  - Interpolates two vector fields

- Stochastic equivalence between rectified flow ODE and SDE

- State-of-the-art zero-shot performance w/o training, optimization, prompt tuning and complex attention processors

- Effectiveness in stroke-to-image synthesis, face editing, stylization, content-style composition, w/ large-scale human evaluations

“a butterfly”



“a baby penguin”

“a boat”

“a piano”