

Image Manipulation is Hard!

The Lack of "Safety Wheels":

- any less-than-perfect edit immediately makes the image look unrealistic.
- classic visual manipulation paradigm does not prevent the user from "falling off" the manifold of natural images

A desired output

- stay close to the input.
- satisfy user's constraint.
- lie on the **natural image manifold** $M = \{x | x = G(z)\}$

[Zhu et al. 15']: $M = \{x | P(\text{real}|x) = 1\}$

Learning Natural Image Manifold

Generative Adversarial Network (GAN)
[Goodfellow et al. 14'] [Radford et al. 15']

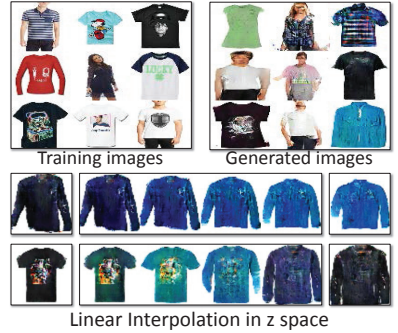
$$G(z): \mathbb{Z} \rightarrow \mathbb{X}$$

$N(0, I), \text{Unif}[-1, 1]^d$ Natural images

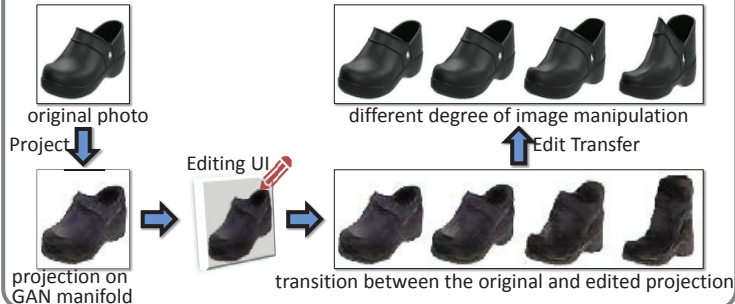
Generator $x = G(z)$

Generate an image sample x from a latent vector z

Discriminator $D(x) \rightarrow 0/1$
Distinguish between real images and fake samples



Overview



Manipulating the Latent Vector

constraint loss L_g

user guidance image

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



Projecting an Image onto the Manifold

Input: real image x^R
Output: latent vector z

Optimization

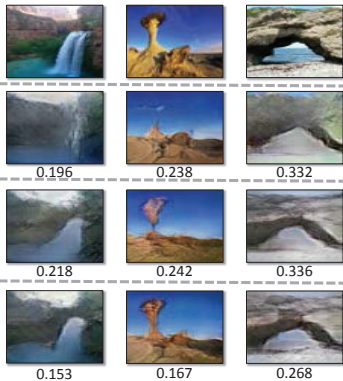
$$z^* = \arg \min \mathcal{L}(G(z), x^R)$$

Inverting Network $z = P(x)$

$$\theta_P^* = \arg \min_{\theta_P} \sum_{x_n^R} \mathcal{L}(G(P(x_n^R; \theta_P)), x_n^R)$$

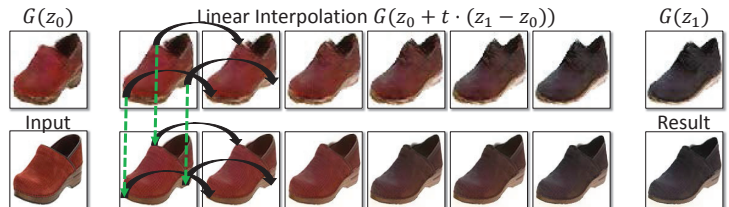
Hybrid Method

Use the **network** as initialization for the **optimization** problem

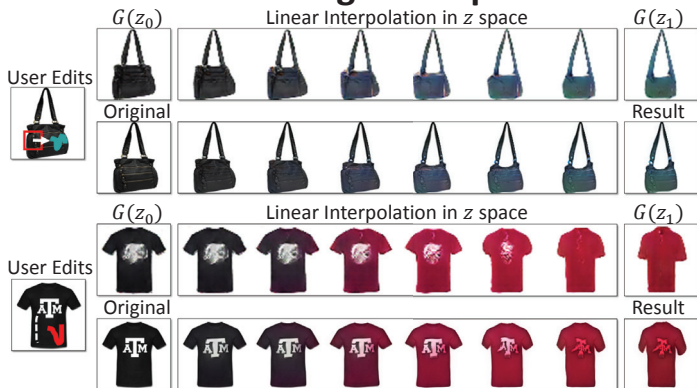


Edit Transfer

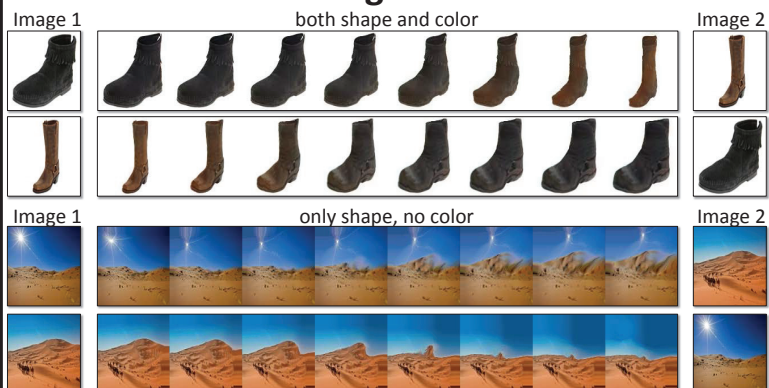
Motion (u, v) + **Color** ($A_{3 \times 4}$): estimate per-pixel geometric and color variation

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


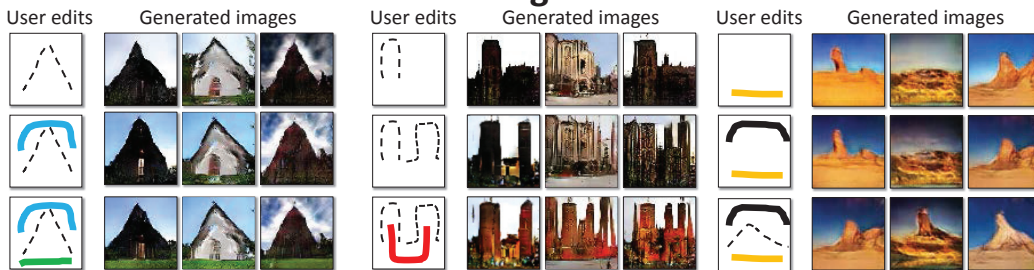
Realistic Image Manipulation



Generative Image Transformation



Interactive Image Generation



Reference

- [1] Zhu et al. Learning a Discriminative Model for the Perception of Realism in Composite Images. ICCV 2015.
- [2] Goodfellow et al. Generative Adversarial Nets. NIPS 2014
- [3] Radford et al. Unsupervised representation learning with deep convolutional generative adversarial networks. ICLR 2016