Idempotet Generative Network

Assaf Shocher[1,2], Amil Dravid[1] Yossi Gandelsman[1]
Inbar Mosseri[2] Michael Rubinstein[2] Alexei A. Efros[1]

[1] UC Berkeley
[2] Google Research

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Make It Real

The Idempotent Generative Network (IGN) aims to create a model that handles diverse inputs and projects them onto the target distribution in one step.

Unlike GANs or VAEs, which need specific inputs, IGN acts as a “global projector.” It turns any input—corrupted images, sketches, or noise—into real images instantly, like a “Make It Real” button.

x $\quad x+n$ $\quad f(x+n)$ $\quad f(f(x+n))$

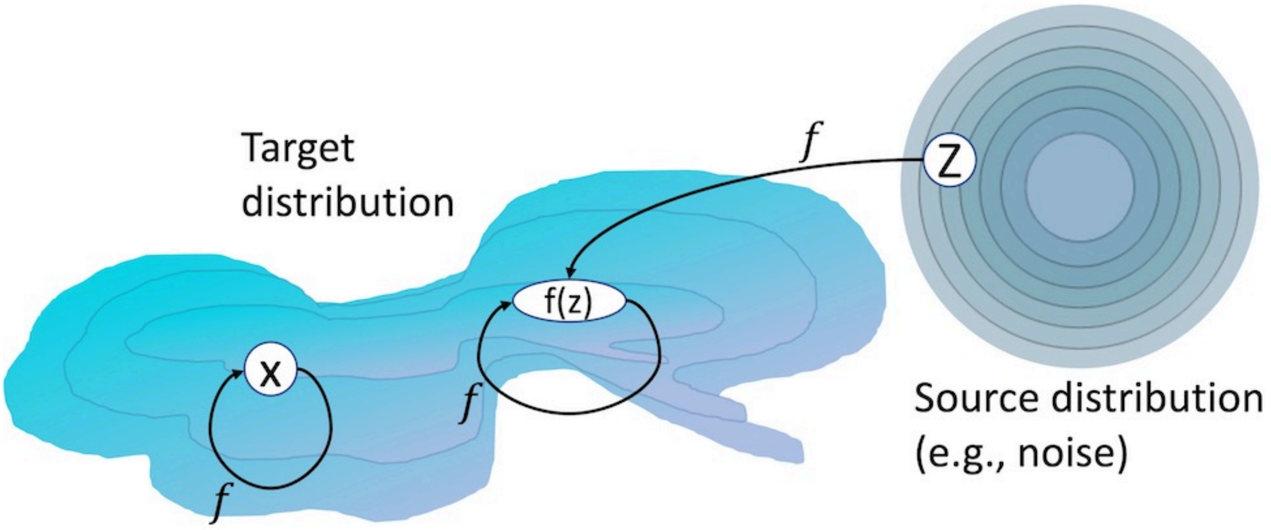
x $\quad g(x)$ $\quad f(g(x))$ $\quad f(f(g(x)))$

x $\quad m(x)$ $\quad f(m(x))$ $\quad f(f(m(x)))$

Idempotency: One Step Generation, Optional Refinement

Disadvantages and Problems

IGN is built on idempotency, where its operator f ensures $f(f(z)) = f(z)$ and $f(x) = x$ for target data. It generates outputs in one step like GANs, with optional refinement akin to diffusion models. Unlike those, IGN keeps a consistent latent space for easy manipulation.



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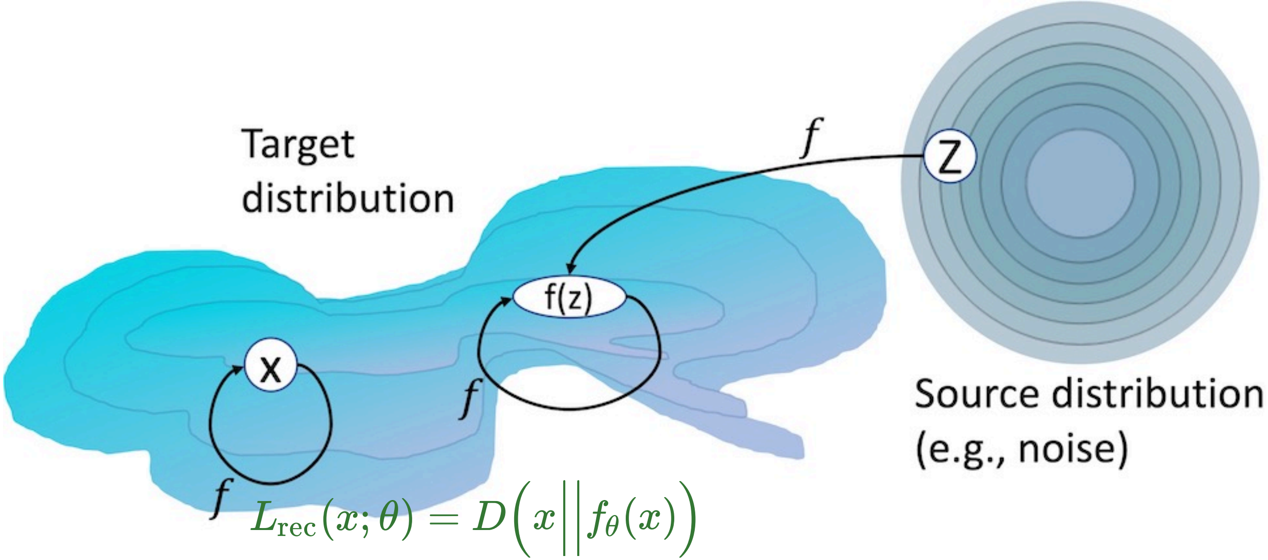

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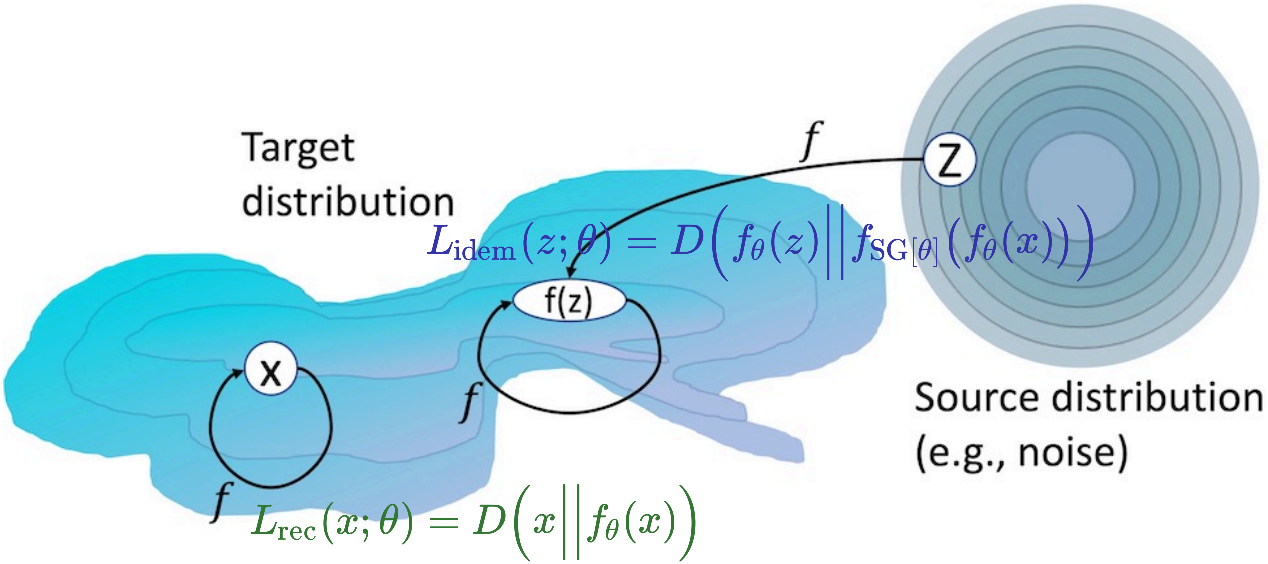
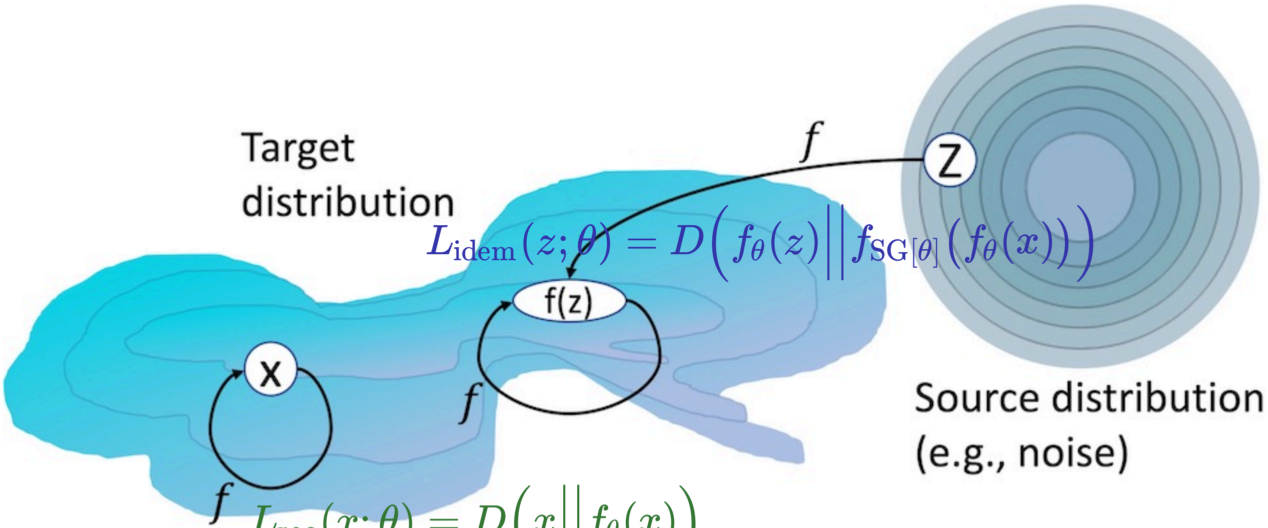
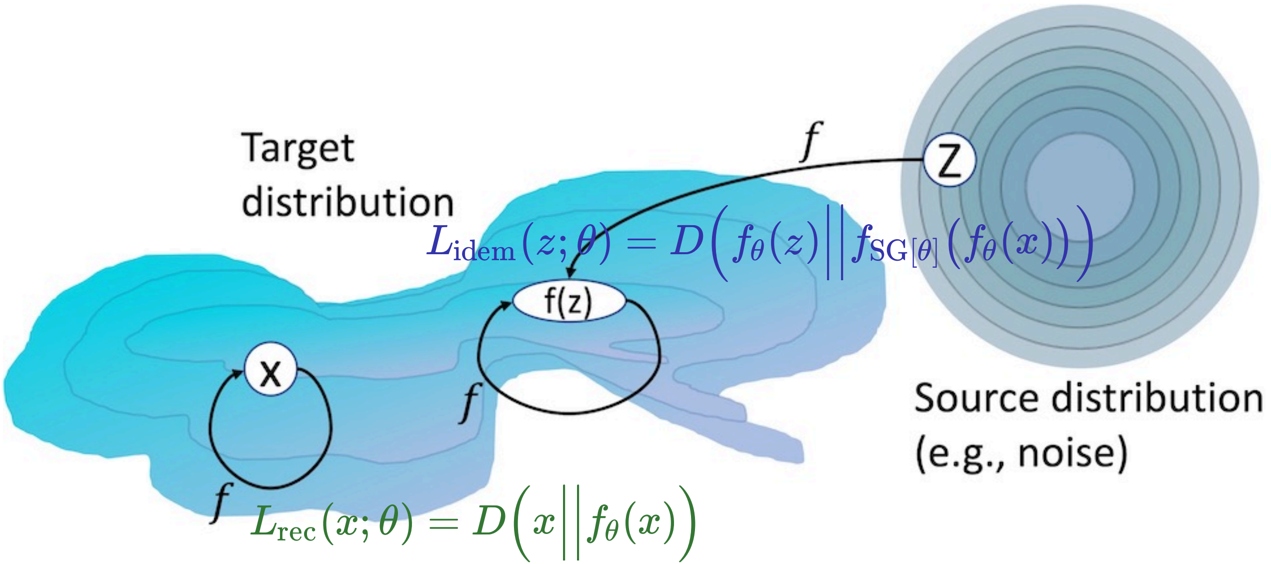




$$L_{\text{idem}}(z;\theta) = D\Big(f_\theta(z)\Big|\Big|f_{\text{SG}[\theta]}\big(f_\theta(x)\big)\Big)$$

$$L_{\text{rec}}(x;\theta) = D\Big(x\Big|\Big|f_\theta(x)\Big)$$

However, the combination of these two loss functions by itself does not guarantee that the target manifold is compact and contains only the true data distribution.



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The Issue of Manifold Expansion

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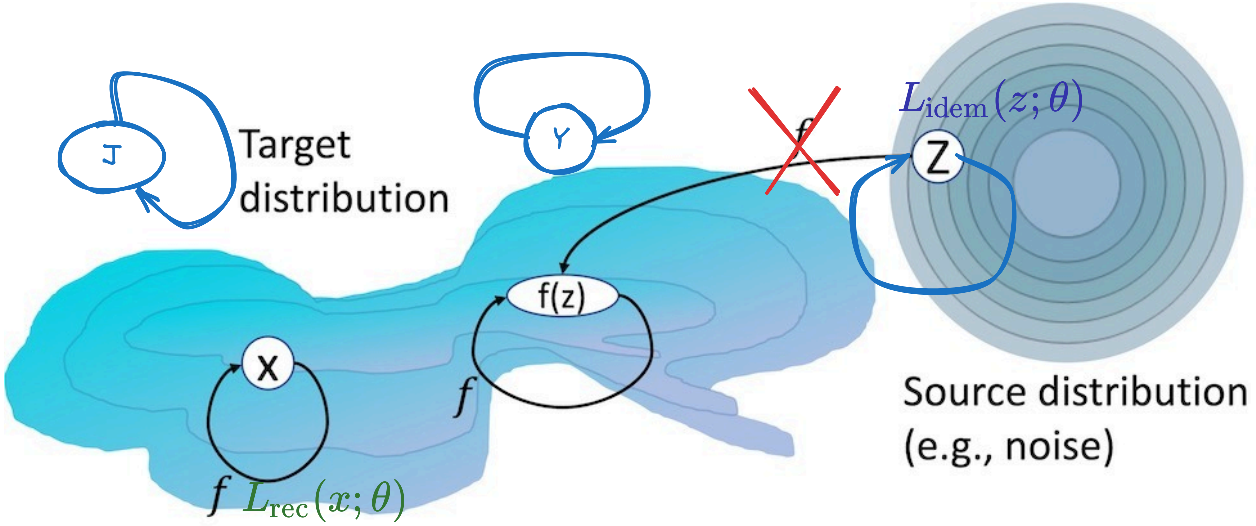
If the model f directly becomes the identity function, that is, $f(z) = z, \forall z$. Both L_{rec} and L_{idem} are perfectly satisfied. However, this model does **NOT LEARN** to generate any new samples that **RESEMBLE THE TARGET DISTRIBUTION**.



Tightness Objective

$$\tilde{L}_{\text{tight}}(z;\theta) = -D\left(f_{\text{SG}[\theta]}(z) \middle\| f_\theta(f_{\text{SG}[\theta]}(z))\right)$$

Tightness Objective: Self-Adversarial Training

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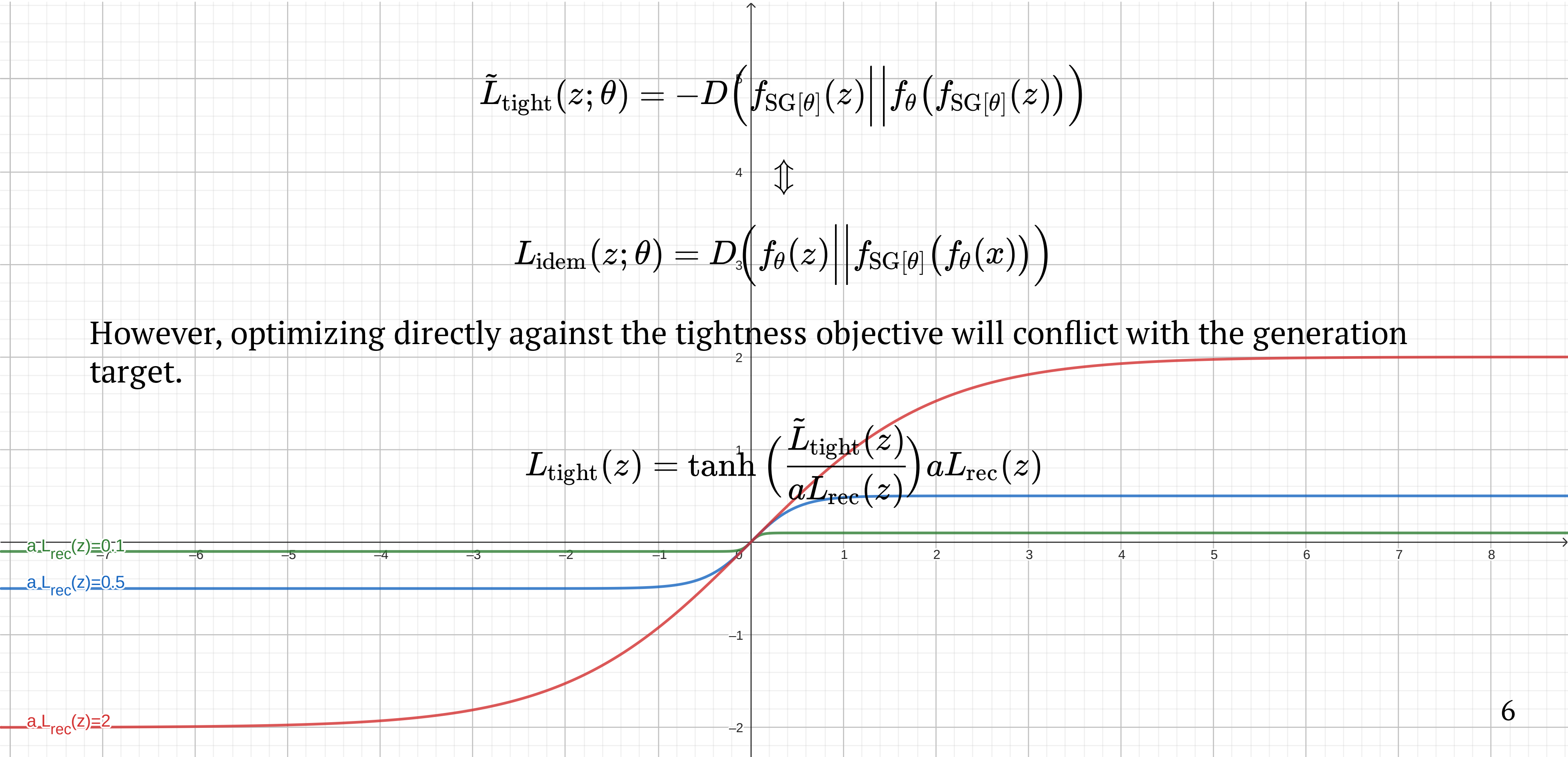
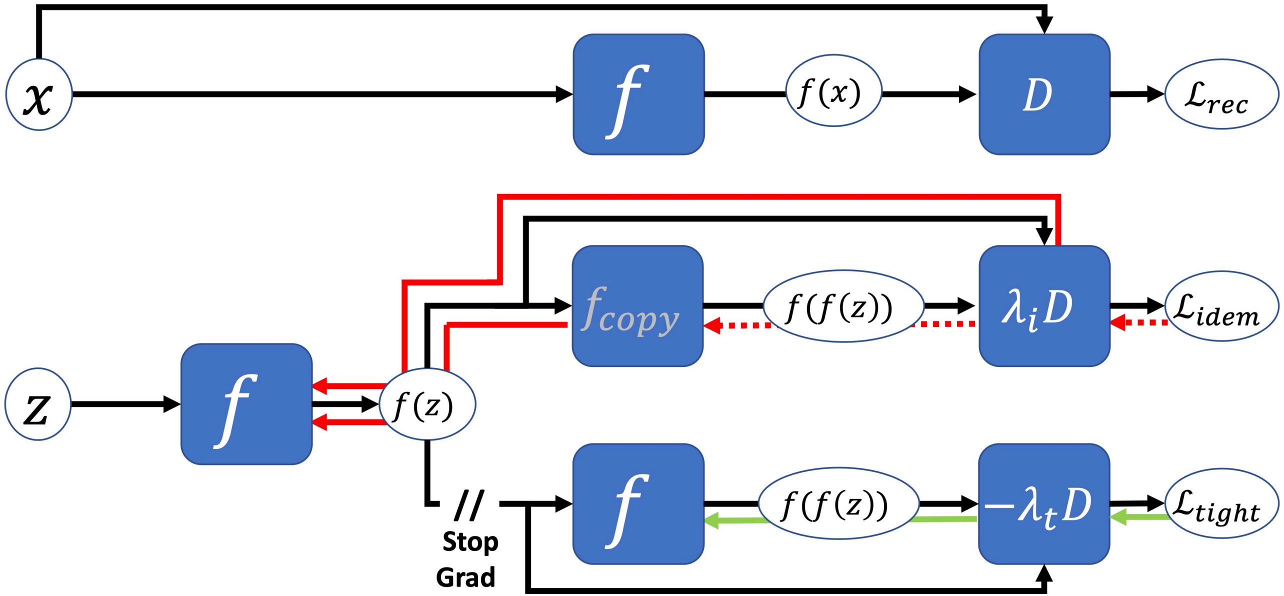
However, optimizing directly against the tightness objective will conflict with the generation target.

$$L_{\text{tight}}(z) = \tanh\left(\frac{\tilde{L}_{\text{tight}}(z)}{aL_{\text{rec}}(z)}\right)aL_{\text{rec}}(z)$$

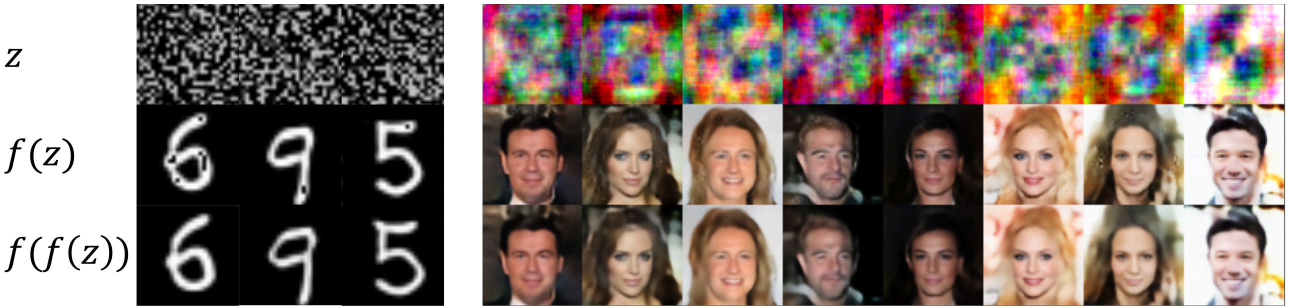


Training Objective

$$\mathcal{L}(\theta) = \lambda_r \mathbb{E}_x [L_{\text{rec}}(x;\theta)] + \lambda_i \mathbb{E}_z [L_{\text{idem}}(z;\theta)] + \lambda_t \mathbb{E}_z [L_{\text{tight}}(z;\theta)]$$



Experiment



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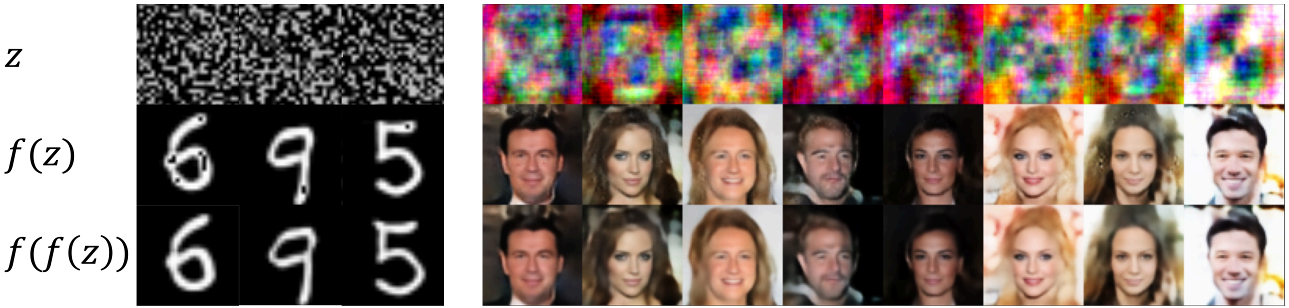
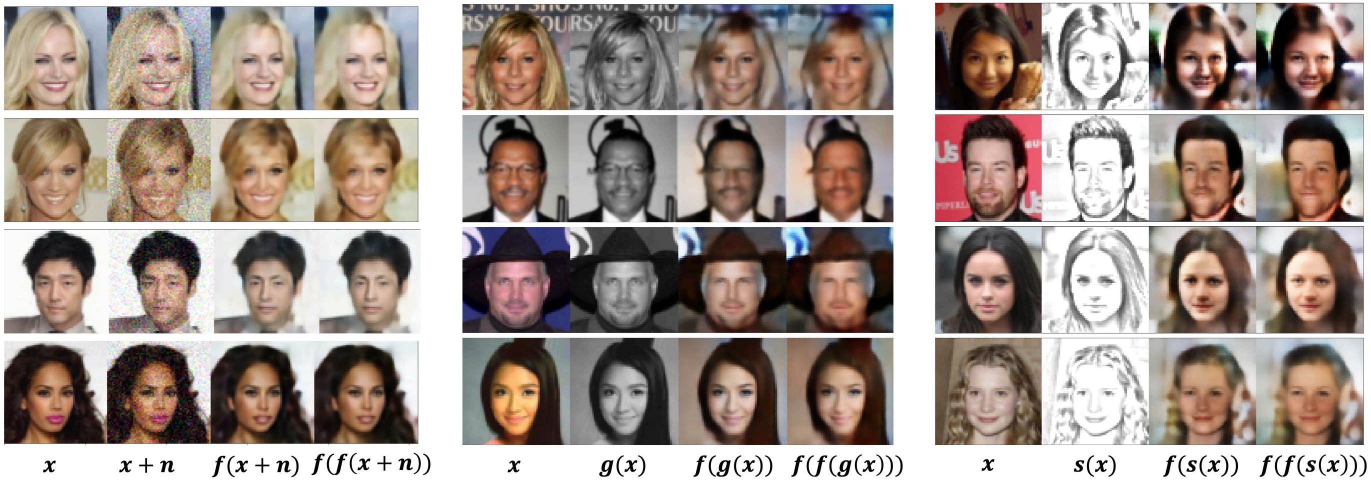
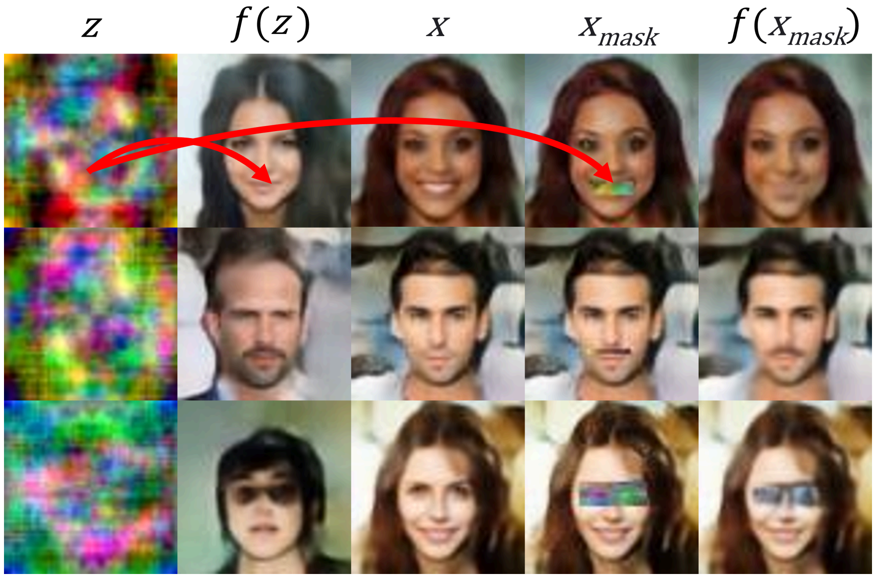


Make It Real



Experiment

Latent Space Manipulations.



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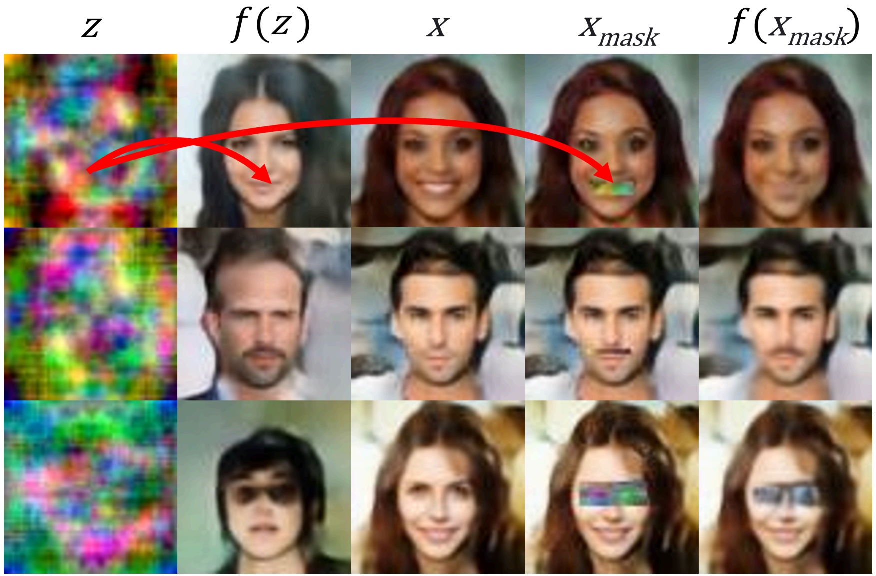

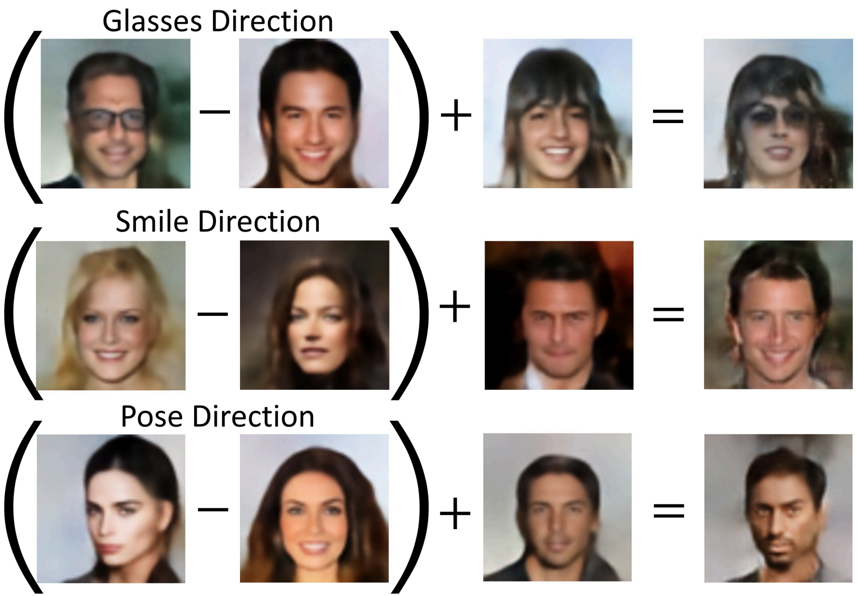

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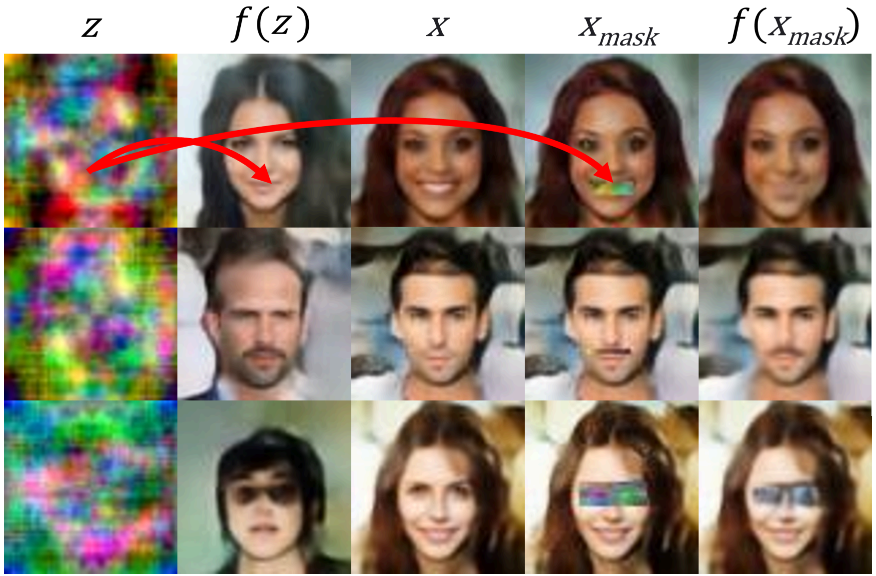
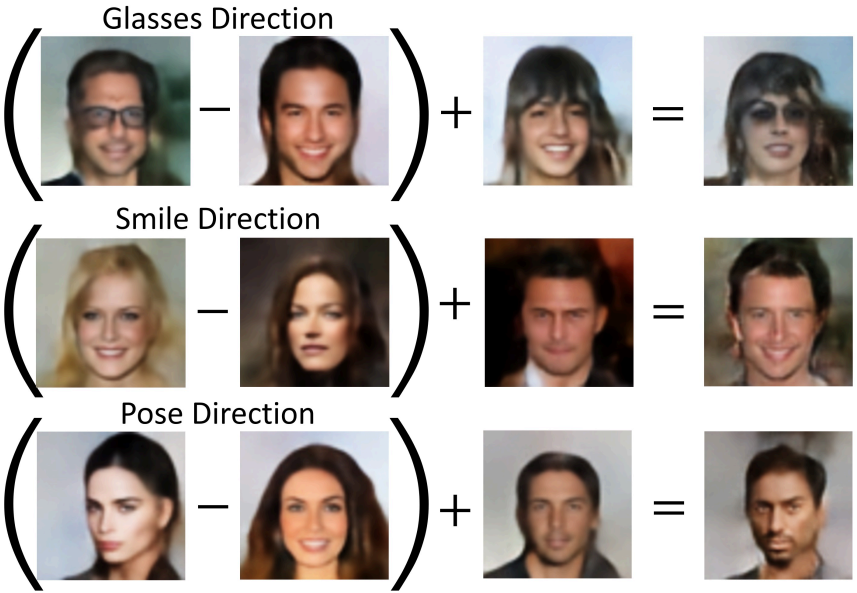
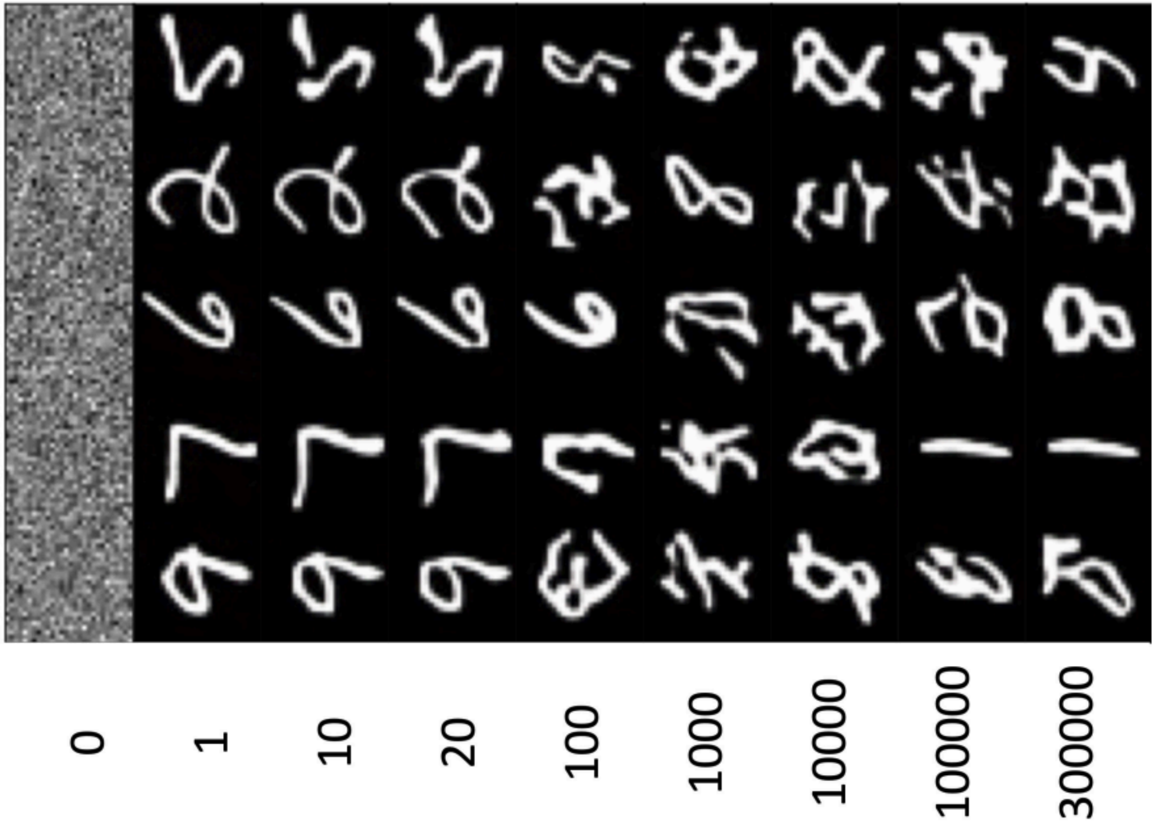




Experiment

$f^{k \to \infty}(z)$



Conclusions

Advantages

- Single-step generation is fast and efficient.
- Optional sequence refinement.
- Maintains consistent latent space.
- Good generalization and projection capabilities.
- Simplifies editing process.

Weaknesses

- Generation quality needs to be improved.
- Mode collapse may occur.
- Potential issue tightness objective.
  It may impose large modifications on relatively good generated instances and may encourage high gradients and instability.

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