# Image Editing with Optimization (part I)

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# Style Transfer vs. Image-to-Image Translation

- Data (how to define Style)
  - A single image? A collection of images?
- Applications
  - Photo -> Painting (Neural Style Transfer, Image-to-Image Translation)
  - Photo -> Photo (Image-to-Image Translation, Photo Style Transfer (Color) )
  - Painting -> Photo (Image-to-Image Translation, Deep Image Analogy)
- Algorithms:
  - Patch-based method (i.e., correspondence between output and input)
  - Optimization-based method
  - Feed-forward network
- Loss functions
  - Style Loss: GAN loss, Gram matrix loss
  - Content Loss: Perceptual Loss (L2 reconstruction loss), identity loss, conditional GAN Loss, Cycle-consistency loss, Contrastive Loss (InfoNCE)

# Image Editing with Optimization

$\hat{y}$

$y$

$$|\mathrm{Gram}($$  $$) - \mathrm{Gram}($$  $$)|$$

optimized output

style image

$\hat{y}$

$x$

$$+ \quad |\mathrm{F}($$  $$) - \mathrm{F}($$  $$)|$$

optimized output

content image

$$\arg\min_{\hat{y}} \mathcal{L}_{\text{style}}(\hat{y}, y) + \lambda \mathcal{L}_{\text{content}}(\hat{y}, x)$$

User input

Input image

# Image Editing with Optimization

input photo

Image Editing Program

User Input

result

$$\arg\min_{\hat{y}} \mathcal{L}_{\text{background\_boundary}}(\hat{y}, y) + \lambda \mathcal{L}_{\text{source\_gradient}}(\hat{y}, x)$$

result background result object

[Tao et al. 2014]

# Image Editing with Optimization

input photo

Image Editing Program

User Input

result

Desired output:

- stay close to the input.
- satisfy user's constraint.

[Tao et al. 2014]

# Image Editing with Optimization

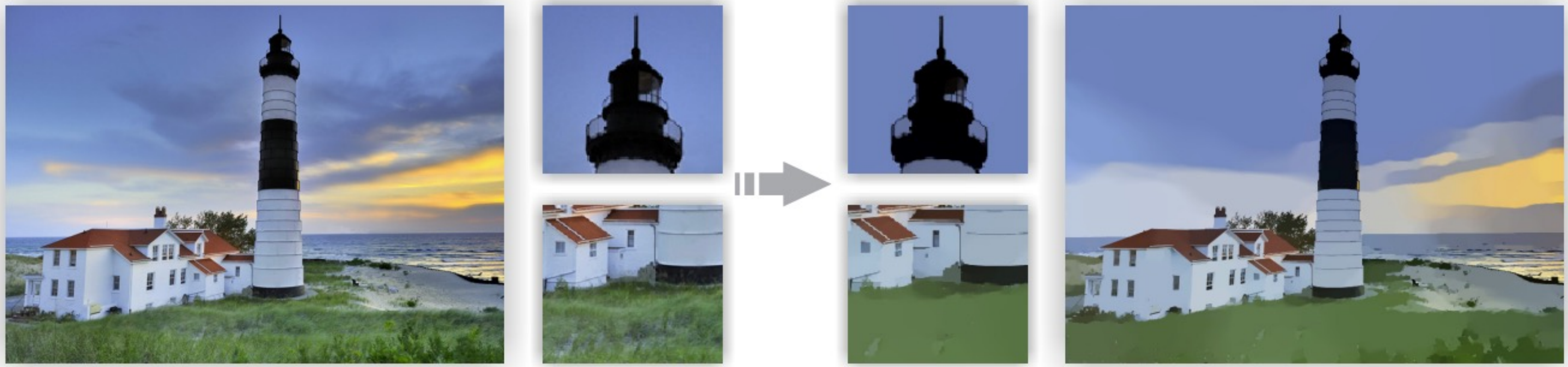


Image Smoothing via L0 Gradient Minimization [Xu et al., SIGGRAPH Asia 2011]

$$\arg\min_{\hat{y}}\{||\hat{y} - x|| + \lambda C(\hat{y})\}$$

output input L0 norm on image gradients
(the total number of nonzero elements)

# Image Editing with Optimization

Colorization using Optimization [Levin et al., SIGGRAPH 2004]

YUV color space (Y is fixed)
constant: scribbles
variables: rest of the pixels

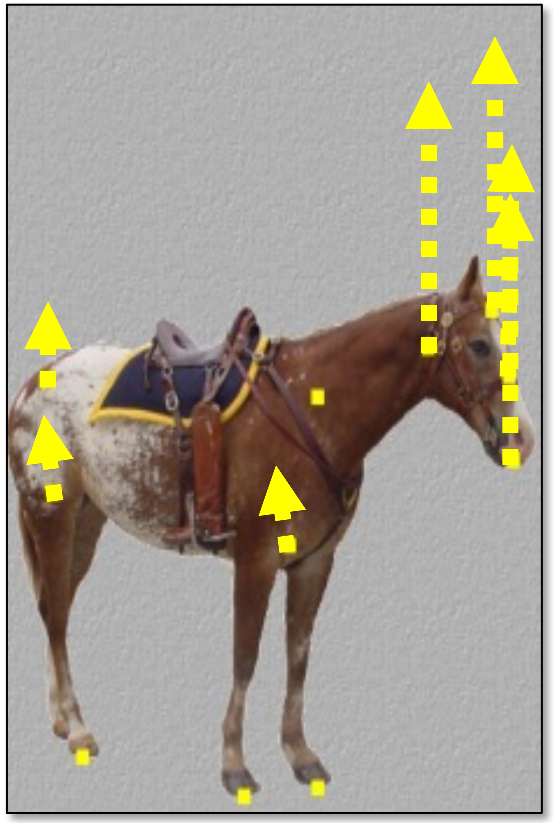
$$\sum_{\mathbf{r}} \left( U(\mathbf{r}) - \sum_{\mathbf{s} \in N(\mathbf{r})} w_{\mathbf{rs}} U(\mathbf{s}) \right)^2$$

visual similarity between r and s
Intensity, location, edge, motion, etc.

the color of pixel r

the color of pixel s (s is r’s neighbor)

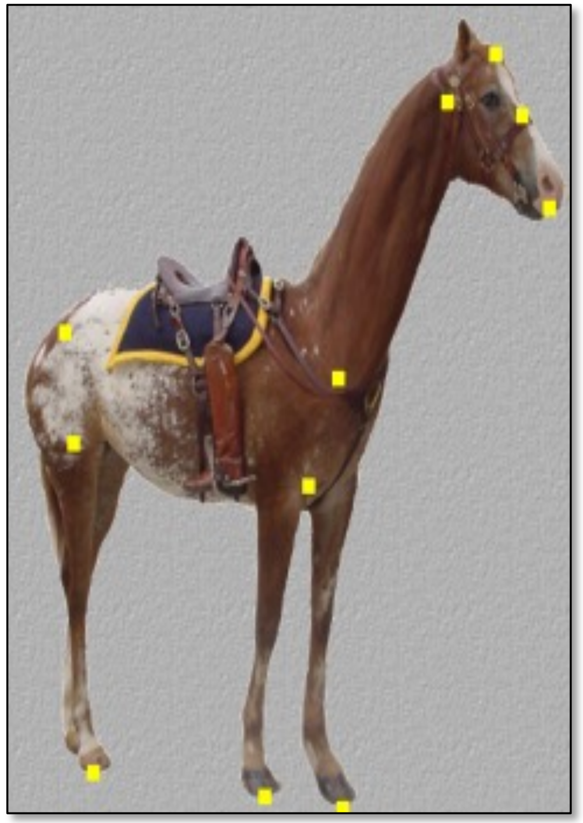
# Image Editing with Optimization



input photo

Image Editing Program

User Input



result

Moving least squares + transformation parameters.

Desired output:

- stay close to the input.
- satisfy user's constraint.

[Schaefer et al. 2006]

# So far so good

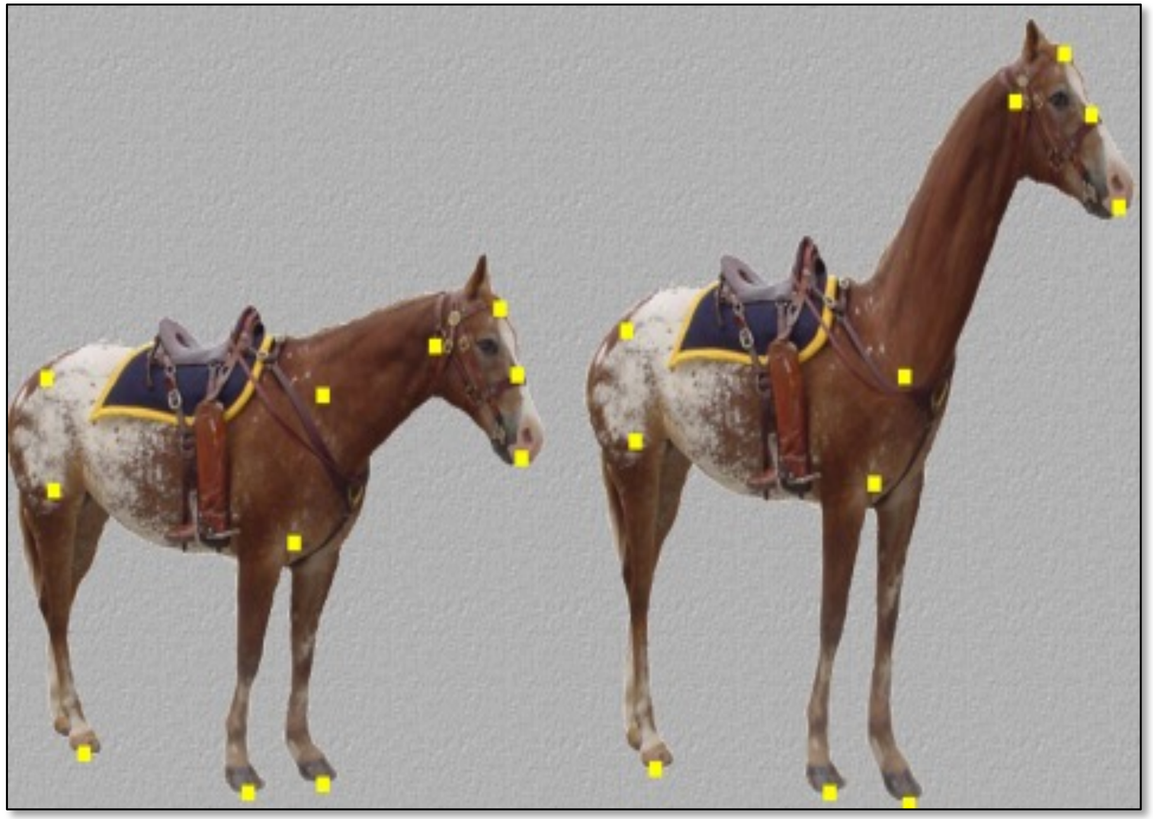


Image Warping

Image Composition

# Things can get really bad

Image Warping

Image Composition

The lack of “safety wheels”

# Adding the "safety wheels"

Input Photo

Image Editing Program

User Input

Output Result

Natural Image Manifold

A desired output:

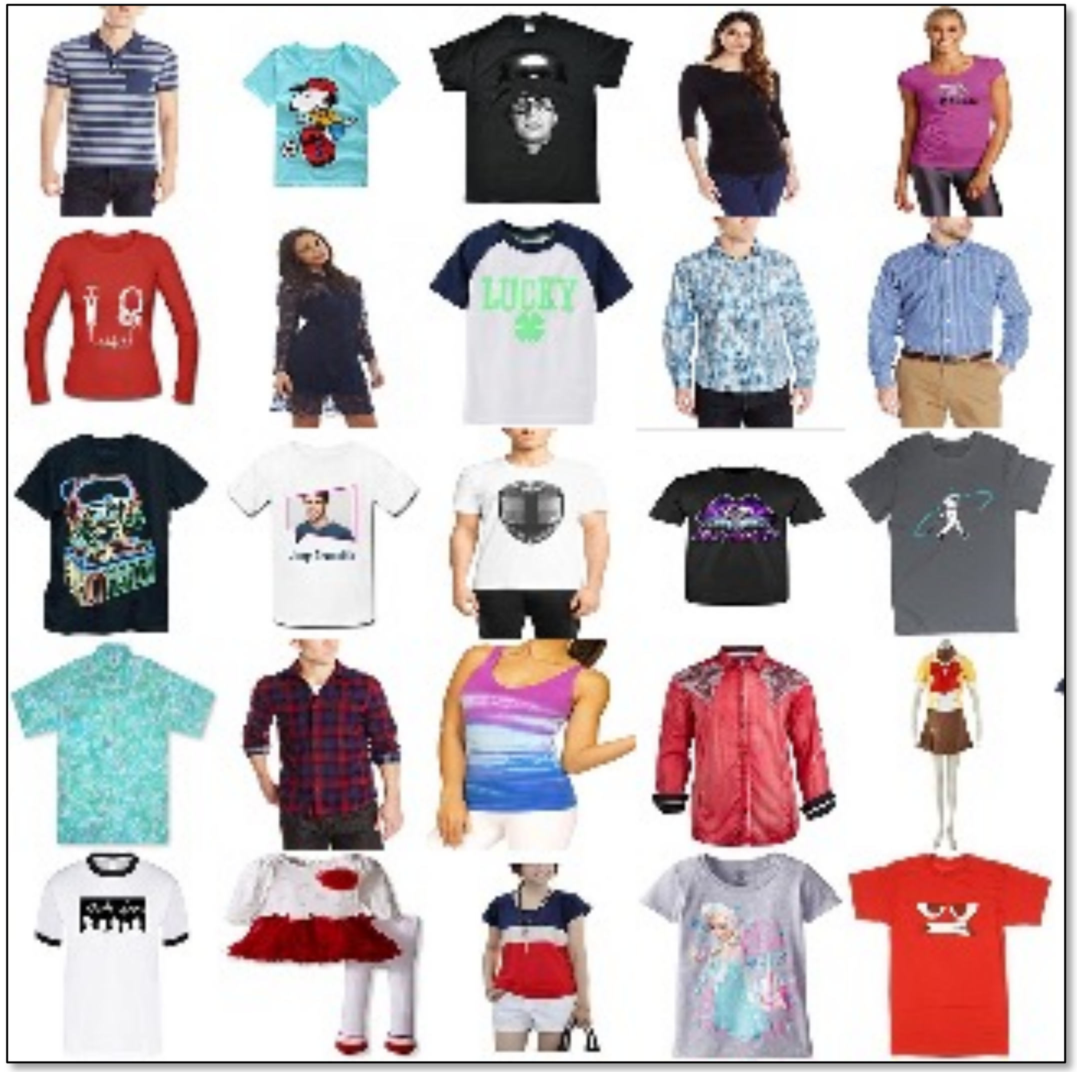
- stay close to the input.
- satisfy user's constraint.
- Lie on the natural image manifold

# Learning Natural Image Manifold

- Deep generative models: $G(z): z \rightarrow x$
  - Generative Adversarial Network (**GAN**)
    (e.g., DCGAN, StyleGAN2, BigGAN)
  - Variational Auto-Encoder (**VAE**)
    (e.g., VQ-VAE2)
  - Flow-based models (e.g., RealNVP, Glow)…
  - Diffusion models (e.g., DDPM, DDIM)

  …

# GAN as Manifold Approximation



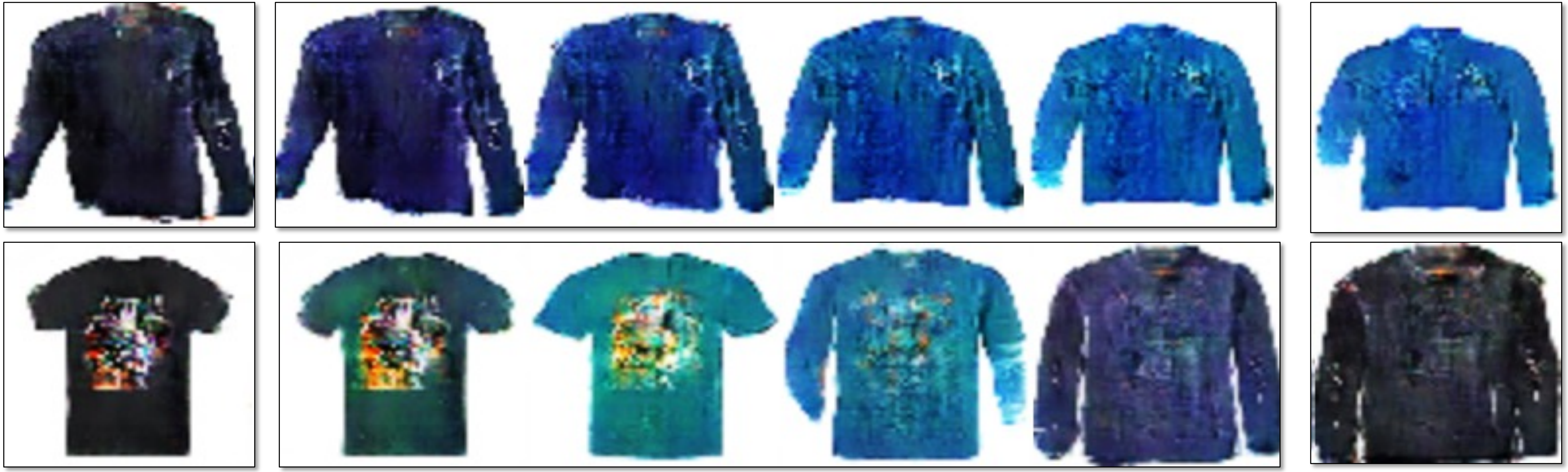
Sample training images
from “Amazon Shirts”

Random image samples
from Generator $G(z)$

DCGAN [Radford et al. 2015]

# Traverse on the GAN Manifold

$G(z_0)$ Linear Interpolation in z space: $G(z_0 + t \cdot (z_1 - z_0))$ $G(z_1)$



**Limitations of DCGAN**:

- not photo-realistic enough, low resolution
- produce images randomly, no user control

DCGAN [Radford et al. 2015]

# Changing Variables

- Traditional method: Optimizing the image

user constraint

$$\hat{y}^* = \arg\min_{\hat{y}} \mathcal{L}(x, y, \hat{y})$$

input output

- New method: Optimizing the latent code

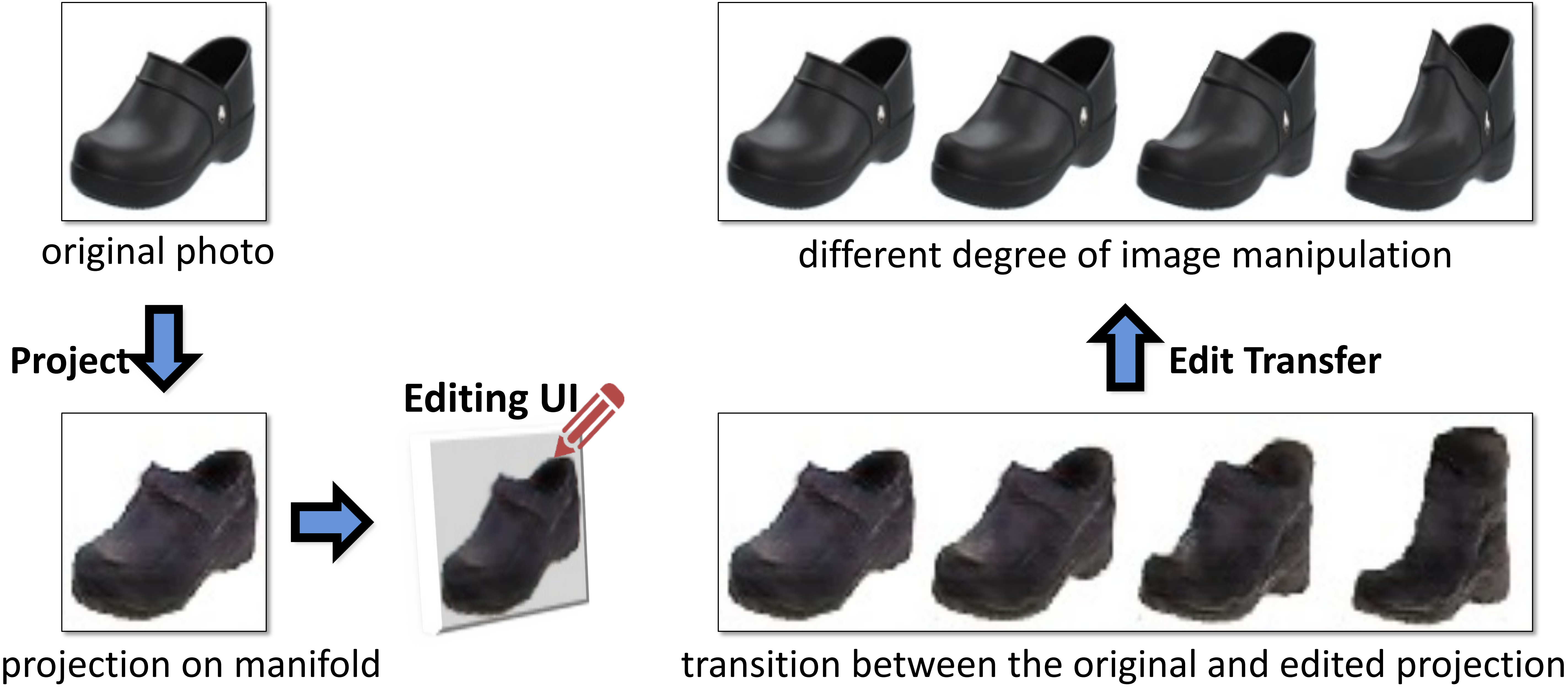
user constraint

$$z^* = \arg\min_{z} \mathcal{L}(x, y, G(z))$$

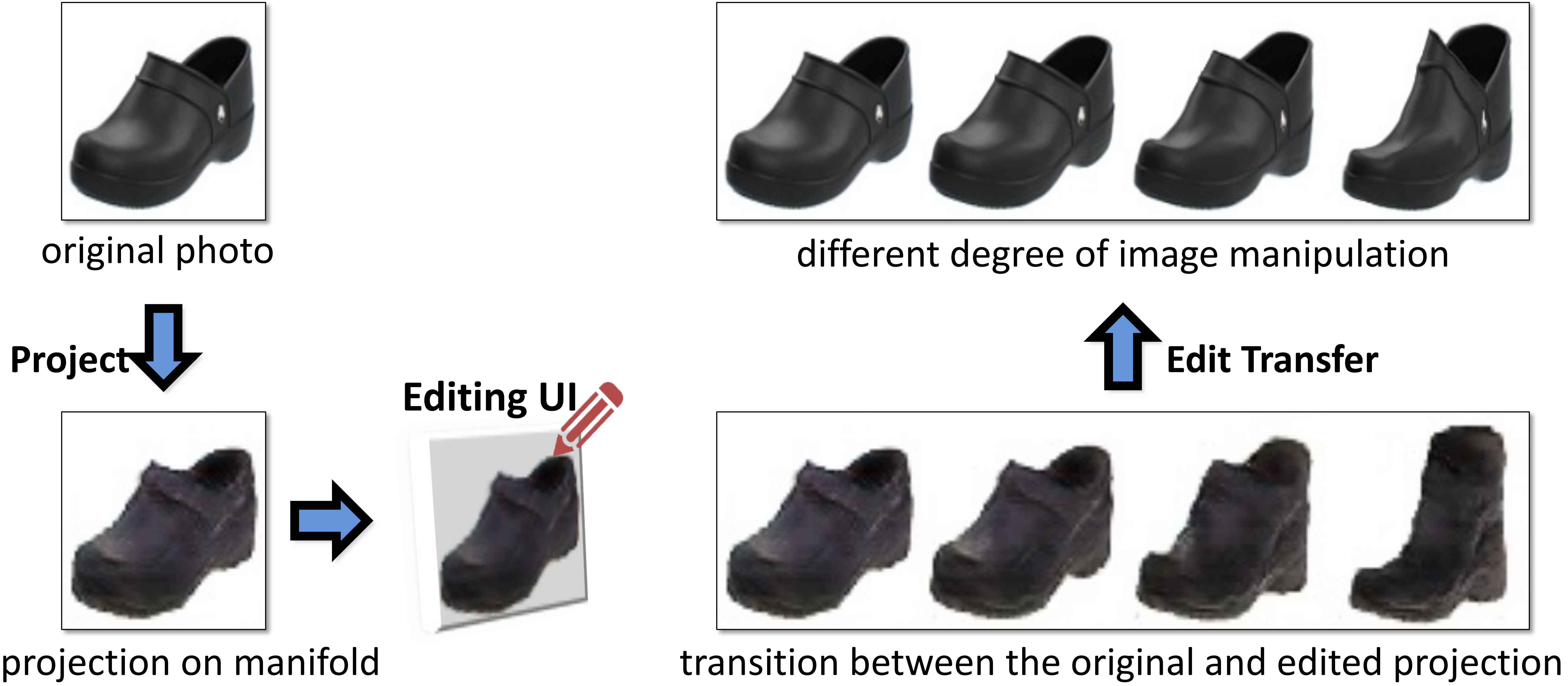
input Latent code

Generator

# Projecting and Editing an Image



# Projecting and Editing an Image



# Projecting an Image into GAN Manifold

Input: real image $x$

Output: latent vector $z$

Optimization

$$z^* = \arg\min_z \mathcal{L}(G(z), x)$$

Reconstruction loss

Generative model

0.196 0.238 0.332

# Projecting an Image into GAN Manifold

Input: real image $x$

Output: latent vector $z$

Optimization

$$z^* = \arg\min_z \mathcal{L}(G(z), x)$$

Inverting Network $z = E(x)$

$$E = \arg\min_E \mathbb{E}_x \underbrace{\mathcal{L}(G(E(x)), x)}_{\text{Auto-encoder with a fixed decoder}}$$

# Projecting an Image into GAN Manifold

Input: real image $x$

Output: latent vector $z$

**Optimization**

$$z^* = \arg\min_z \mathcal{L}(G(z), x)$$

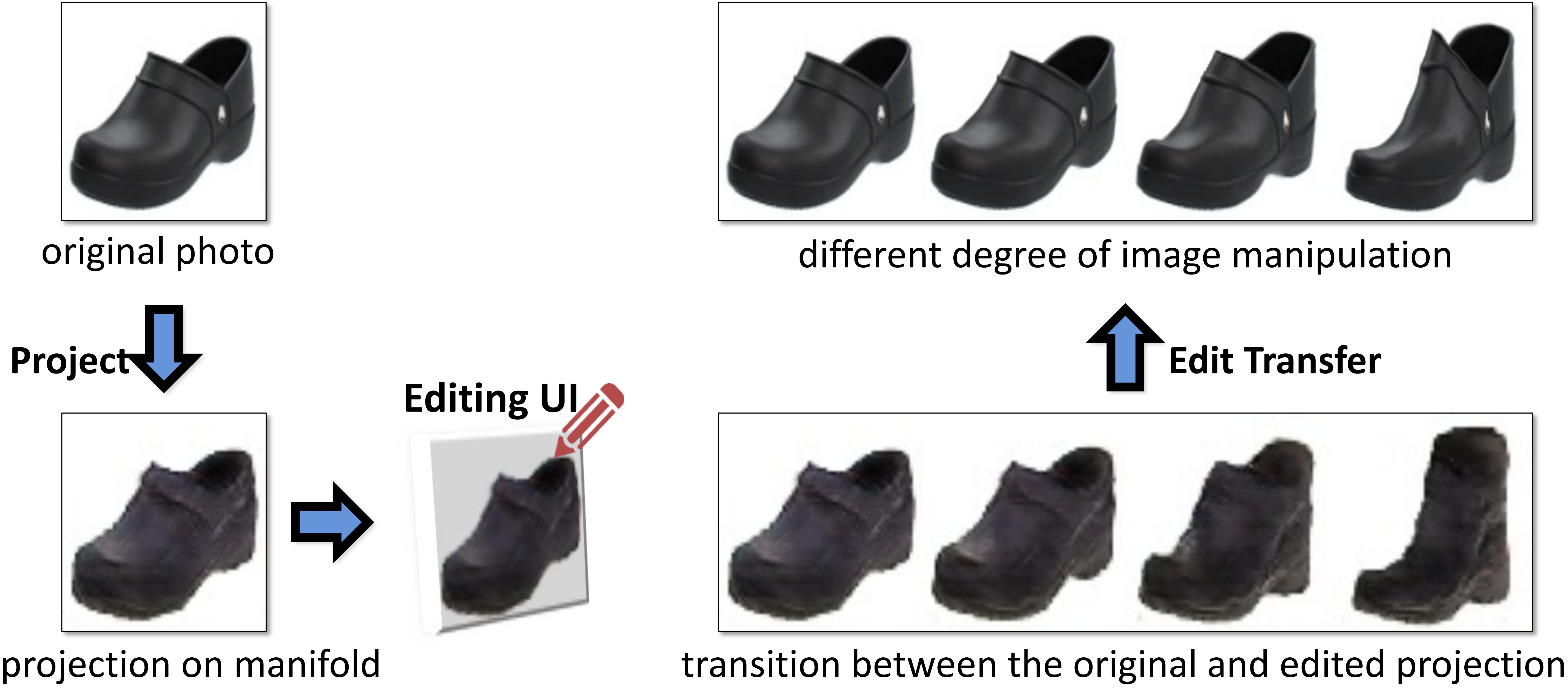
**Inverting Network** $z = E(x)$

$$E = \arg\min_E \mathbb{E}_x \mathcal{L}(G(E(x)), x)$$

**Hybrid Method**

Use the network as initialization for the optimization problem

# Manipulating the Latent Code



# Manipulating the Latent Code

constraint violation loss $L_g$

user guidance image

Objective:

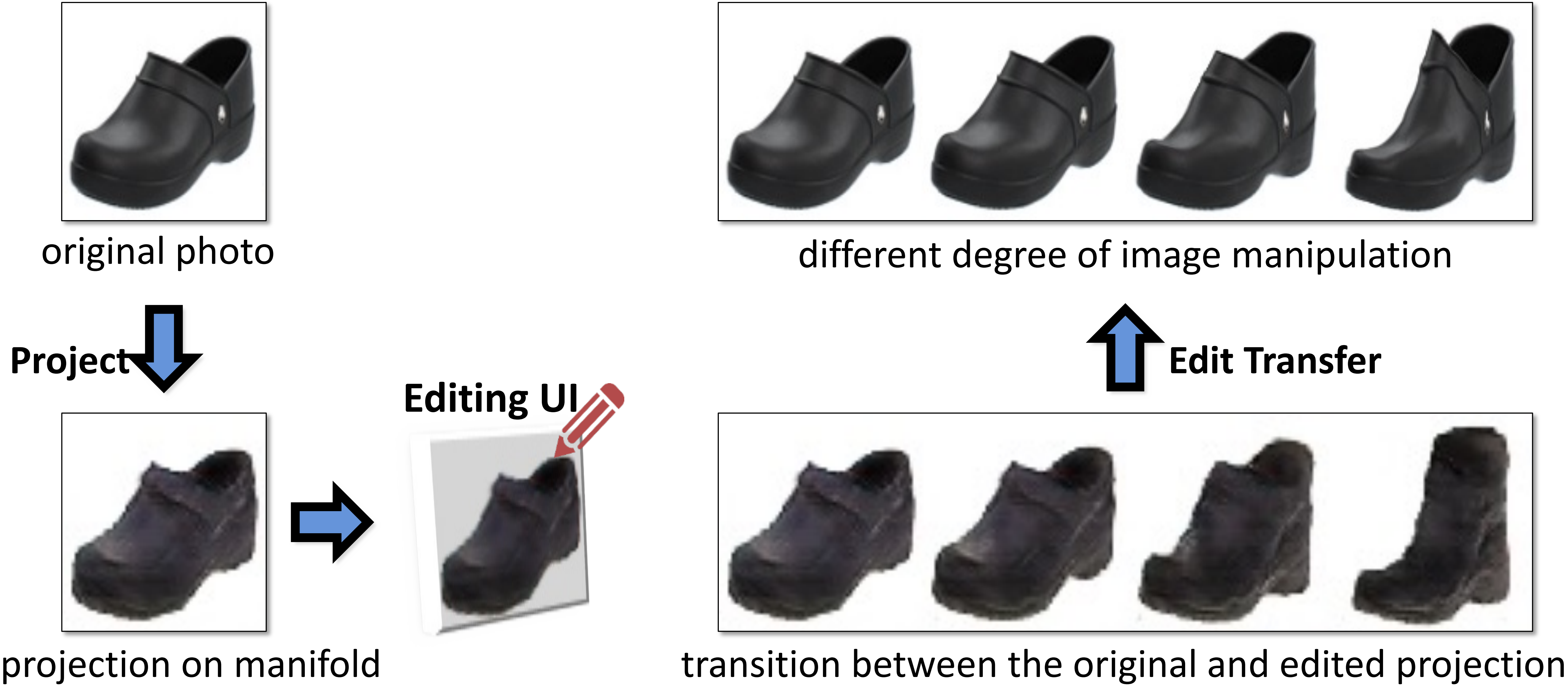
$$z^* = \arg\min_{z \in \mathbb{Z}} \Big\{ \underbrace{\sum_g (\mathcal{L}_g(G(z), v_g))}_{\text{data term}} + \underbrace{\lambda_s \cdot \|z - z_0\|_2^2}_{\text{manifold smoothness}} \Big\}.$$

Guidance $v_g$

$G(z)$

$z_0$

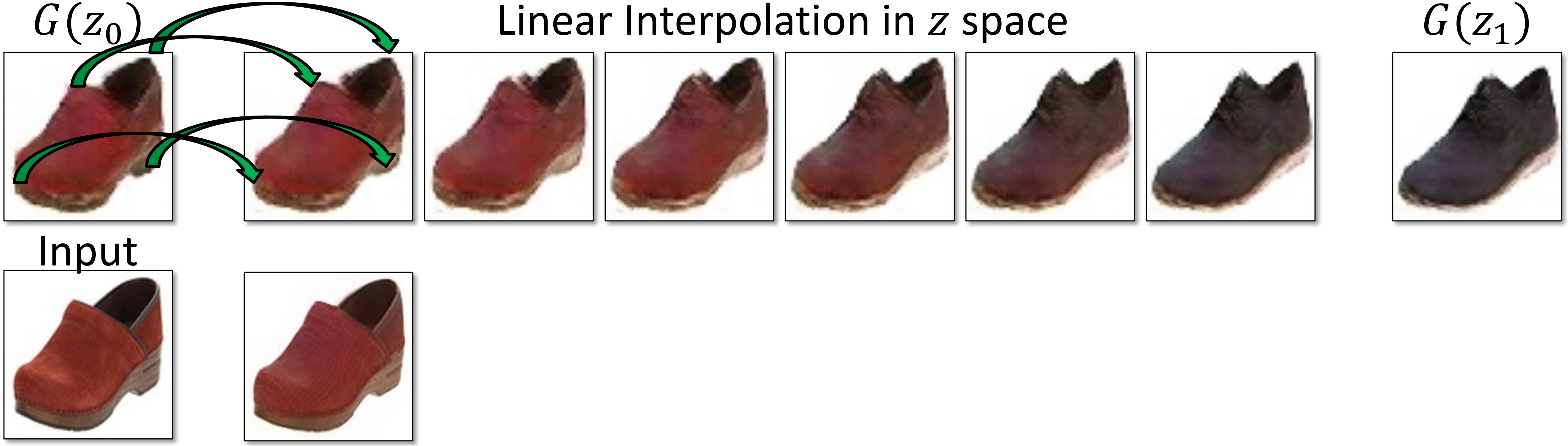
# Post-Processing



# Edit Transfer

**Motion** **(u, v)+** **Color** **($A_{3\times4}$):** estimate per-pixel geometric and color variation

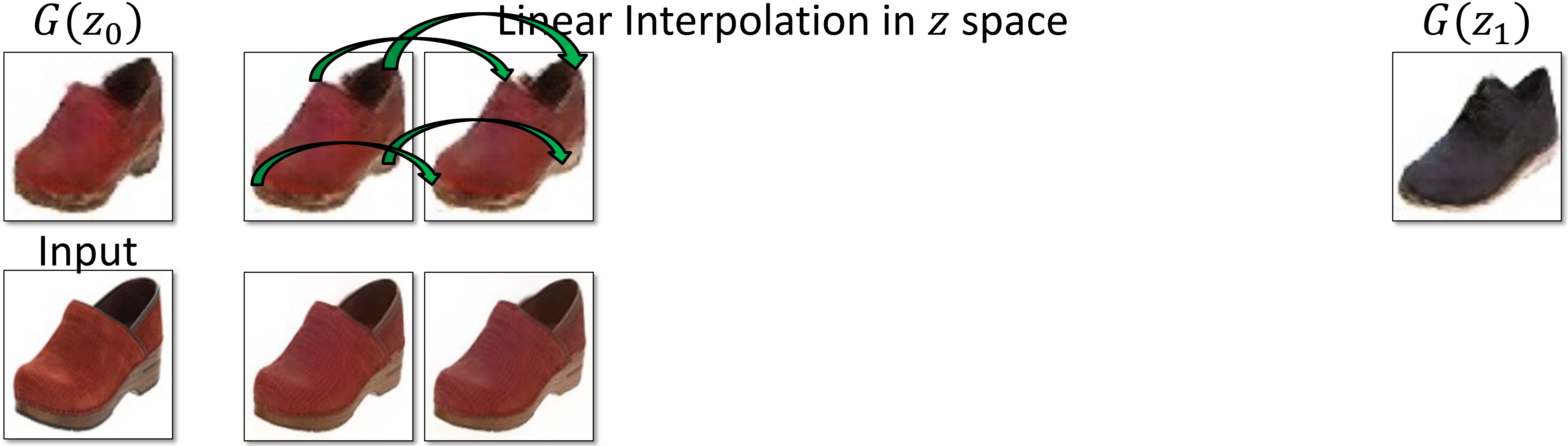
$$\iint \underbrace{\|I(x,y,t) - \boxed{A}\cdot I(x+\boxed{u}, y+\boxed{v}, t+1)\|^2}_{\text{data term}} + \underbrace{\sigma_s(\|\nabla u\|^2 + \|\nabla v\|^2)}_{\text{spatial reg}} + \underbrace{\sigma_c\|\nabla A\|^2}_{\text{color reg}} dxdy$$



# Edit Transfer

**Motion (u, v)+ Color ($A_{3\times4}$):** estimate per-pixel geometric and color variation

$$\iint \underbrace{\|I(x,y,t) - \boxed{A}\cdot I(x+\boxed{u}, y+\boxed{v}, t+1)\|^2}_{\text{data term}} + \underbrace{\sigma_s(\|\nabla u\|^2+\|\nabla v\|^2)}_{\text{spatial reg}} + \underbrace{\sigma_c\|\nabla A\|^2}_{\text{color reg}} dxdy$$



# Edit Transfer

**Motion (u, v)+ Color ($A_{3\times4}$):** estimate per-pixel geometric and color variation

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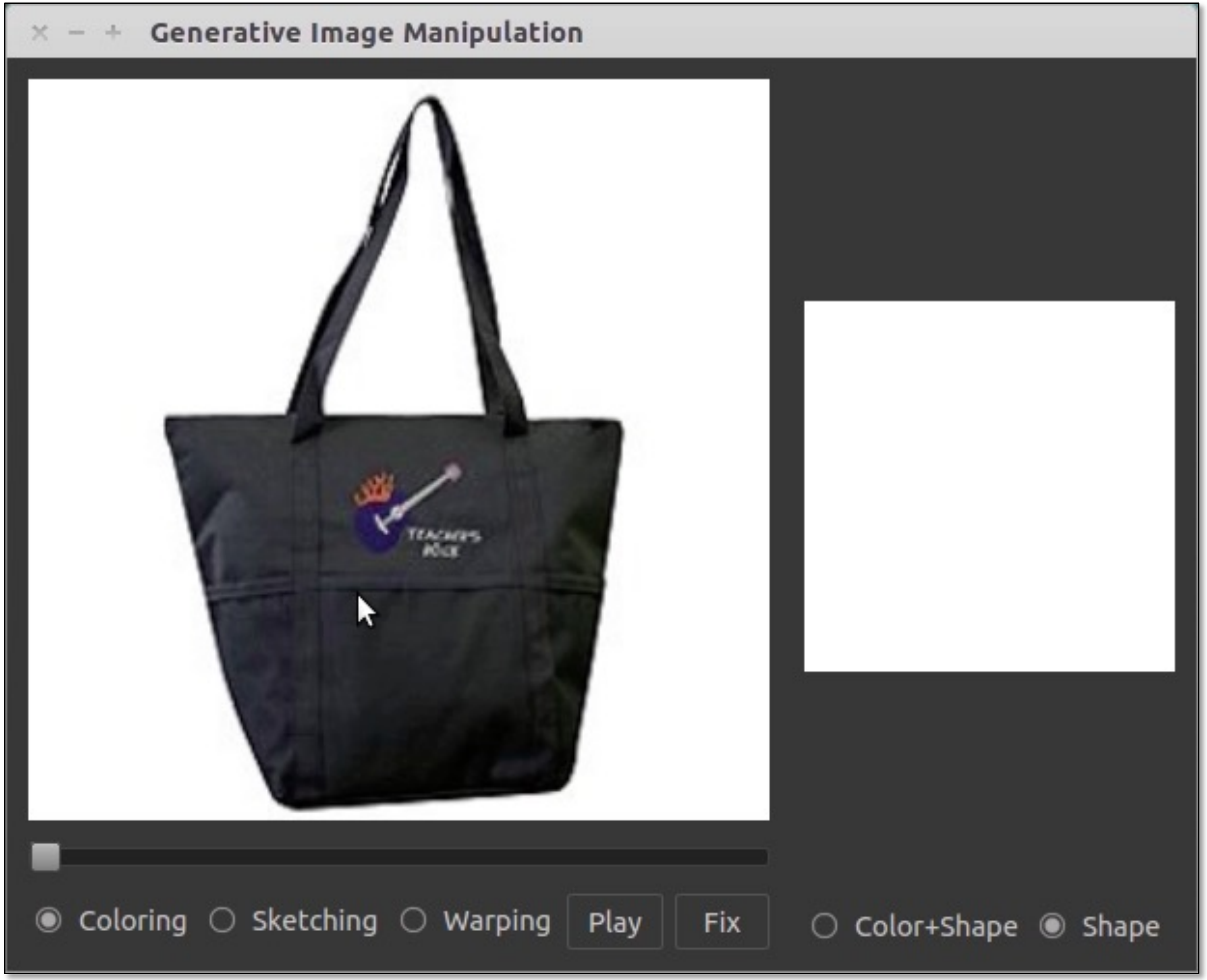
$G(z_0)$ Linear Interpolation in $z$ space $G(z_1)$

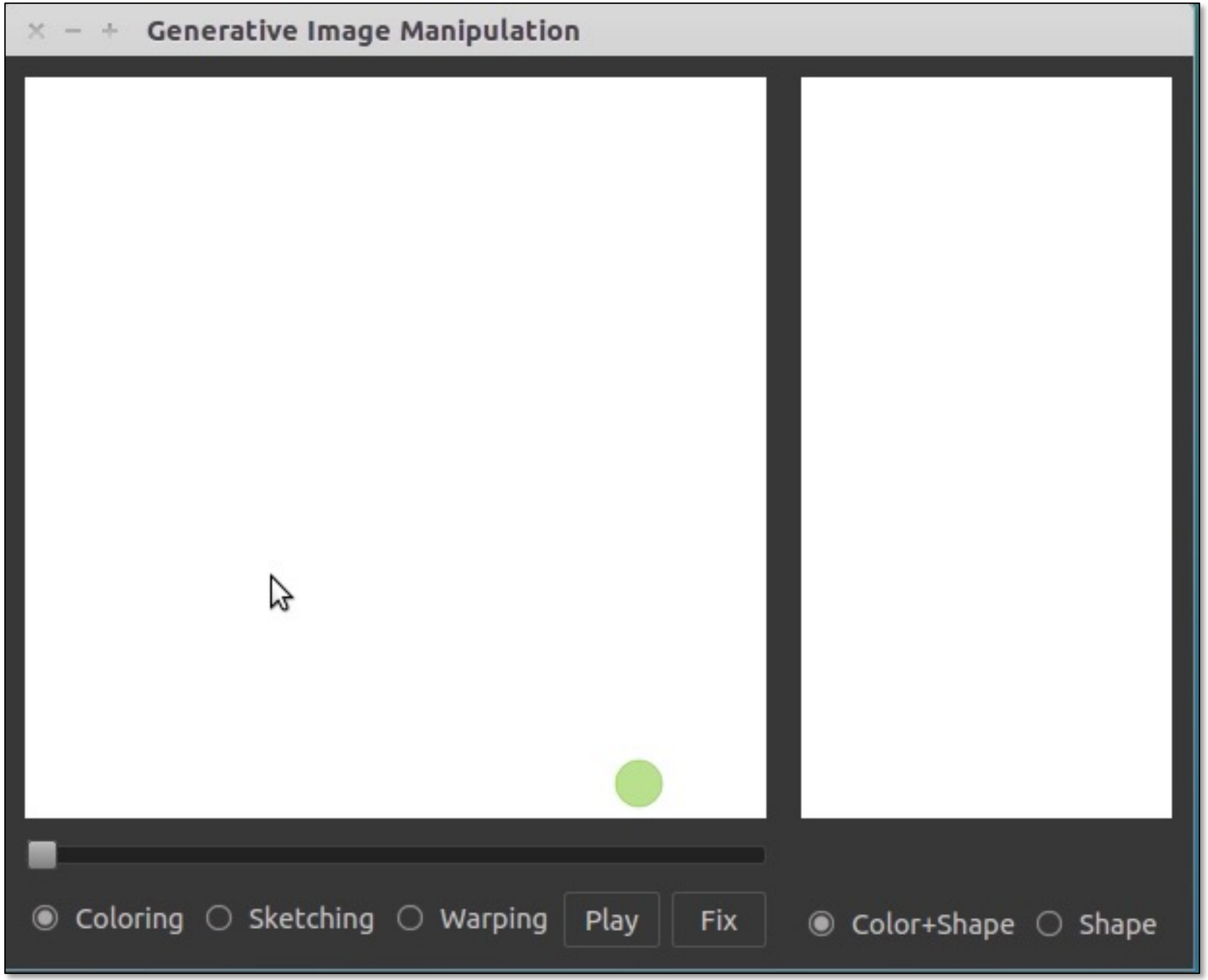
Input Result

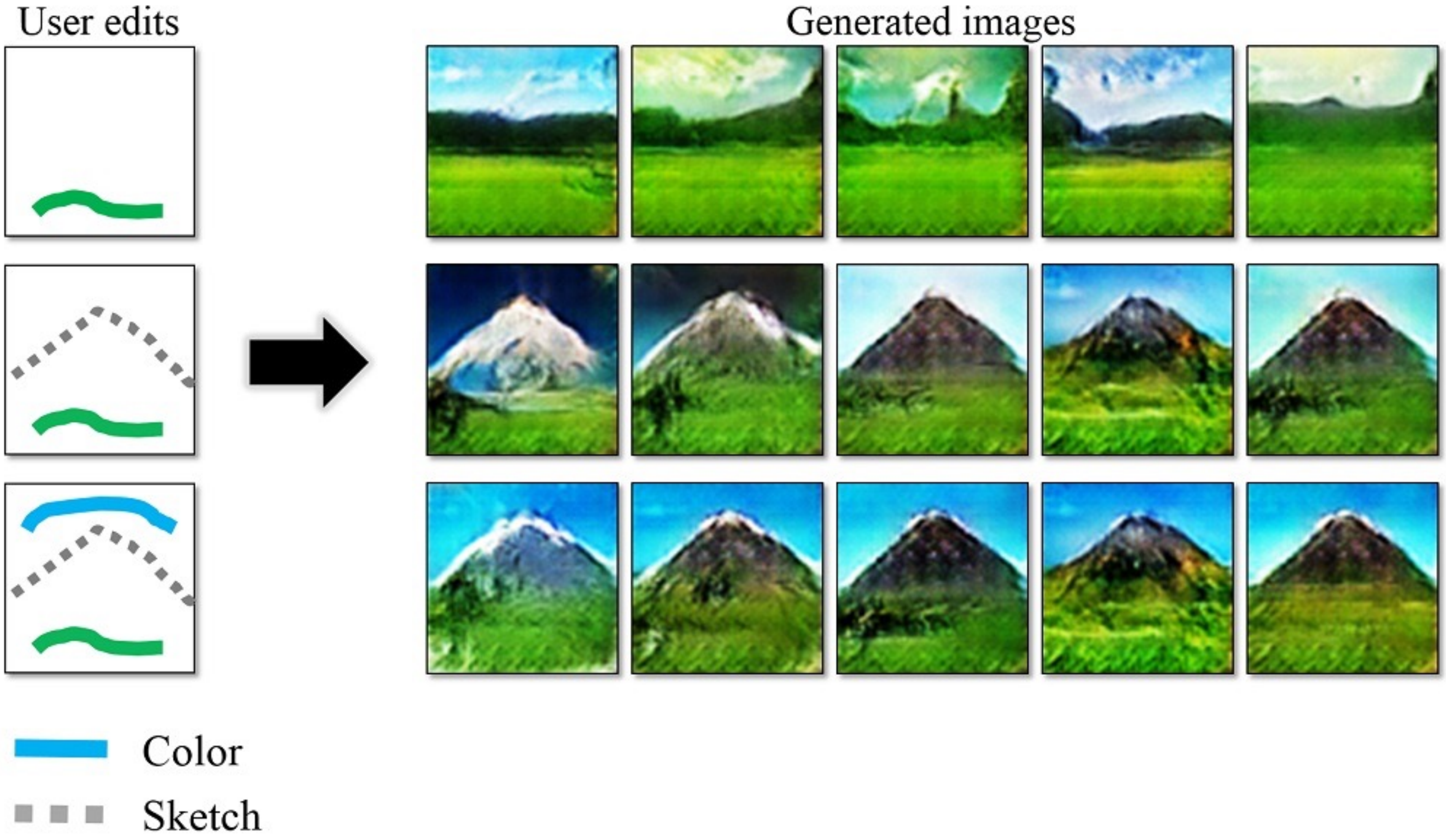
# Image Manipulation Demo



# Image Manipulation Demo

# Interactive Image Generation






iGAN [Zhu et al. 2016]. Also see Neural Photo Editor [Brock et al. 2017]

# Changing Variables

- Traditional method: Optimizing the image

user constraint

$$\hat{y}^* = \arg\min_{\hat{y}} \mathcal{L}(x, y, \hat{y})$$

input result

- New method: Optimizing the latent code

user constraint

$$z^* = \arg\min_{z} \mathcal{L}(x, y, G(z))$$

input Latent code

Generator

# Projecting and Editing an Image


original photo

**Project**


projection on manifold

**Editing UI**


transition between the original and edited projection

**Post-processing**


different degree of image manipulation

# Image Editing with GANs

- Step 1: Image Projection/Reconstruction

$$z_0 = \arg\min_z \mathcal{L}(G(z), x)$$

- Step 2: Manipulating the latent code

$$z_1 = z_0 + \Delta z$$

- Step 3: Generate the edited result

$$G(z_1)$$

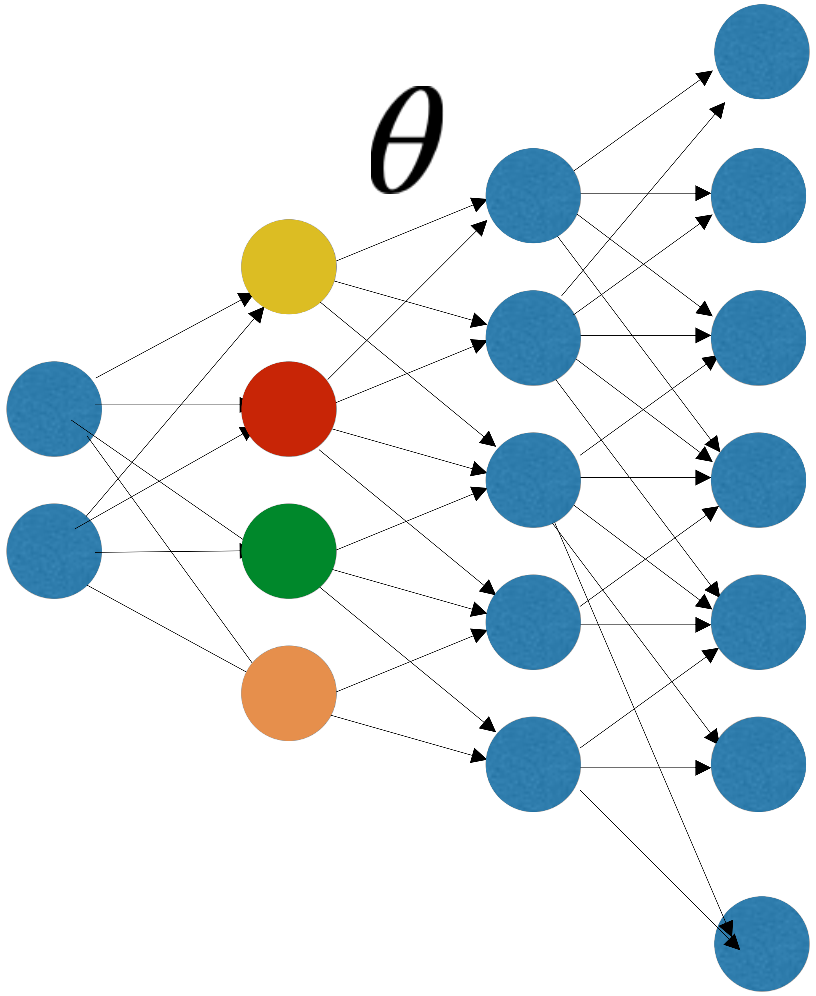
# Image Projection with GANs

# Image Reconstruction (high-res images, Big Models)

Original image $x$

# Image Reconstruction (high-res images, Big Models)

Random vector $z$ ?



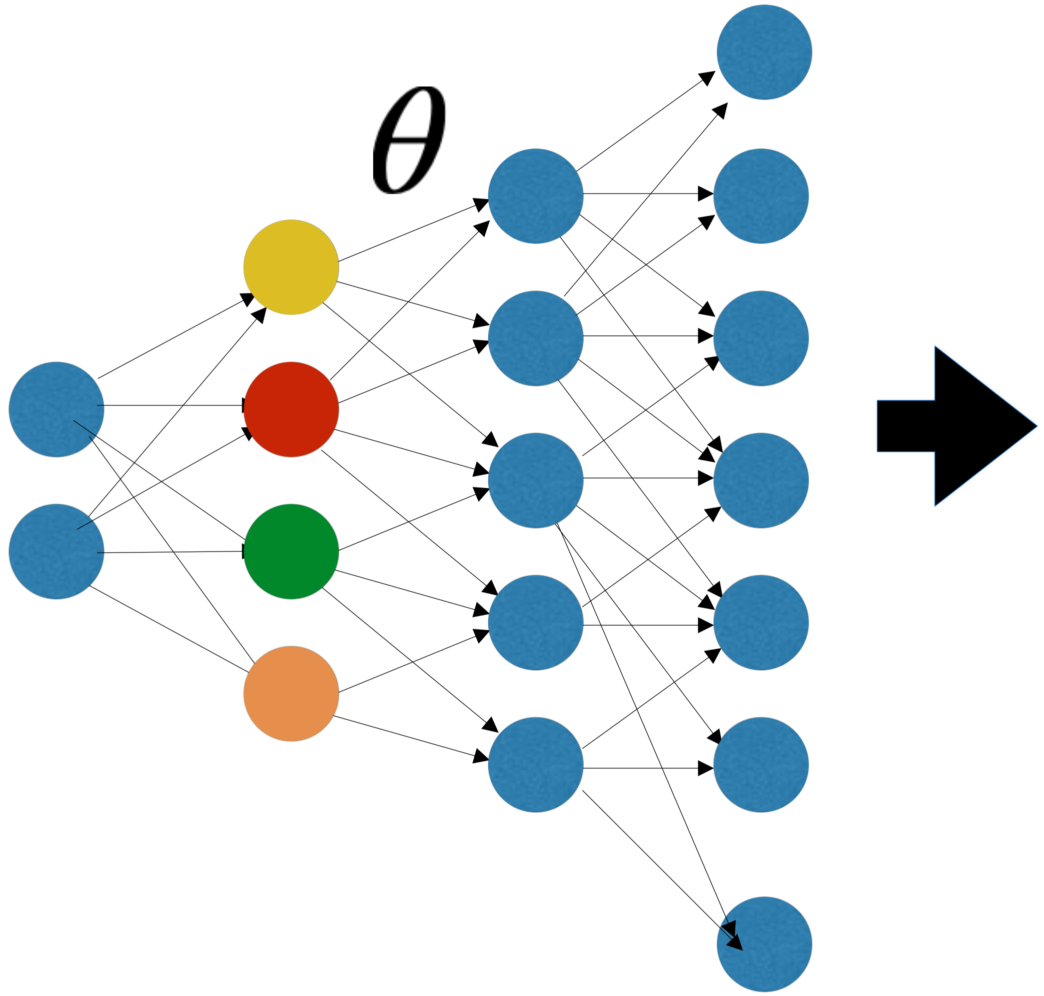

Original image $x$

$$z^* = \arg\min_{z} \mathcal{L}(G(z;\theta), x)$$

iGAN [Zhu et al. 2016]

# Image Reconstruction (high-res images, Big Models)

Random vector $z^*$




Reconstructed image $G(z^*; \theta)$

$$z^* = \arg\min_z \mathcal{L}(G(z;\theta), x)$$

iGAN [Zhu, Krähenbühl, Shechtman, Efros]

# Find the Differences…

Original image

GAN reconstructed image

# Find the Differences...

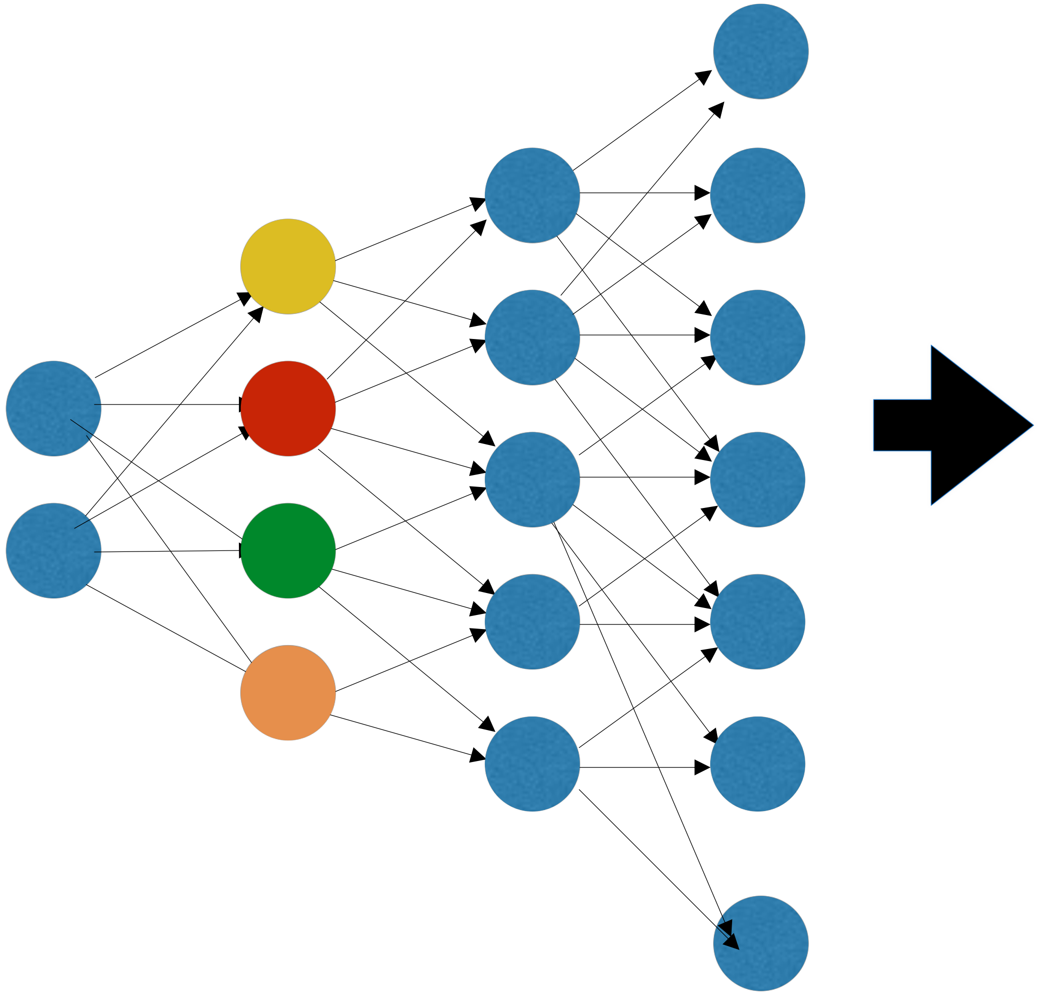
Original image


GAN reconstructed image

# Reconstructing a Real Photo

Original image

Random vector $z^*$



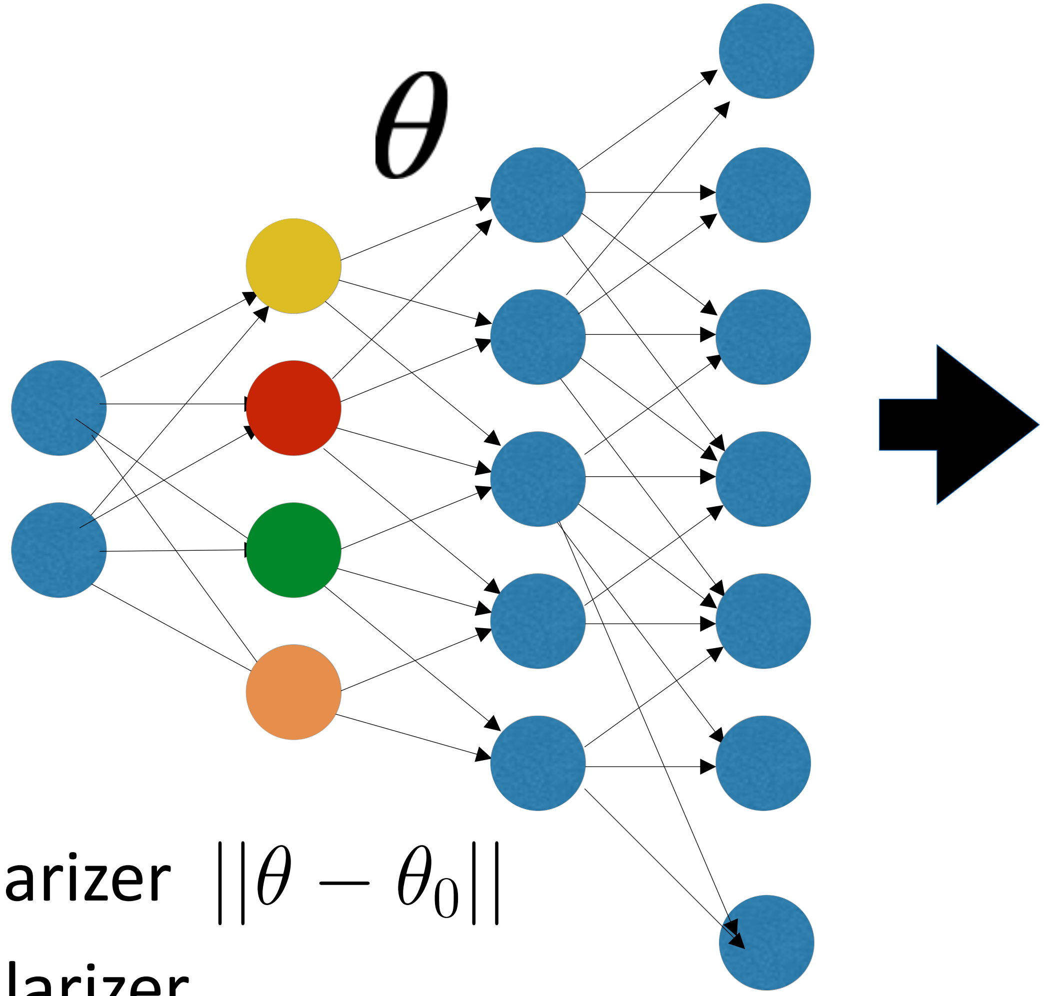
Reconstructed image $G(z^*;\theta)$

$$z^* = \arg\min_z \mathcal{L}(G(z;\theta), x)$$

iGAN [Zhu et al. 2016]

# Reconstructing a Real Photo

Original image




Random vector $z^*$

Reconstructed image $G(z^*; \theta)$

Weight space regularizer $||\theta - \theta_0||$

Feature space regularizer

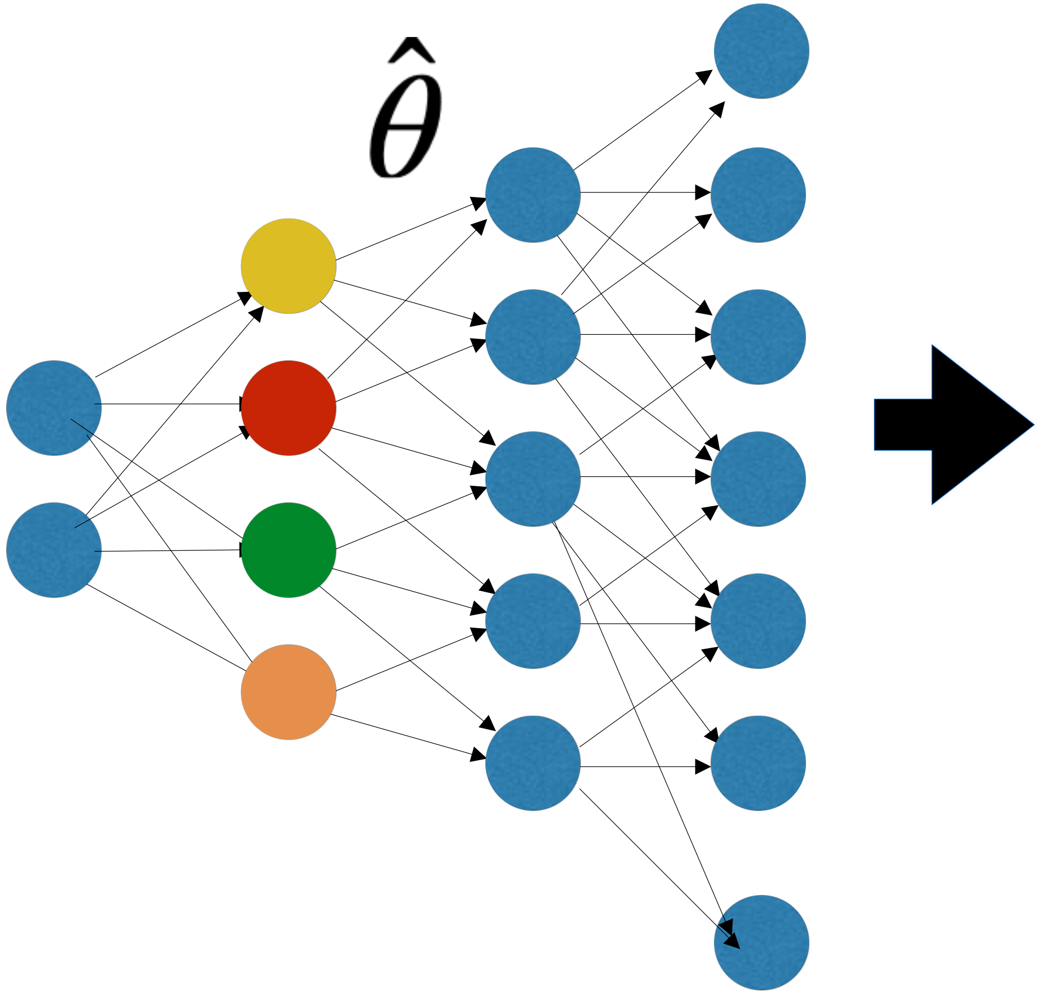
$$z^*, \theta^* = \arg\min_{z,\theta} \mathcal{L}(G(z;\theta), x)$$

← Regularizer

# Reconstructing a Real Photo

Original image

Random vector $z^*$




Reconstructed image $G(z^*;\theta^*)$

$$z^*, \theta^* = \arg\min_{z,\theta} \mathcal{L}(G(z;\theta), x) + R(\theta) \longleftarrow \text{Regularizer}$$

# Reconstructing a Real Photo

Original image

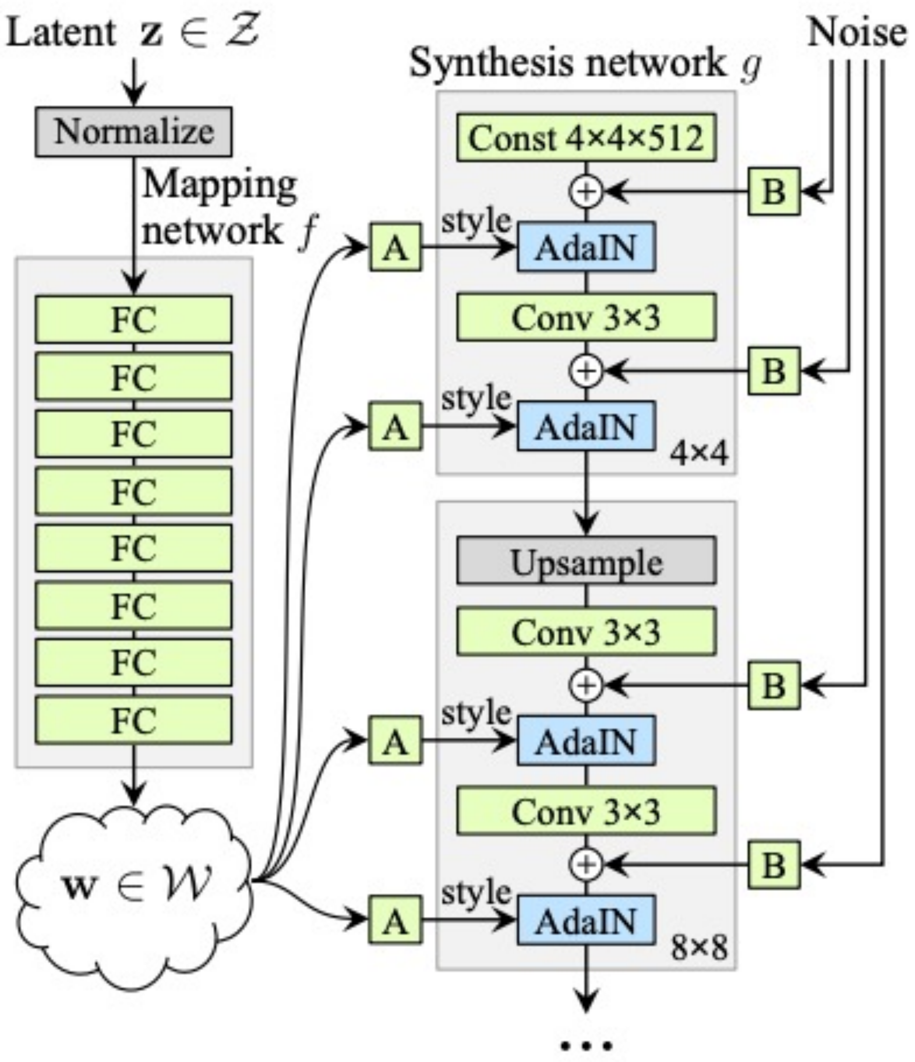
With $z^*$

With $z^*$ and $\theta^*$

Semantic Photo Manipulation [Bau, Strobelt, Peebles, Wulff, Zhou, Zhu, Torralba, SIGGRAPH 2019]

Inspired by Deep Image Prior [Ulyanov et al.] and Deep Internal learning [Shocher et al.]

# Using Different Layers




Optimizing the latent code

$$z^* = \arg\min_z \mathcal{L}(G(z), x)$$

Optimizing the style code

$$w^* = \arg\min_w \mathcal{L}(g(w), x)$$

Optimizing the extended style code

$$w_+^* = \arg\min_{w+} \mathcal{L}(g(w_+), x)$$

Image2StyleGAN [Abdal et al., 2019], StyleGAN2 [Karras et al., 2019]

# Using Different Layers: w space

StyleGAN — generated images StyleGAN2 — generated images

StyleGAN2 [Karras et al., 2019]

# Using Different Layers: w space

StyleGAN2 — real images



StyleGAN2 [Karras et al., 2019]

# Using Different Layers: w+ space

All the results are reconstructed using Face Model



Image2StyleGAN [Abdal et al., 2019]

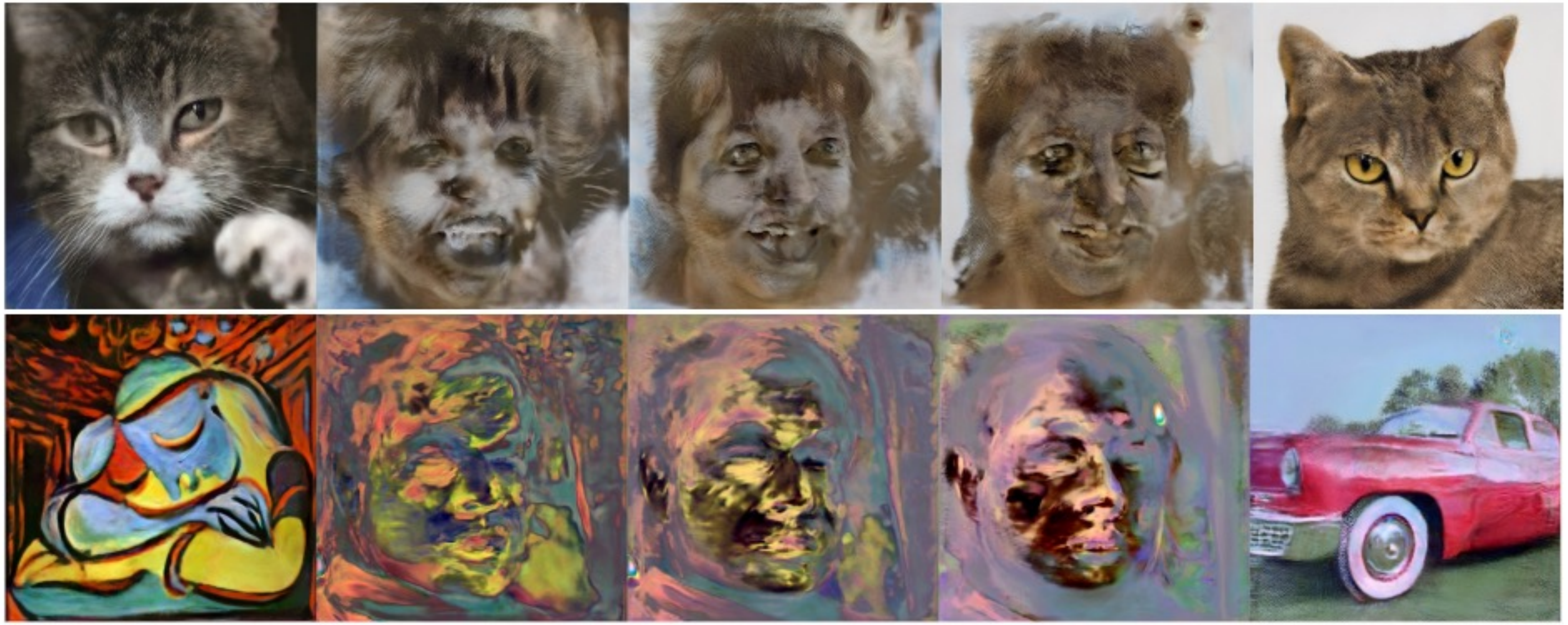
# Reconstruction ≠ Editing

Interpolations between two images



Image2StyleGAN [Abdal et al., 2019]

# Reconstruction $\neq$ Editing



Interpolations between two images



Image2StyleGAN [Abdal et al., 2019]