



SC395: Image Generative Models in Computer Vision

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Lecture 3

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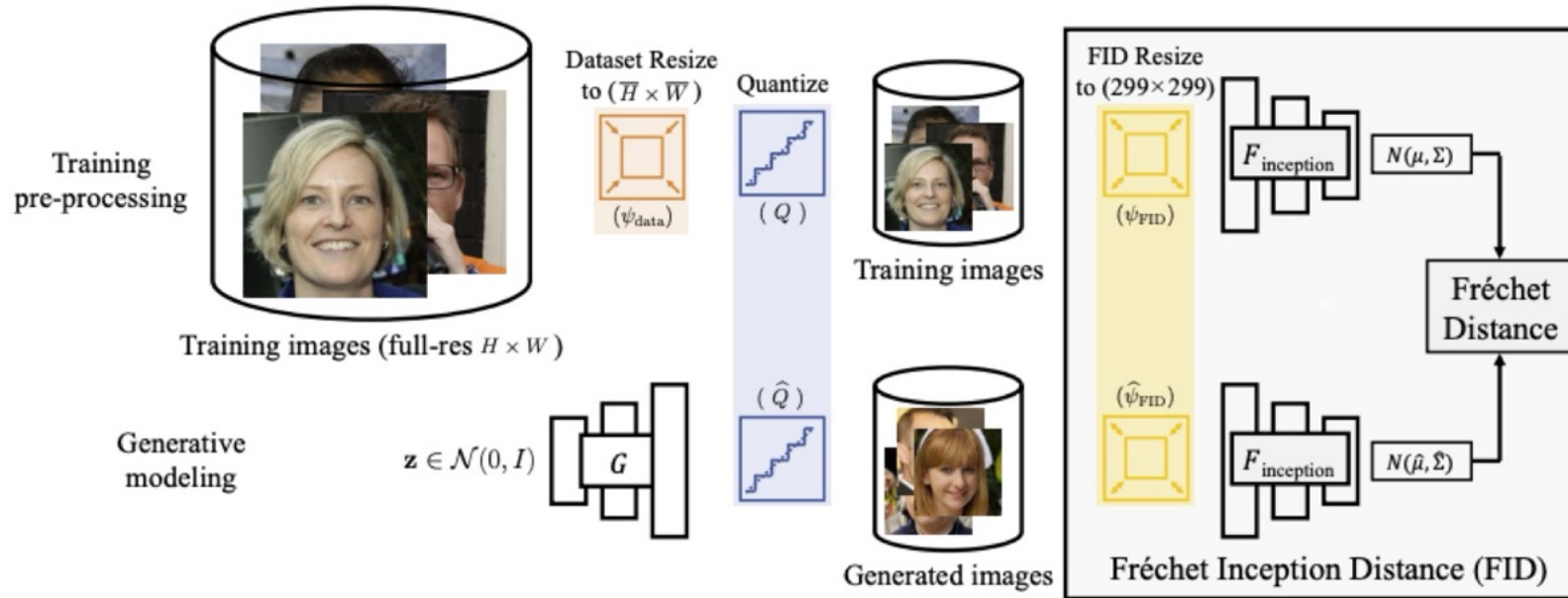




GANs Applications



How to evaluate performance of GAN?



Fréchet Inception Distance (FID)

$$\mathbf{FID} = ||\mu - \hat{\mu}||_2^2 + \mathbf{Tr}(\Sigma + \hat{\Sigma} - 2(\Sigma\hat{\Sigma})^{1/2})$$

Recent Trends in Evaluation of Generative Models

- Metrics that align human preferences
 - VQAScore
 - TIFA
- Human-in-the-loop Studies
 - LMArena:
 - lmarena.ai/leaderboard/text-to-image

Stable Diffusion v1.5



Stable Diffusion v2.1



Text Input: A person sitting on a horse in air over gate in grass with people and trees in background.

GPT-3 generated + verified QAs (pre-generated in TIFA v1.0 benchmark)			
Question: what is the animal?		Answer: horse	
Choices: cow, horse, sheep, dog			
VQA:	Horse ✓	Horse	✓
Question: is there a gate?		Answer: yes	
Choices: yes, no			
VQA:	No ✗	Yes	✓
Question: is the horse in air?		Answer: yes	
Choices: yes, no			
VQA:	No ✗	Yes	✓
...			
Accuracy on 14 questions			
 TIFA	71.4		100.0
✓ Fine-Grained ✓ Accurate ✓ Interpretable			



GANs: Applications

- Rich representation of the image data
- Smooth latent space with interpolation capabilities
- Fast, single step inference

Image Restoration using GANs

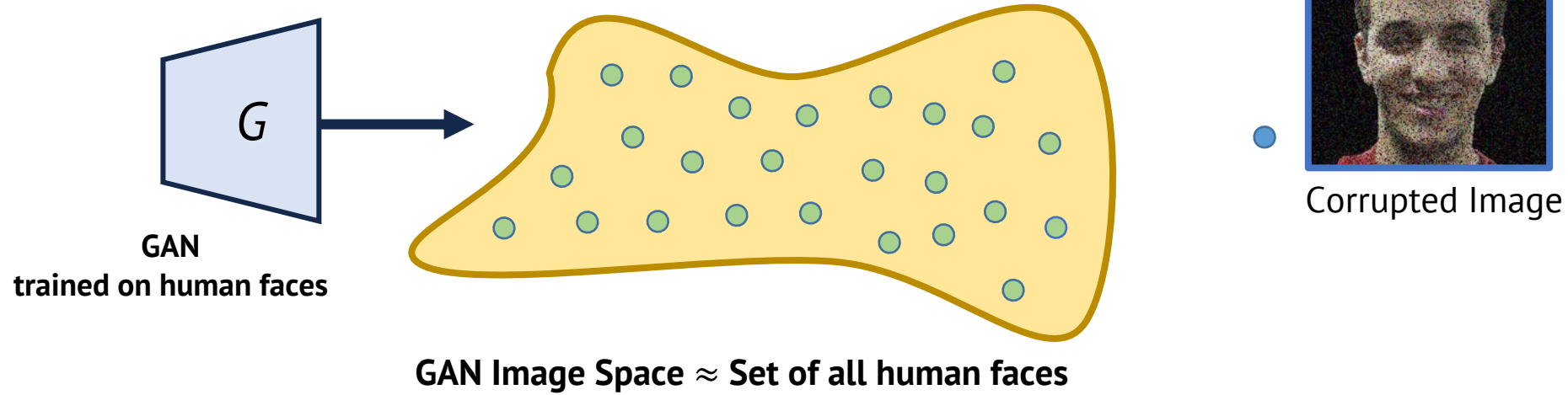


Image Restoration using GANs

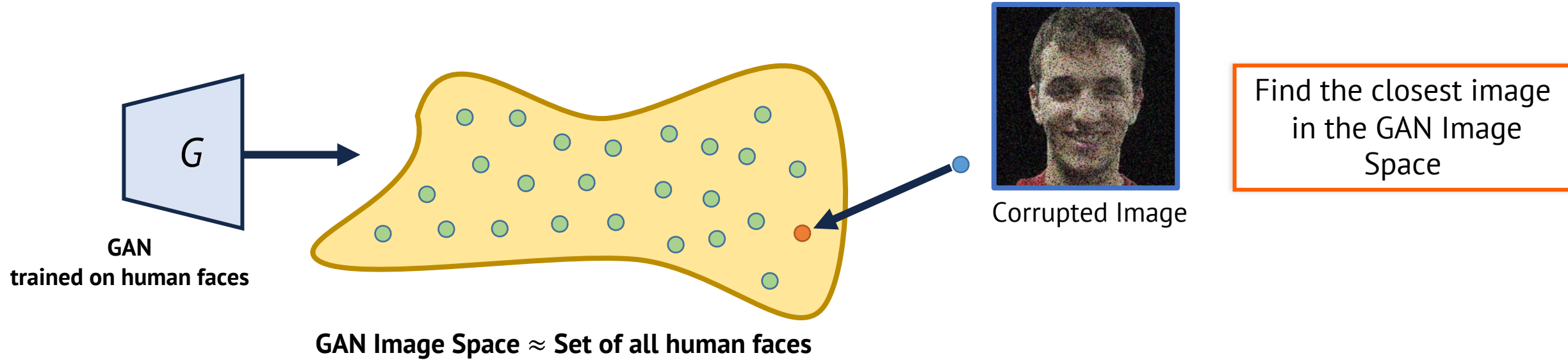
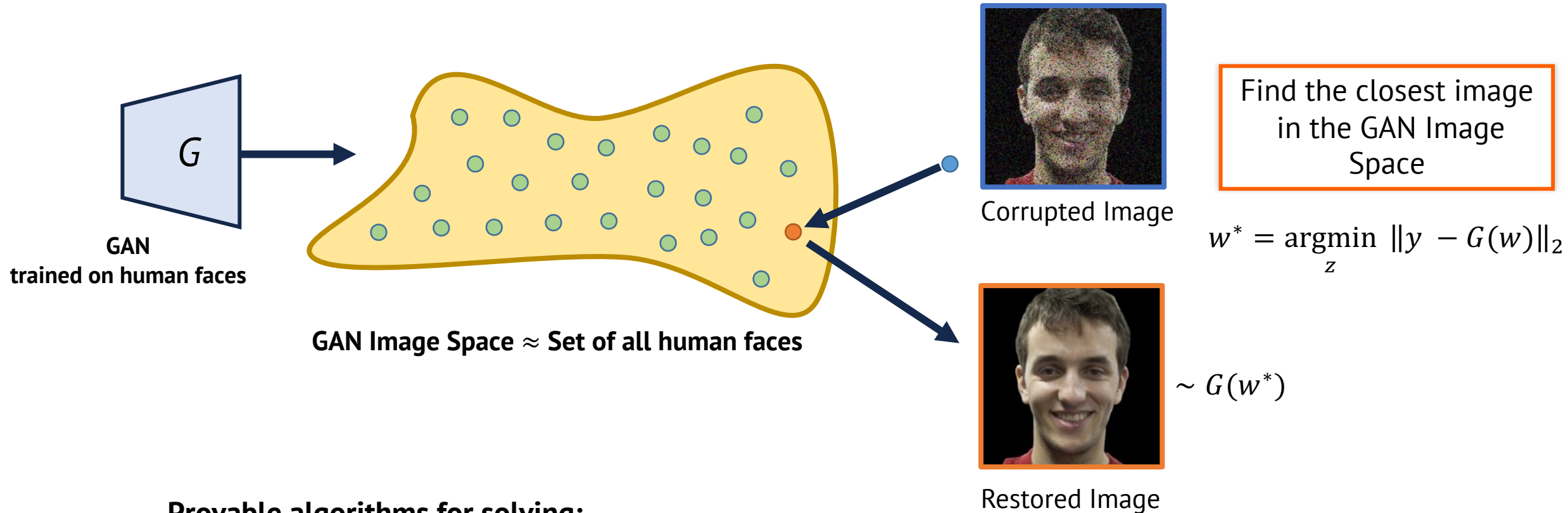


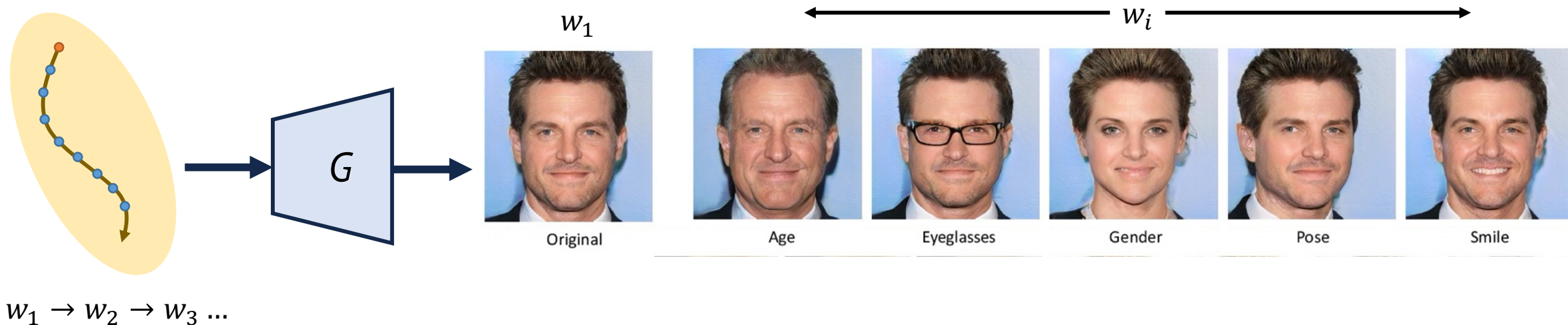
Image Restoration using Generative Models



Provable algorithms for solving:

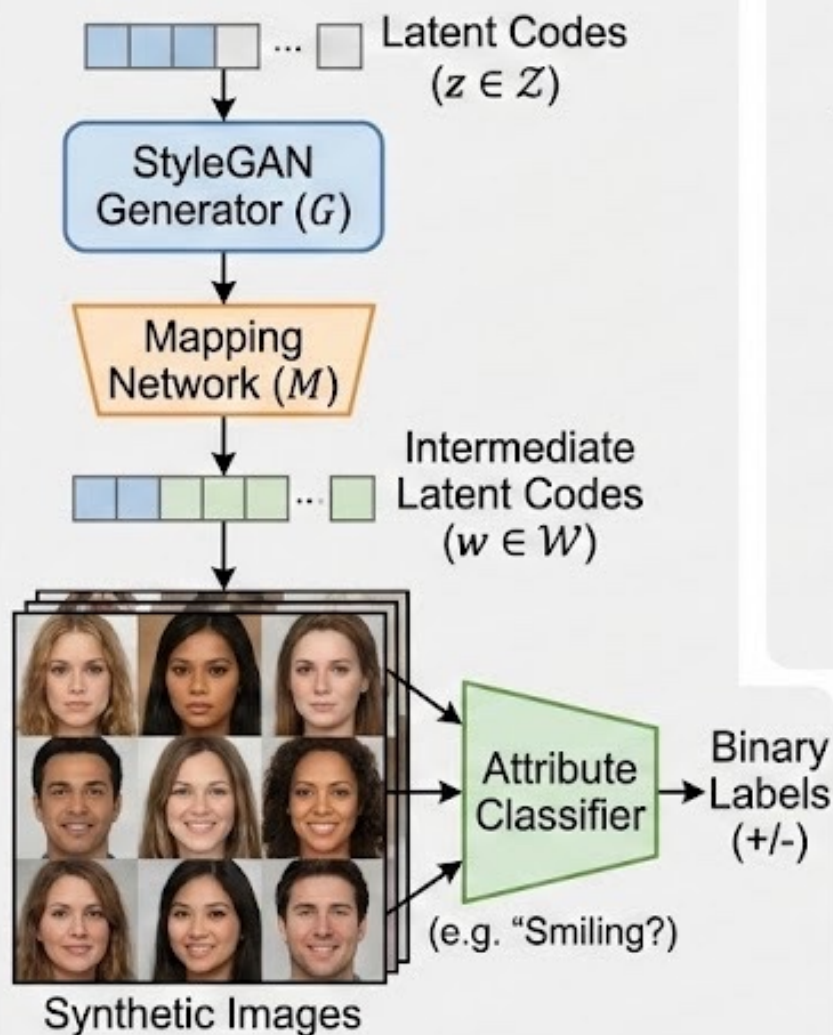
- Image Restoration
- Image Denoising, Inpainting etc.

GAN Inversion is necessary for Image Editing



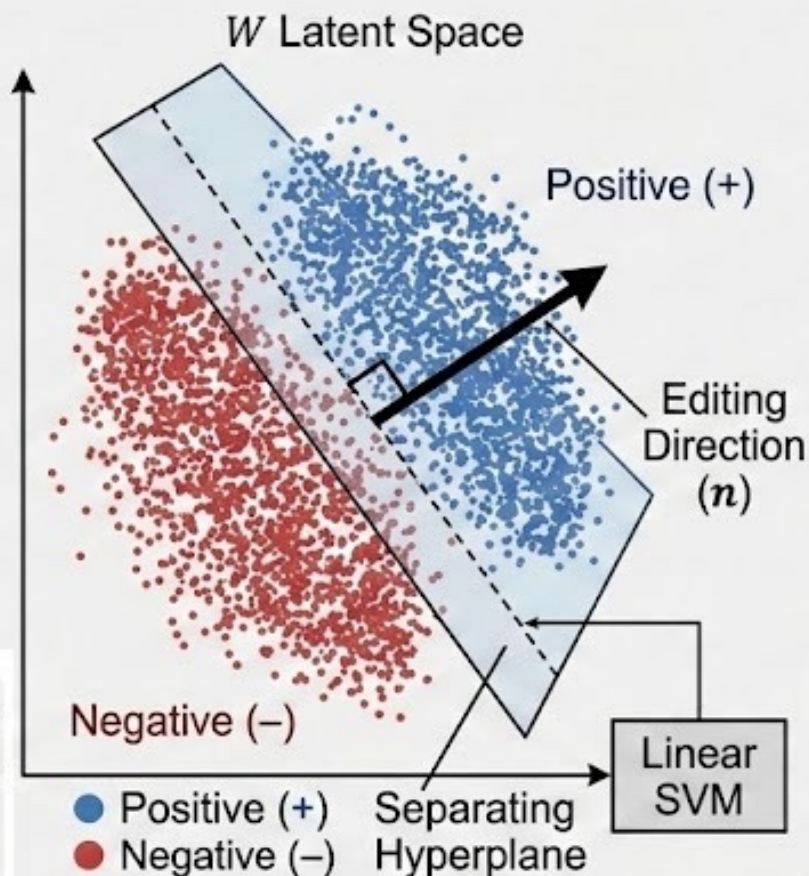


1. Data Generation & Labeling



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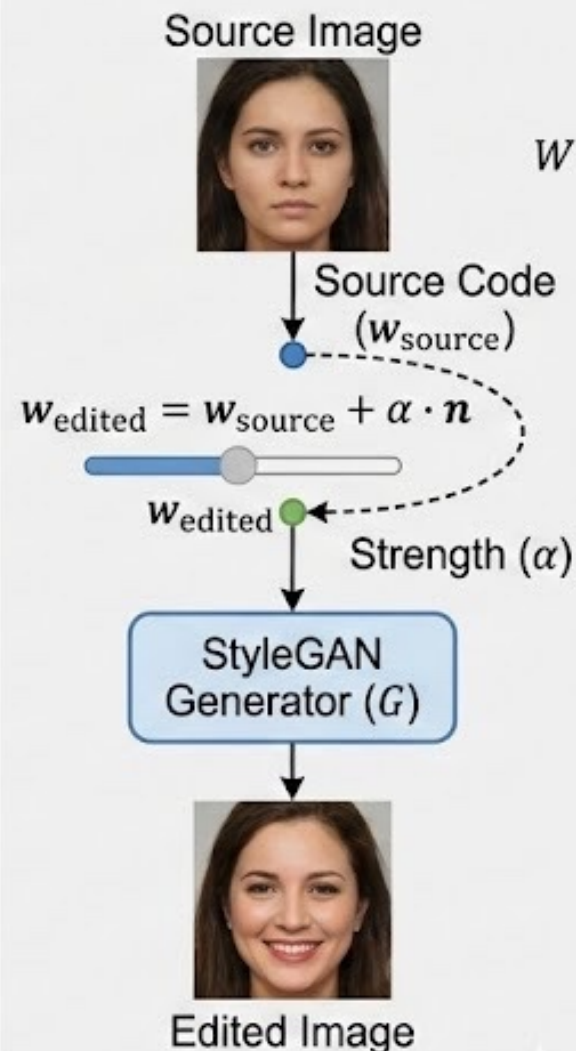
2. Boundary Training



2. Boundary Training

z : Input Latent n : Normal Vector (Attribute Direction)
 w : Intermediate Latent α : Editing Strength

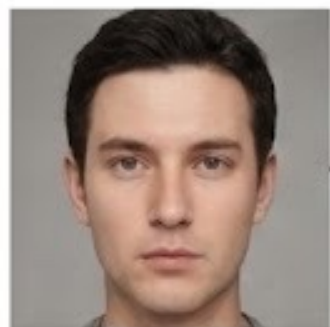
3. Attribute Editing



3. Attribute Editing

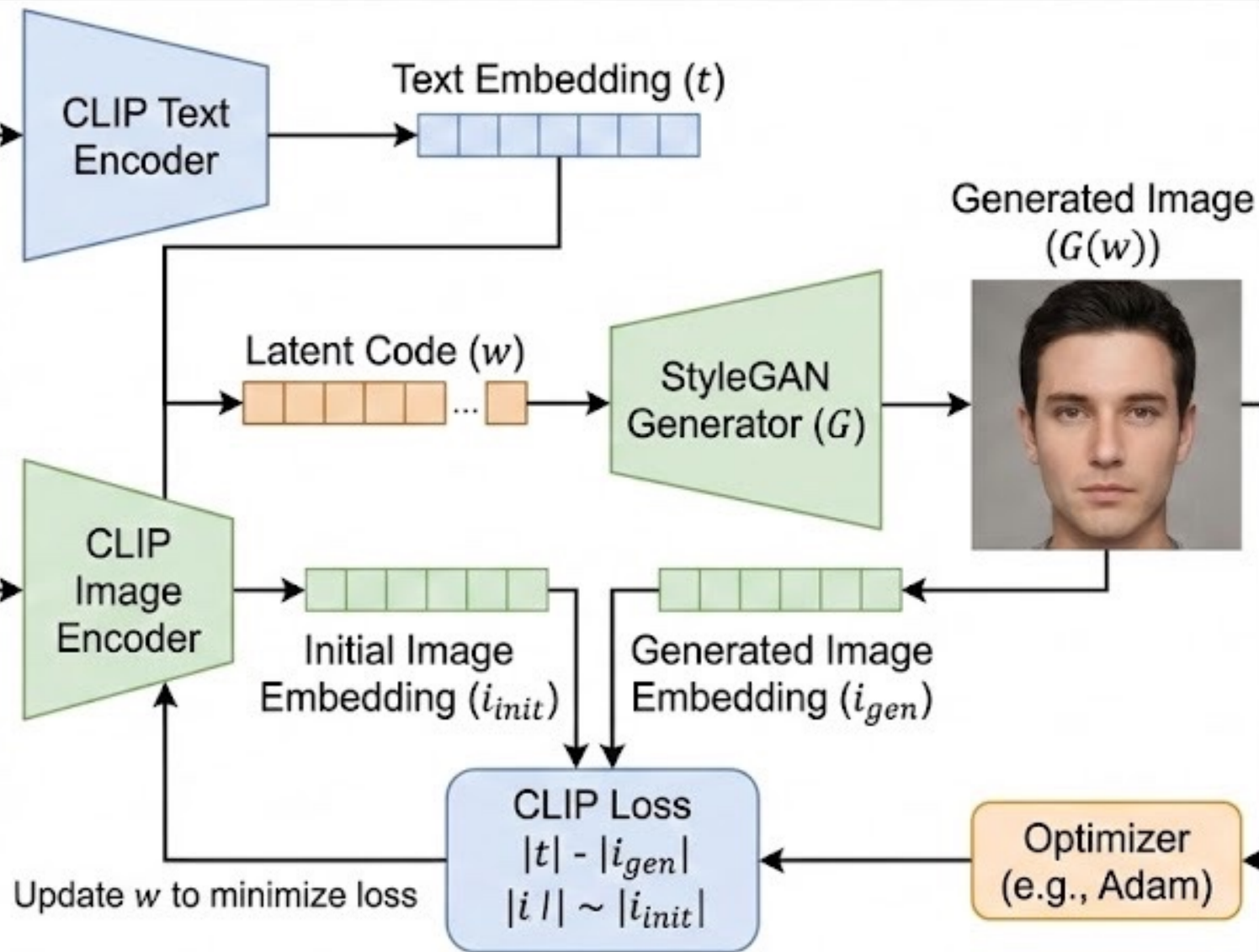
User Input

Text Prompt:
"a person with
a mohawk"



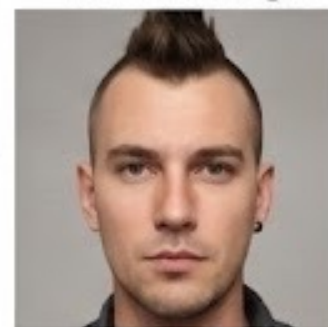
Initial Image

StyleCLIP Optimization Loop



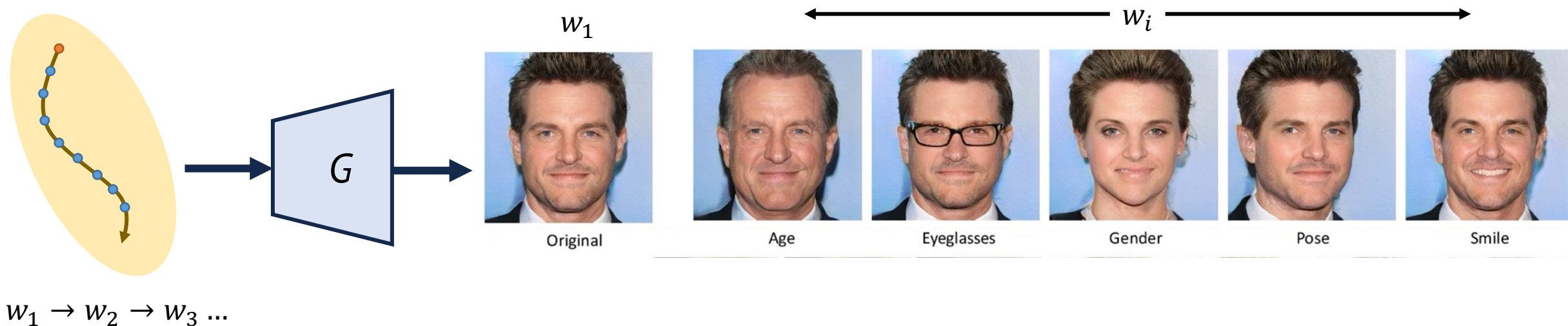
Final Result

Edited Image



w : Latent Code t : Text Embedding i : Image Embedding G : StyleGAN Generator

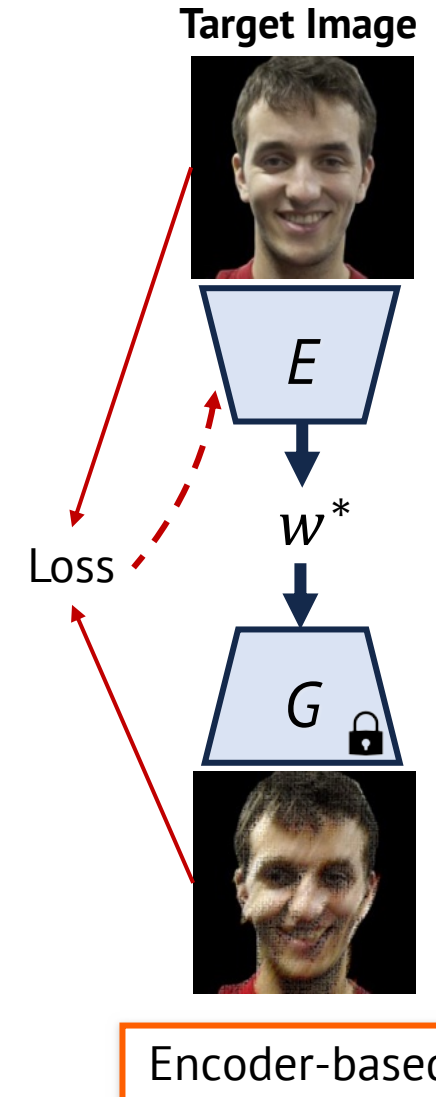
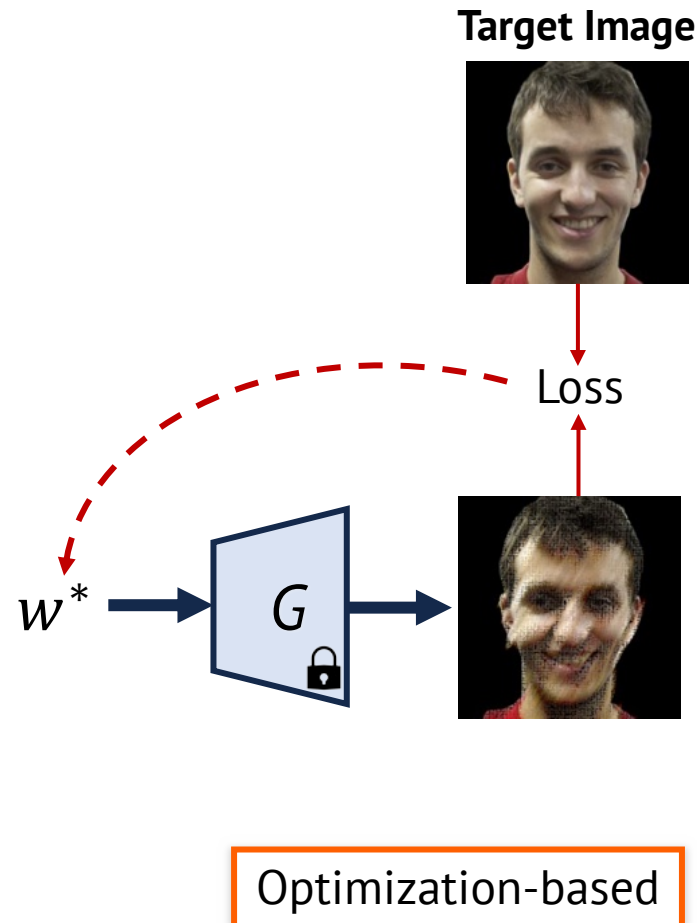
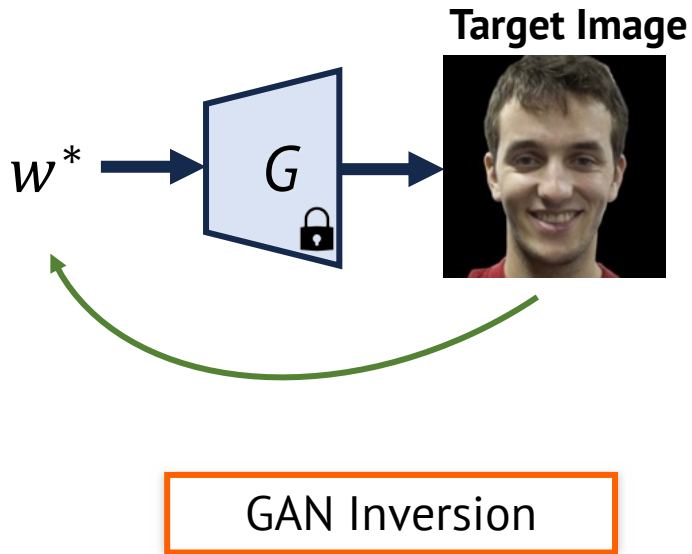
GAN Inversion is necessary for Image Editing



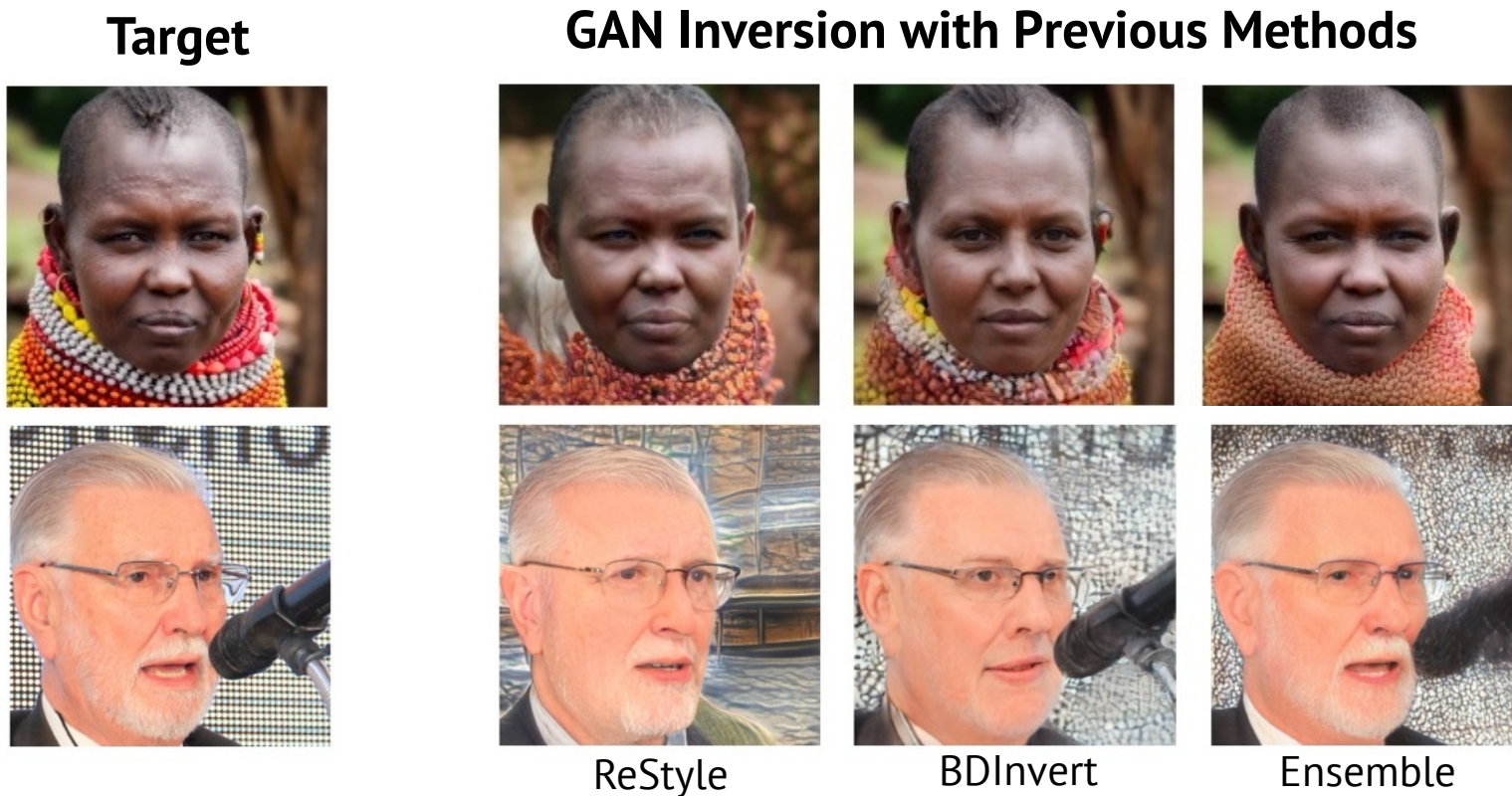
Edit a real image?

Corresponding Latent code must be known!

GAN Inversion

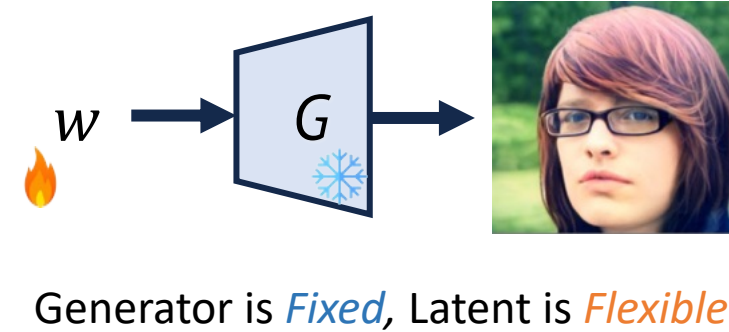
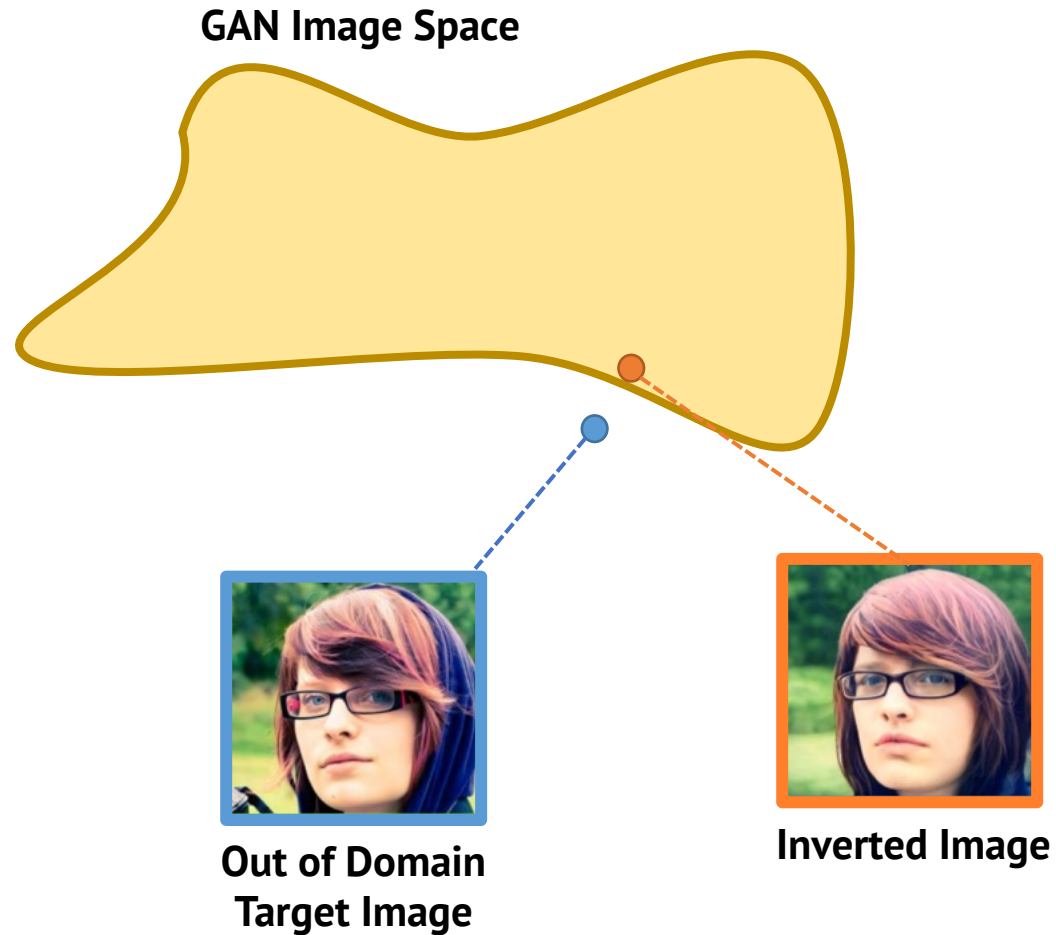


GAN Inversion: Most Techniques Fail on out-of-domain Images



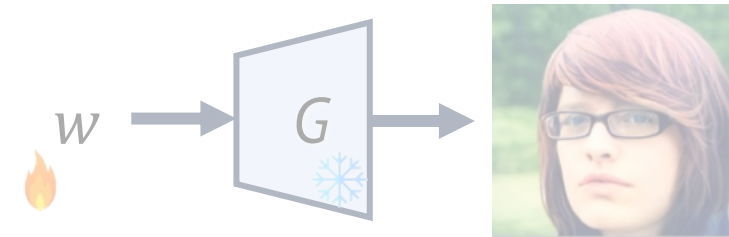
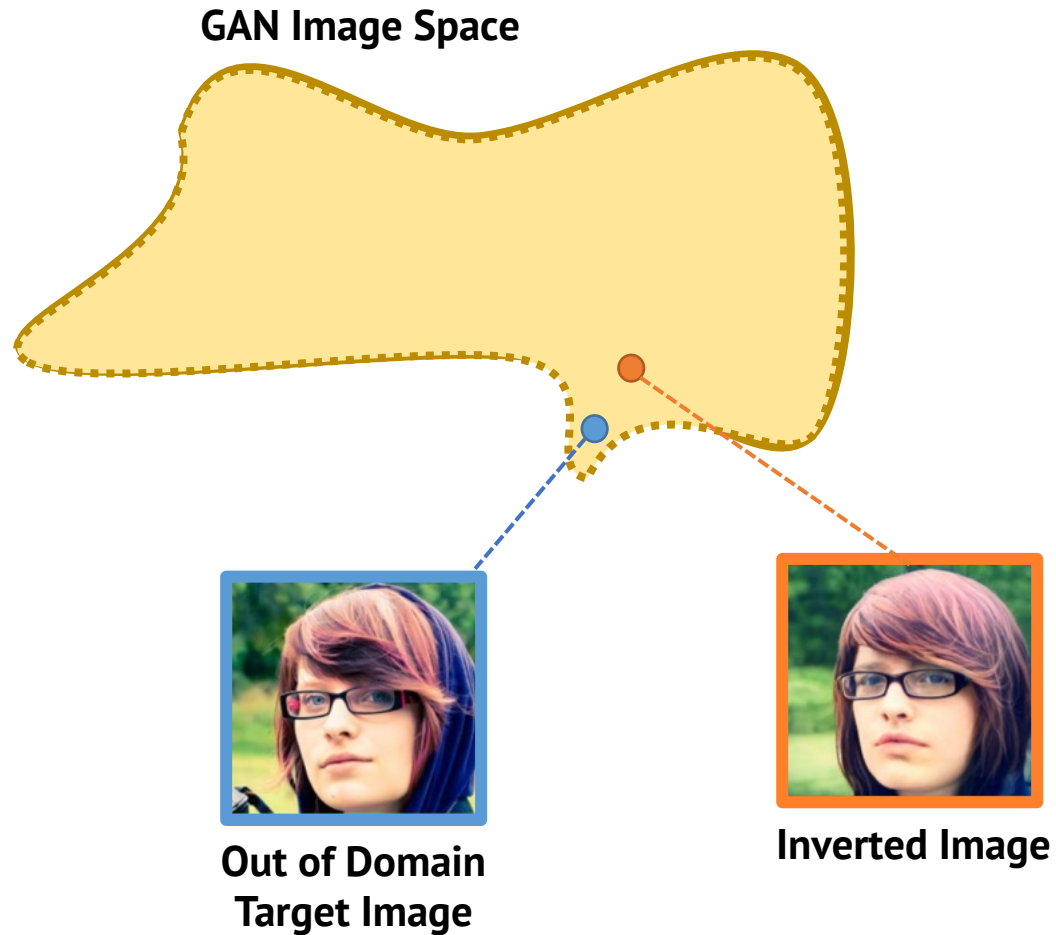
Ref: ReStyle, Alauf et al., ICCV '21
BDInvert, Kang et al., ICCV '21
Ensemble, Cai et al., CVPR '21

Key Challenge in Inverting a Frozen GAN



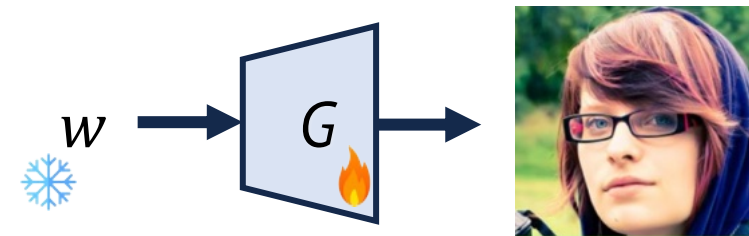


Key Challenge in Inverting a Frozen GAN



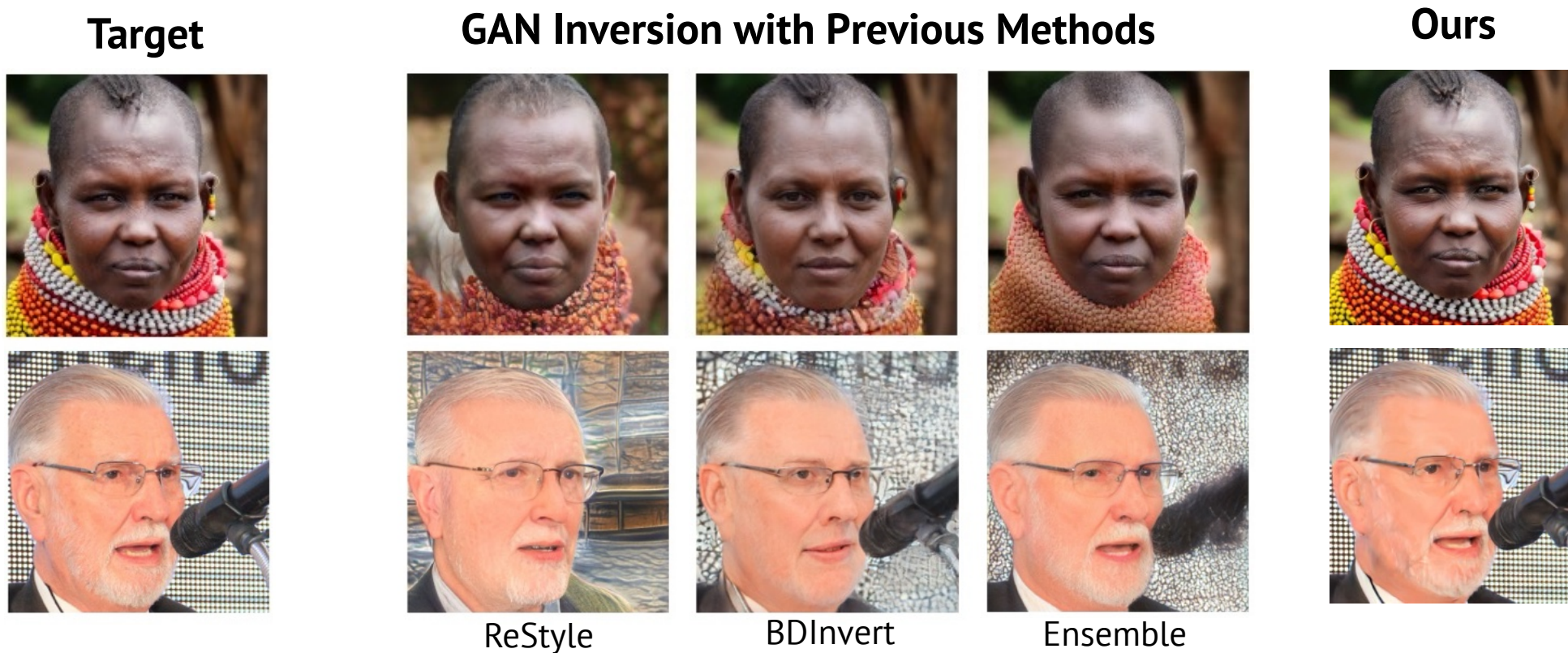
Generator is *Frozen*, Latent is *Trainable*

Proposed Idea:



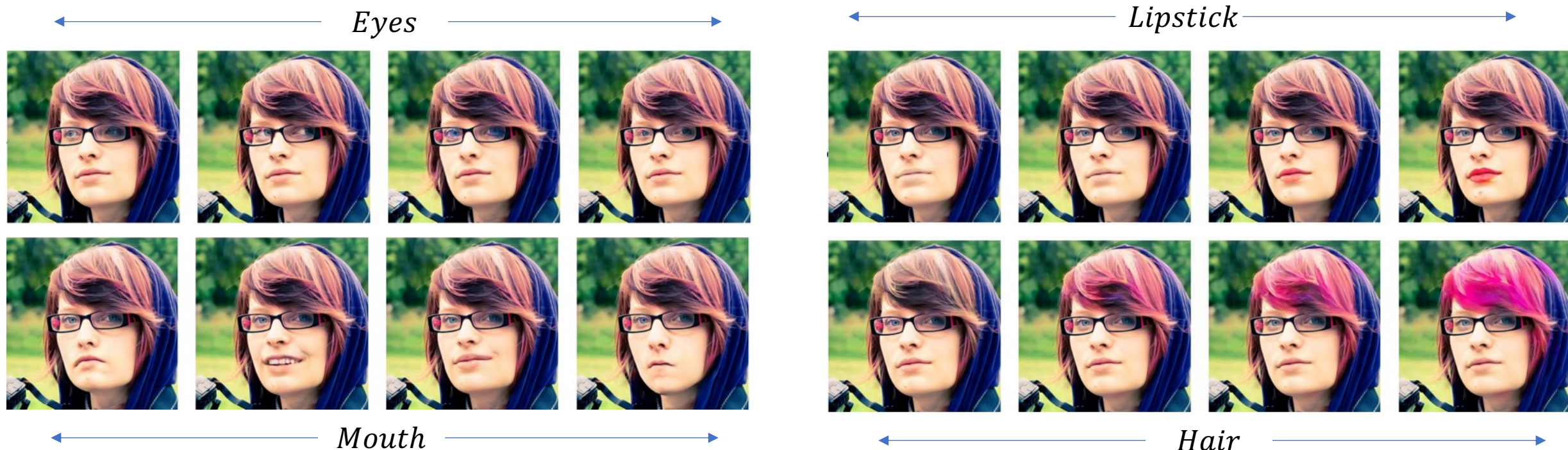
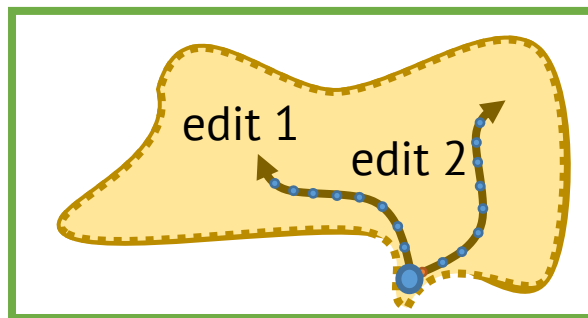
Generator is *Flexible*, Latent is *Fixed*

Our Method Achieves Near-perfect GAN Inversion



Ref: ReStyle, Alauf et al., ICCV '21
BDInvert, Kang et al., ICCV '21
Ensemble, Cai et al., CVPR '21

Most off-the-shelf Editing methods work!



using **StyleSpace Editing Directions**

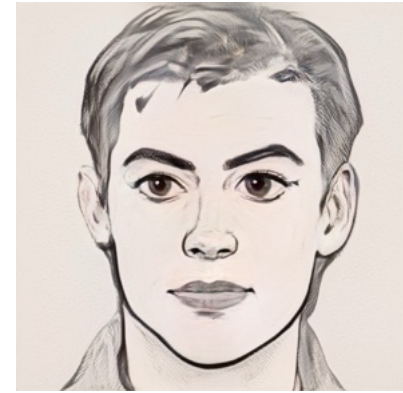
One-shot Image Stylization



Style Reference



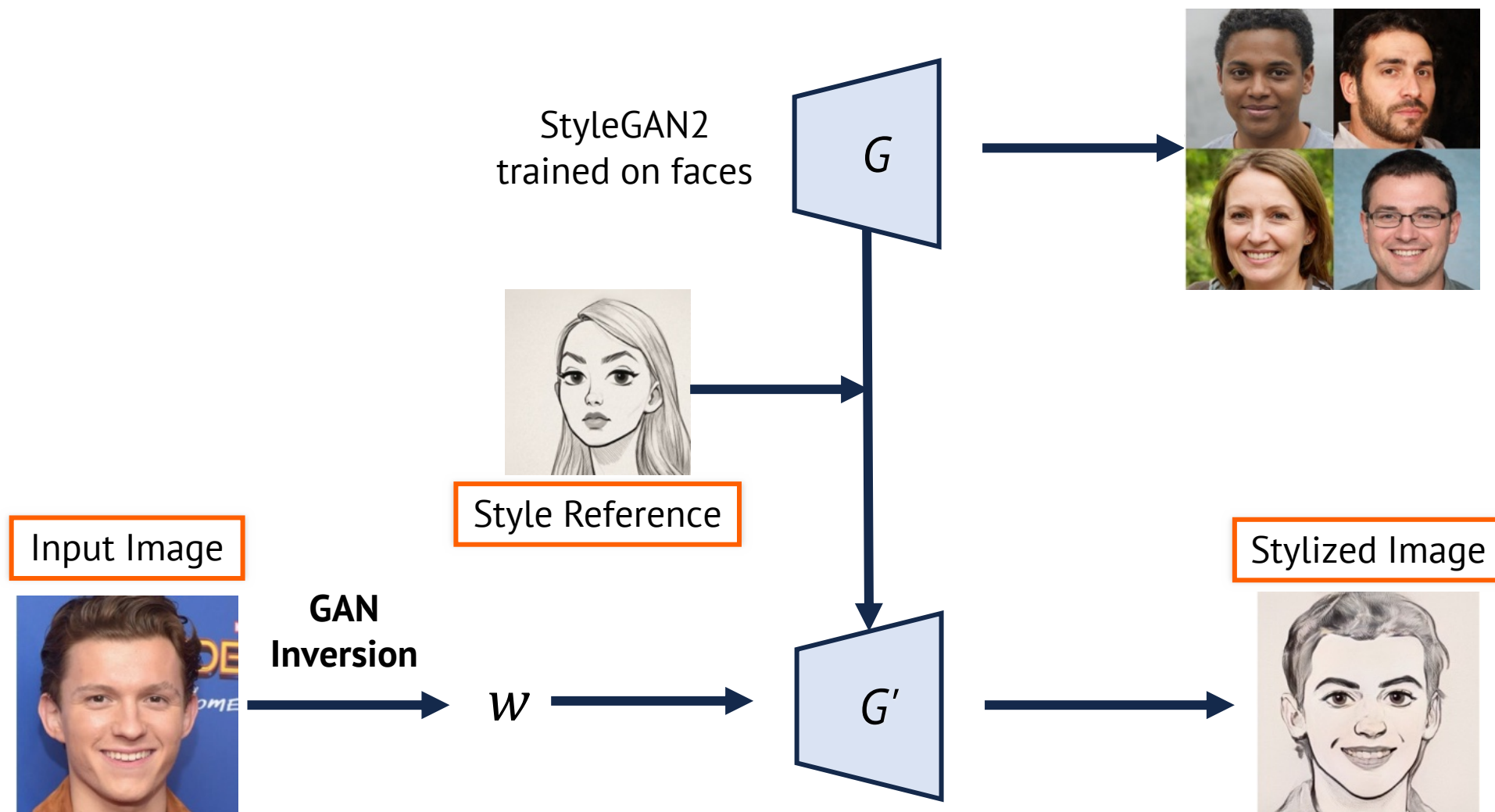
Input Image



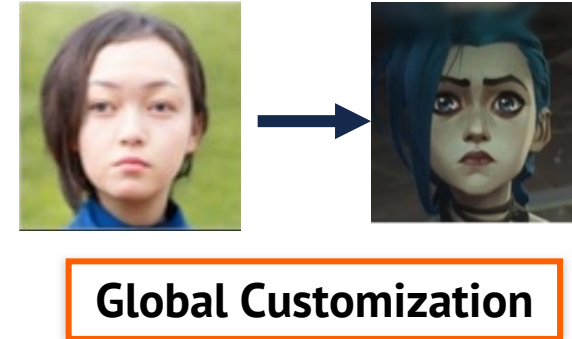
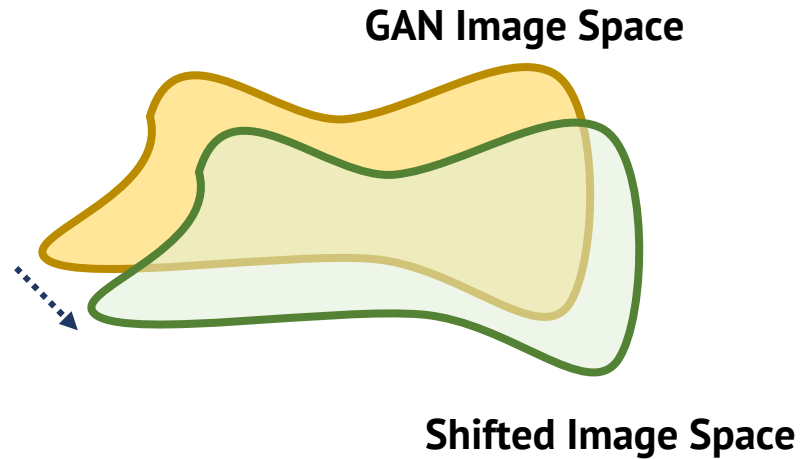
Stylized Image

Stylizing an Input Image in the style of a Reference Style using only *one* example

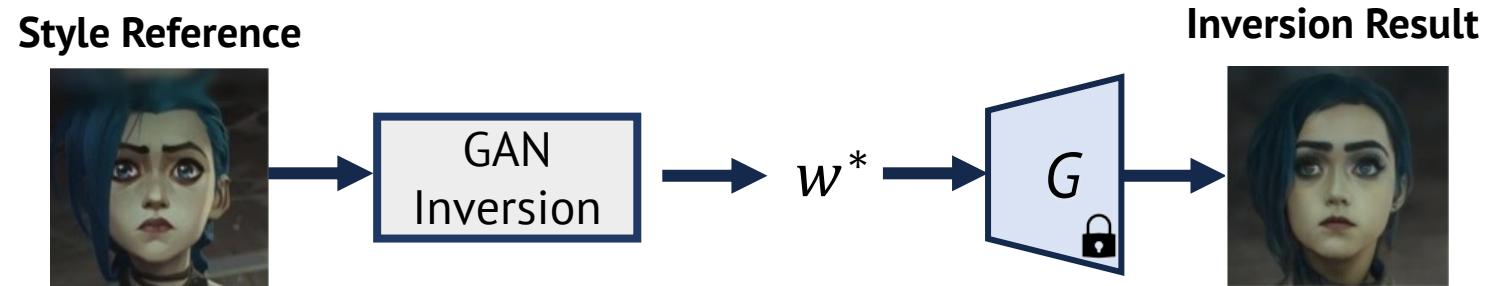
Pre-trained GAN for one-shot Stylization



How to perform global customization of StyleGAN2?



Step 1: GAN Inversion

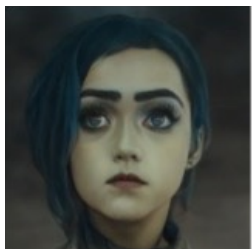


JoJoGAN: Style-mixing

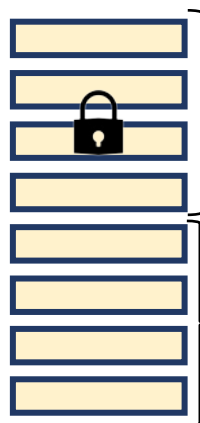


Step 2. Use Style-mixing property to Create a Training Set

Inversion result

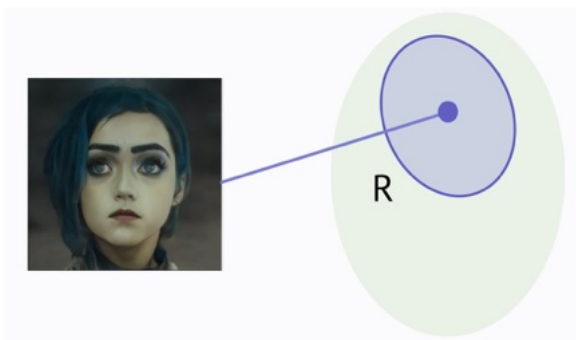


W^*

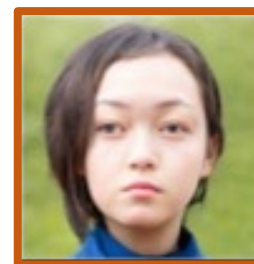


Rows responsible
for identity

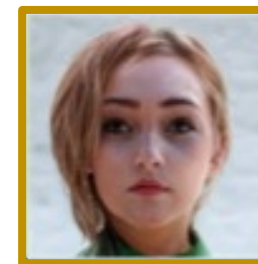
Rows responsible
for stylistic features



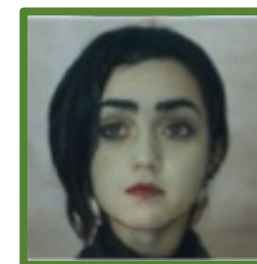
S or W space



W_1

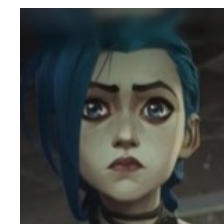


W_2



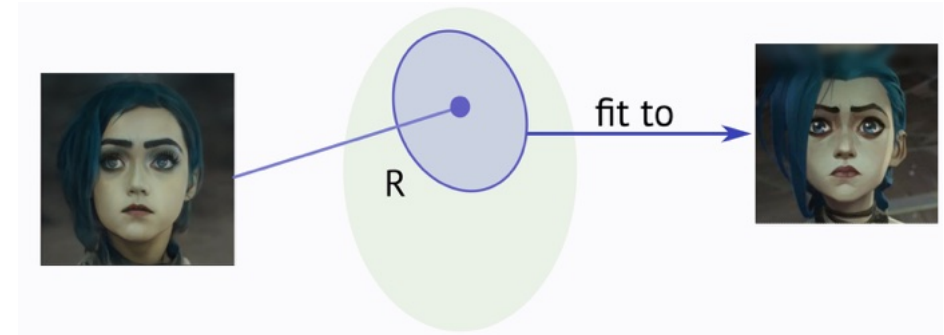
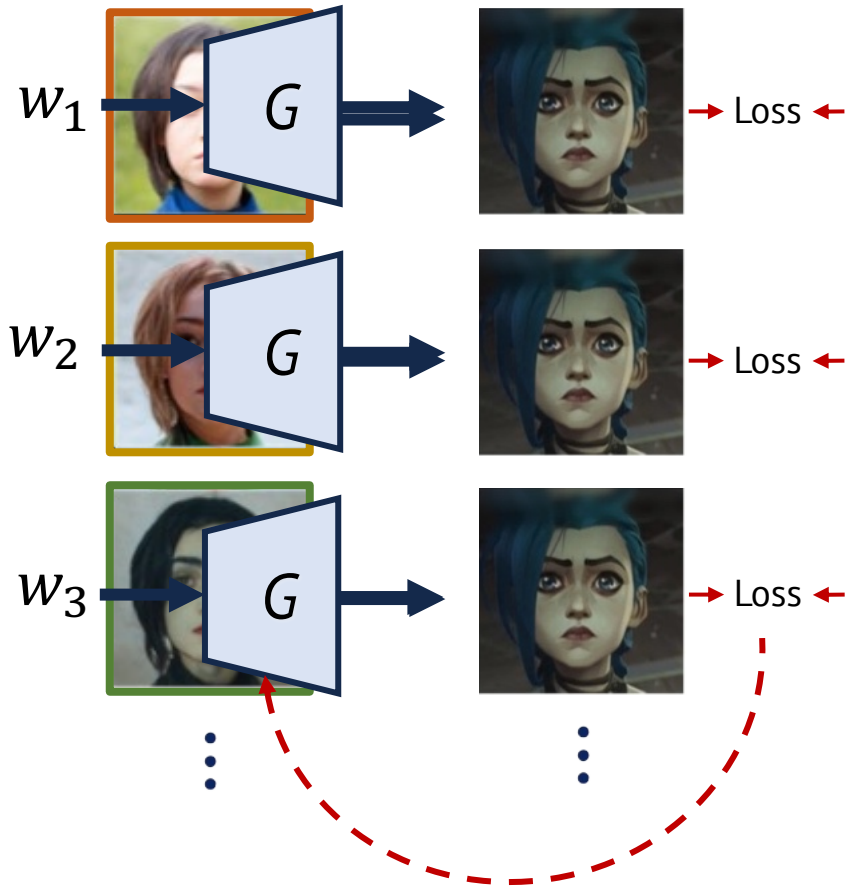
W_3

...

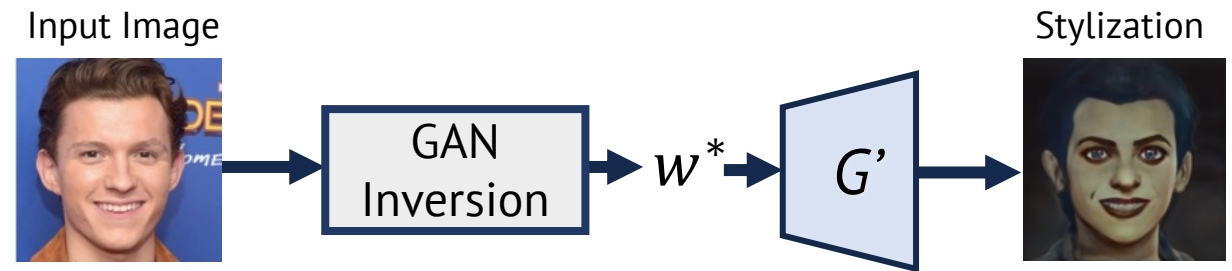


How to Fine-tune StyleGAN2 ? : JoJoGAN

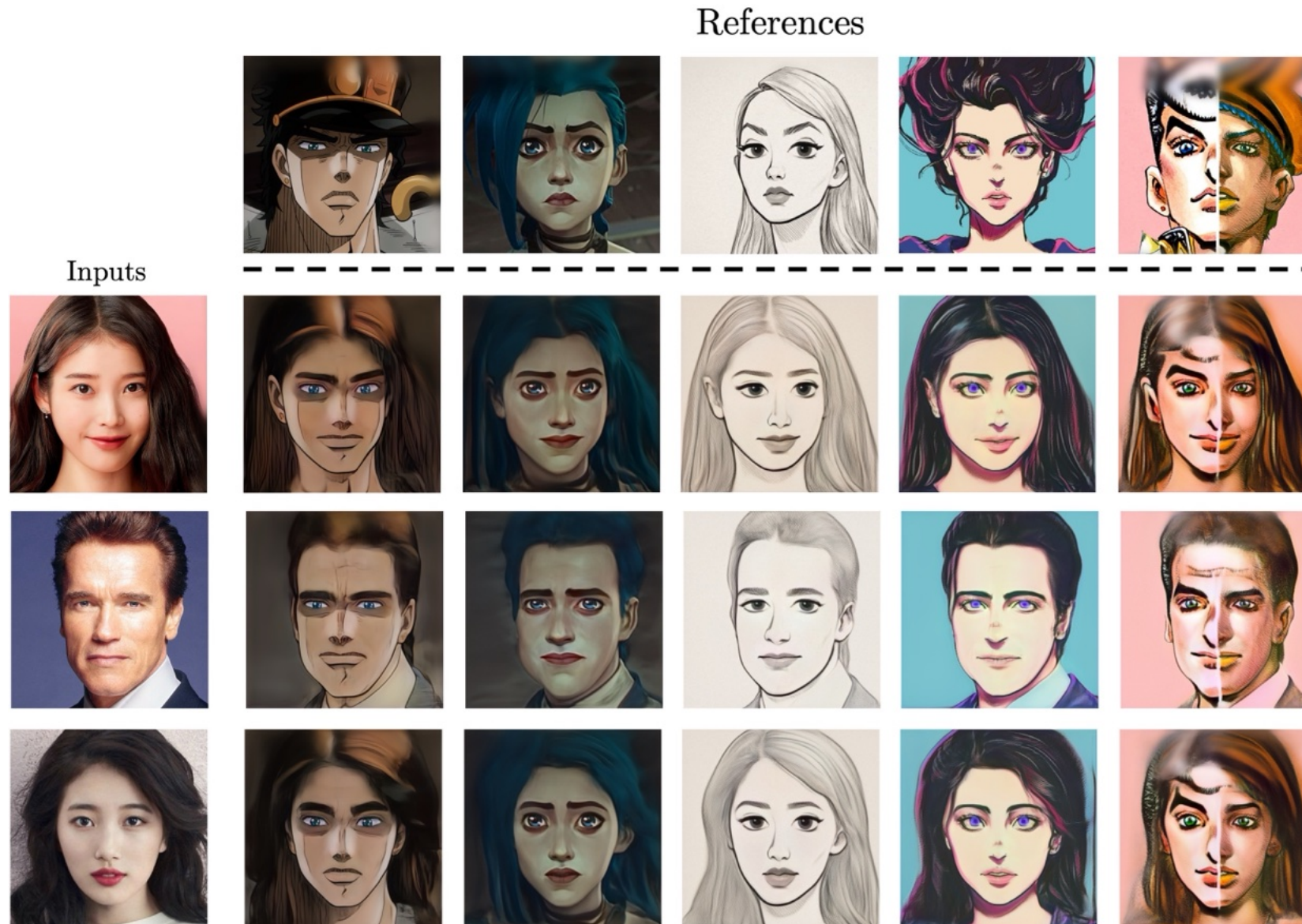
Fine-tune G using pixel-level losses



Inference on fine-tuned G



JoJoGAN: Results





GANs: Limitations and Challenges

- Tricky to train due to two-player dynamics
- Thus, difficult to scale
- Mostly limited to single domain datasets
 - Exceptions: StyleGAN-XL, GigaGAN
- Mode Collapse is common, limited quality
- Are GANs still relevant?! : [current and future trends](#)

Limitations

-  Mode collapse
-  Generating OOD
-  Hard to train

Challenges

-  Stability
-  Efficiency
-  Quality
-  Novelty

- **GANs don't use “direct supervision”**
 - The loss relies on the indirect “real / fake” signal coming from Discriminator

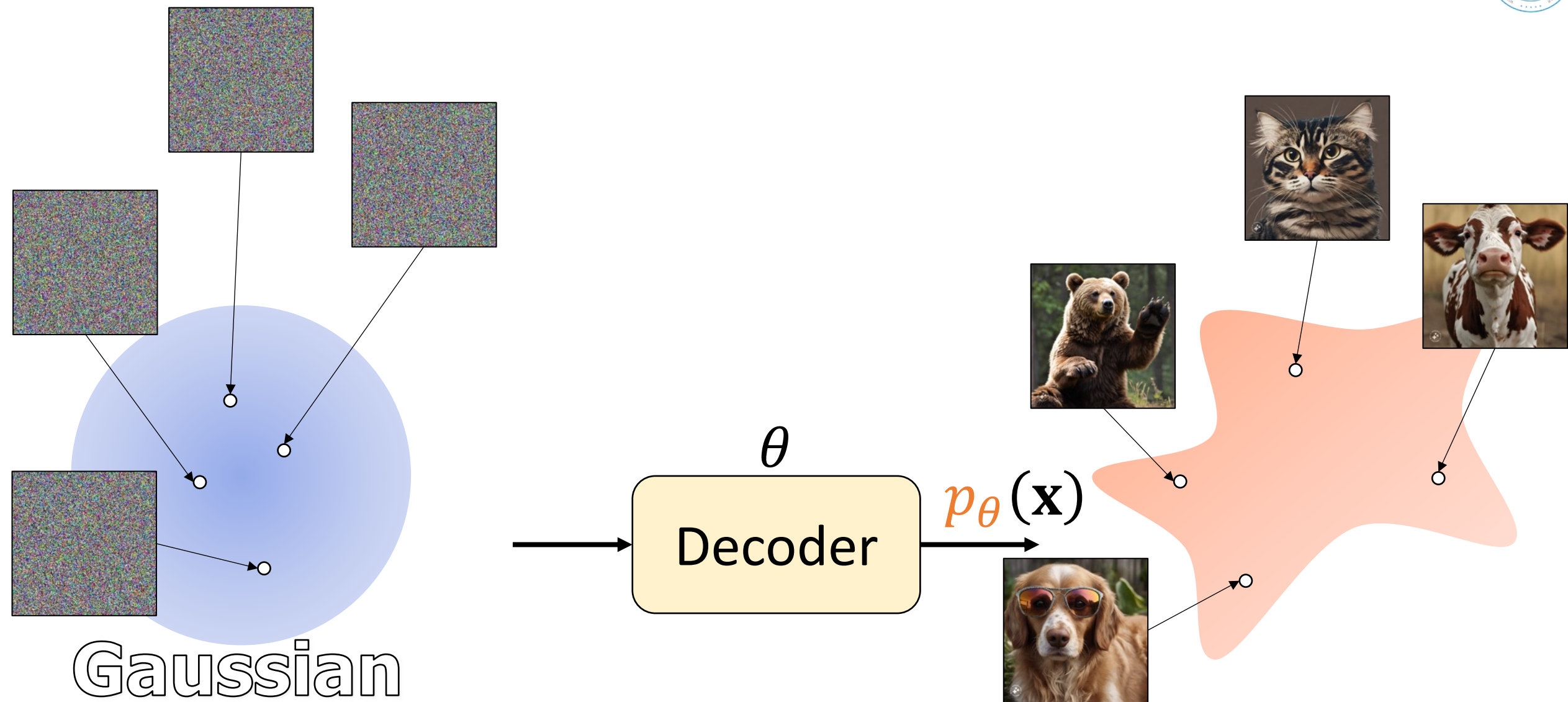


Important GAN concepts

- The idea of two player game and minimax objective
- Standard objective minimizes JS divergence, but other divergences could potentially be more effective
 - E.g. Wasserstein Distance (aka Earth Mover's Distance)
- Scaling the model architecture is important
- Adaptive Instance Normalization introduced by StyleGAN is super-important -- StyleGAN architecture is the cornerstone of “image editing with GAN” literature
- The main advantage of GAN is smooth latent space with intuitive behavior
- Editing a real image requires GAN Inversion; once the inverted latent code is obtained, thousands of latent space traversal techniques are available
- GANs require the dataset to be aligned/single domain
- GANs are difficult to scale with respect to data due to unstable training dynamics



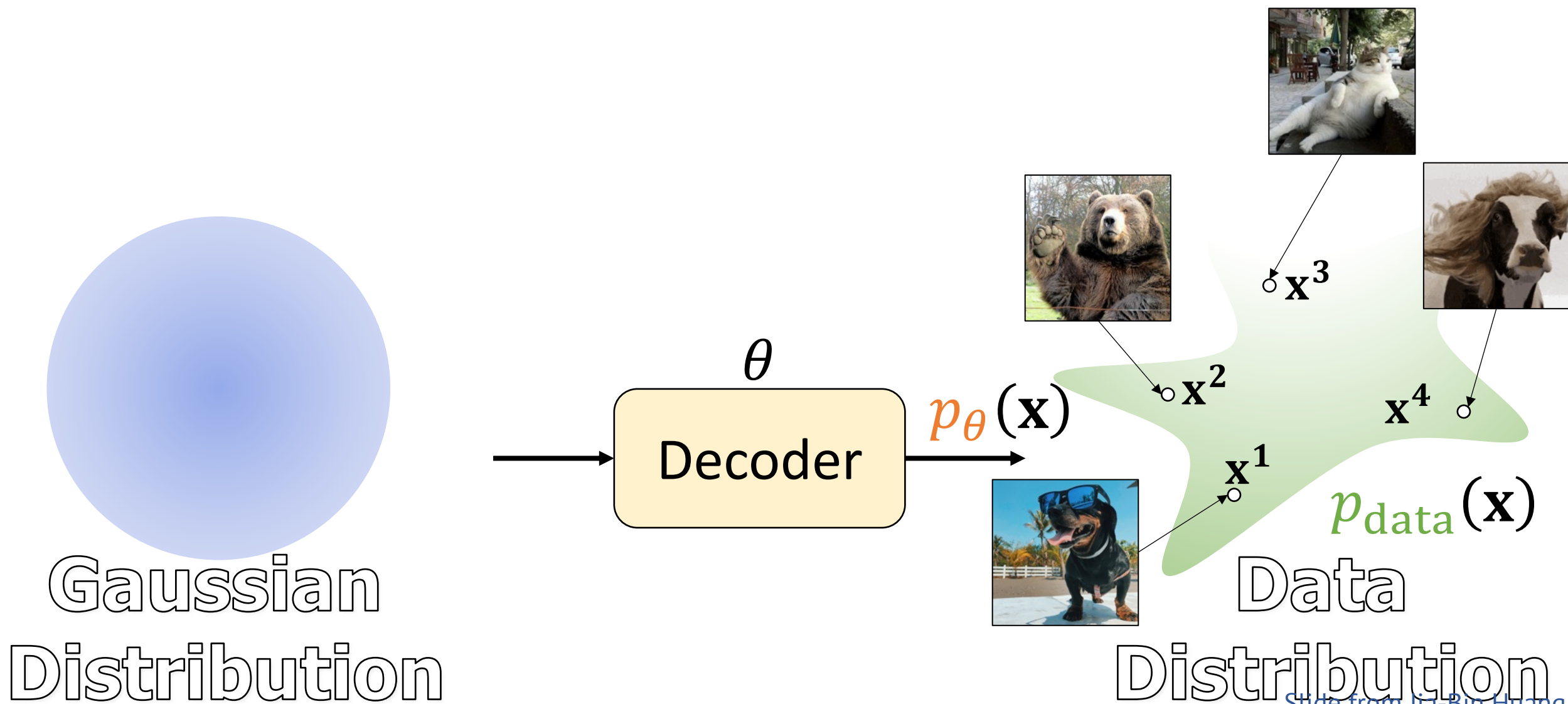
Lecture 3: Diffusion Models



Gaussian
Distribution



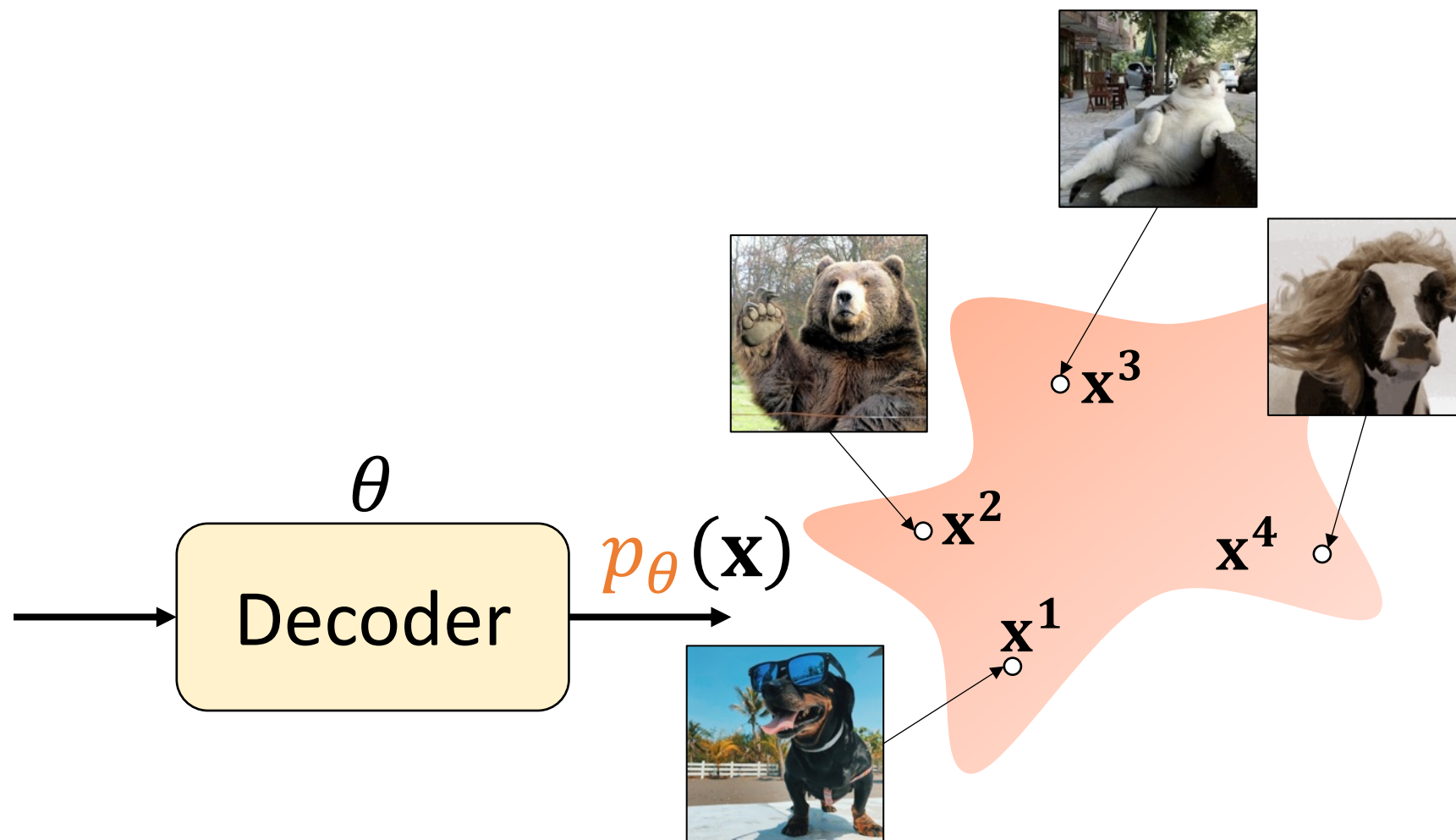
Dataset: $\{\mathbf{x}^1, \mathbf{x}^2, \dots, \mathbf{x}^m\} \sim p_{\text{data}}(\mathbf{x})$





Dataset: $\{\mathbf{x}^1, \mathbf{x}^2, \dots, \mathbf{x}^m\} \sim p_{\text{data}}(\mathbf{x})$

Gaussian
Distribution



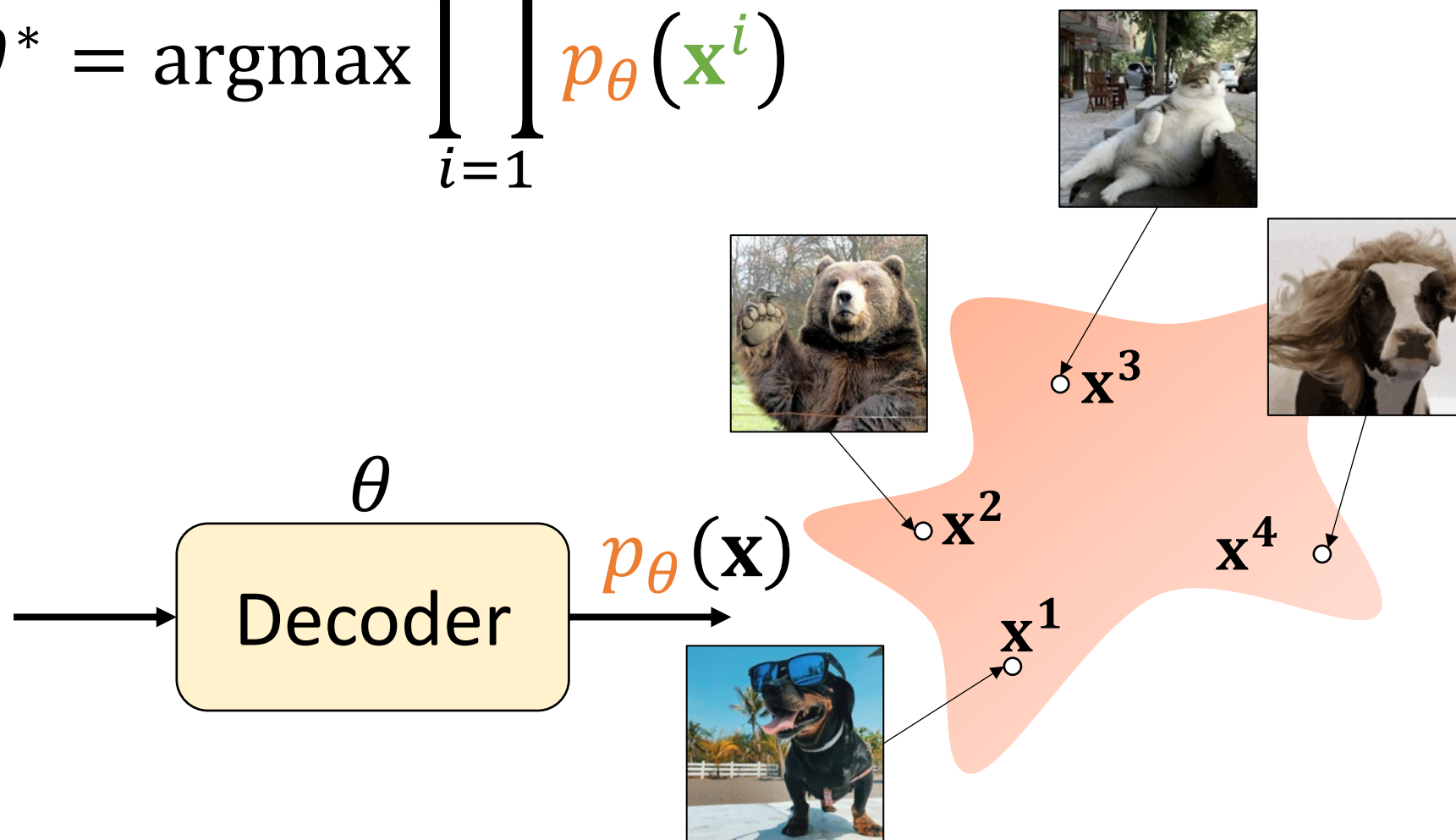


Dataset: $\{\mathbf{x}^1, \mathbf{x}^2, \dots, \mathbf{x}^m\} \sim p_{\text{data}}(\mathbf{x})$

Maximum Likelihood

$$\theta^* = \operatorname{argmax} \prod_{i=1}^m p_{\theta}(\mathbf{x}^i)$$

Gaussian
Distribution

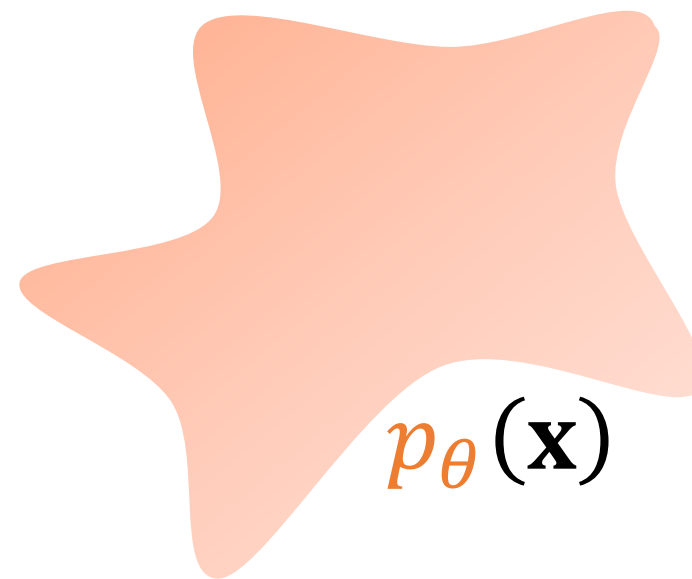
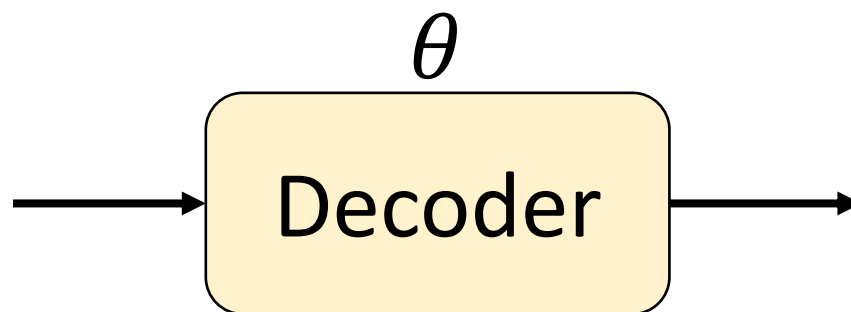




Dataset: $\{\mathbf{x}^1, \mathbf{x}^2, \dots, \mathbf{x}^m\} \sim p_{\text{data}}(\mathbf{x})$

Maximum Likelihood

$$\theta^* = \operatorname{argmax} \prod_{i=1}^m p_{\theta}(\mathbf{x}^i)$$

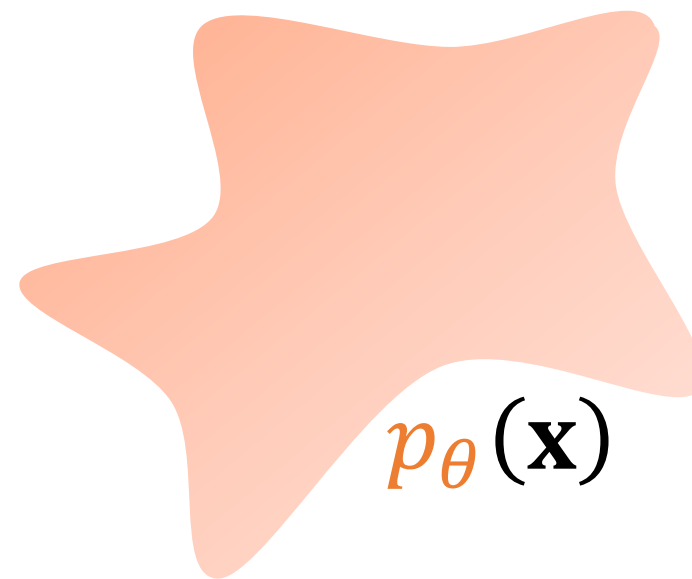
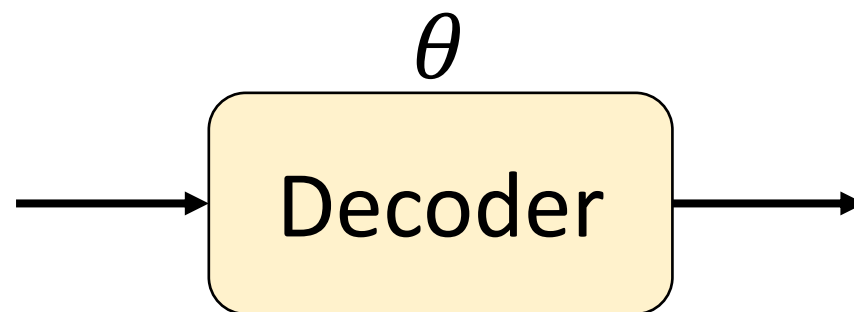




Dataset: $\{\mathbf{x}^1, \mathbf{x}^2, \dots, \mathbf{x}^m\} \sim p_{\text{data}}(\mathbf{x})$

Maximum Likelihood

$$\theta^* = \operatorname{argmax} \prod_{i=1}^m p_{\theta}(\mathbf{x}^i)$$

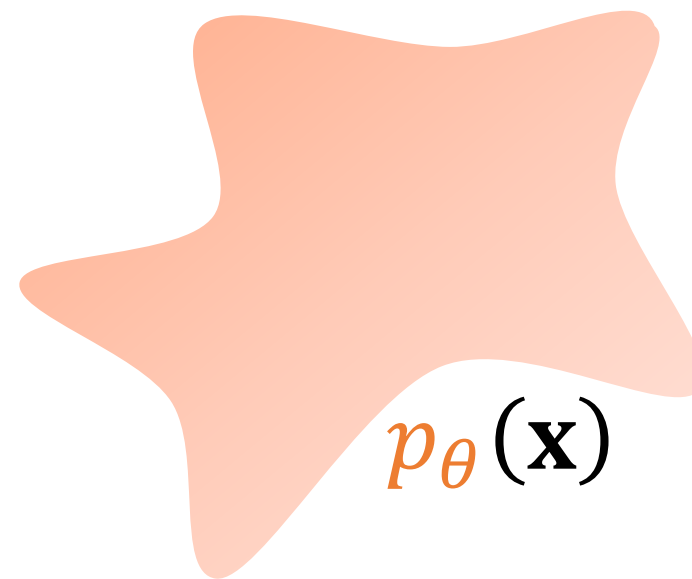
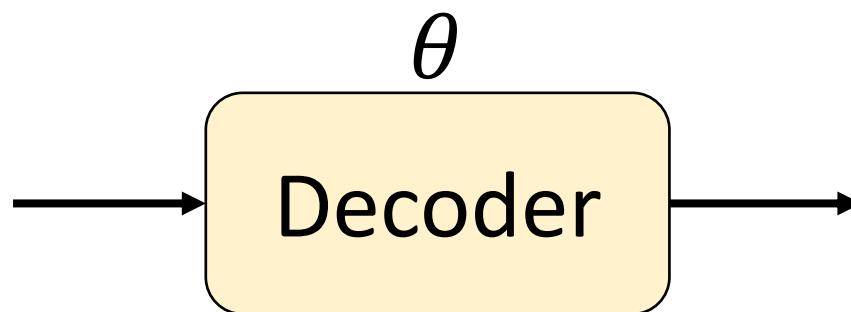




Dataset: $\{\mathbf{x}^1, \mathbf{x}^2, \dots, \mathbf{x}^m\} \sim p_{\text{data}}(\mathbf{x})$

Maximum Likelihood

$$\theta^* = \operatorname{argmax} \log \left(\prod_{i=1}^m p_{\theta}(\mathbf{x}^i) \right)$$

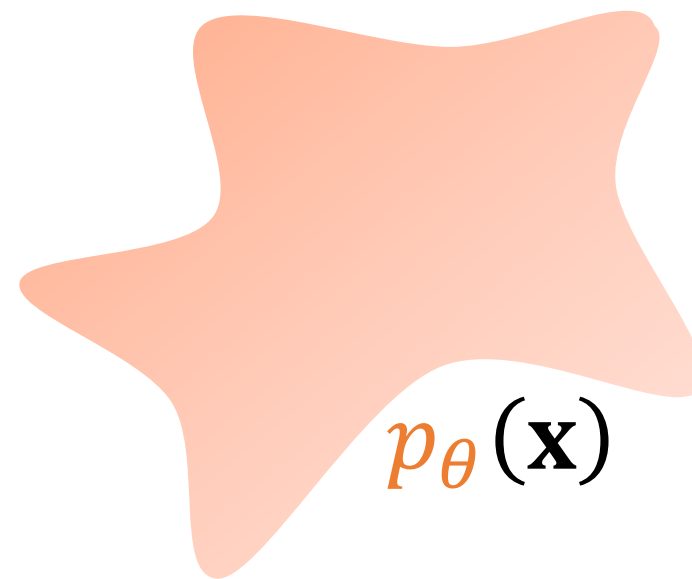
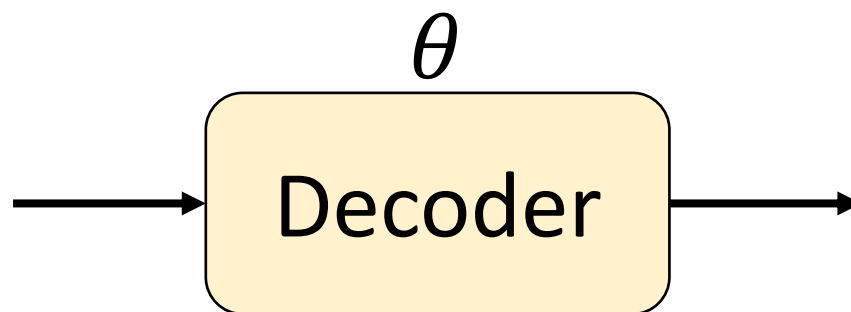




Dataset: $\{\mathbf{x}^1, \mathbf{x}^2, \dots, \mathbf{x}^m\} \sim p_{\text{data}}(\mathbf{x})$

Maximum Likelihood

$$\theta^* = \operatorname{argmax} \sum_{i=1}^m \log p_{\theta}(\mathbf{x}^i)$$

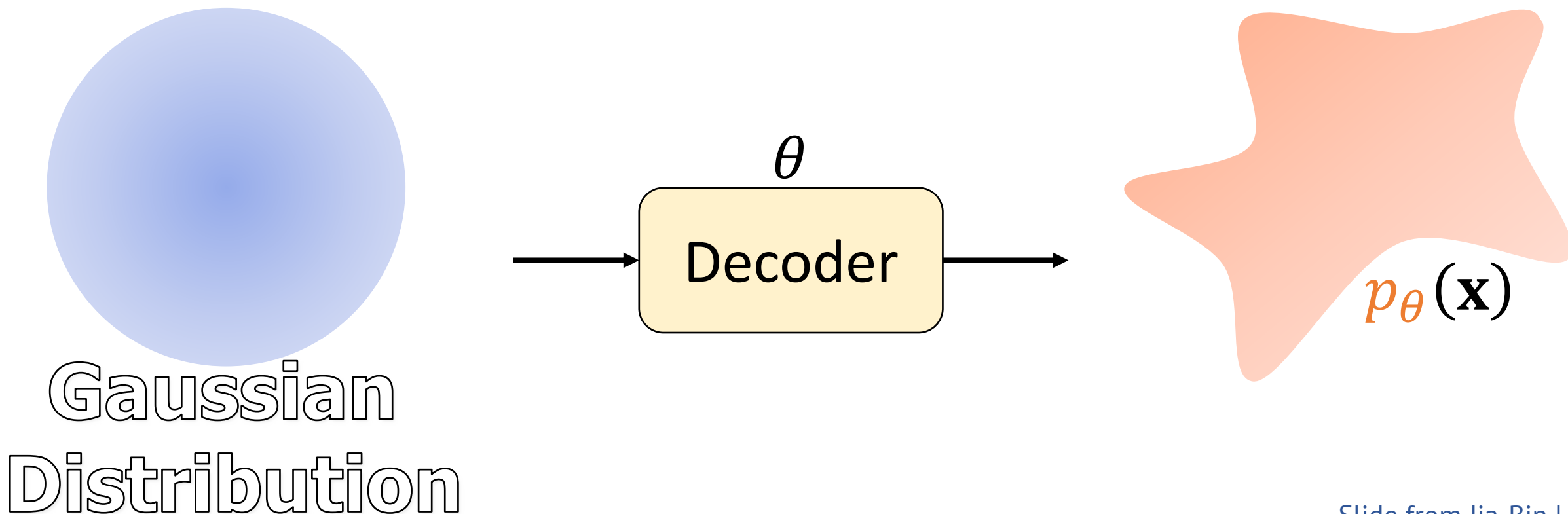




Dataset: $\{\mathbf{x}^1, \mathbf{x}^2, \dots, \mathbf{x}^m\} \sim p_{\text{data}}(\mathbf{x})$

Maximum Likelihood

$$\theta^* \approx \operatorname{argmax} \mathbb{E}_{\mathbf{x} \sim p_{\text{data}}} [\log p_{\theta}(\mathbf{x})]$$

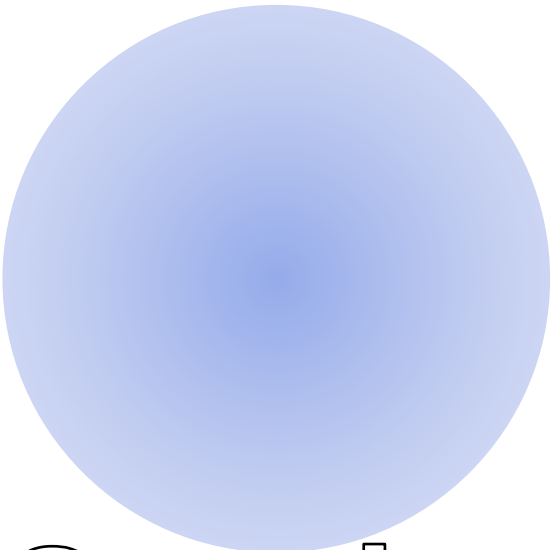




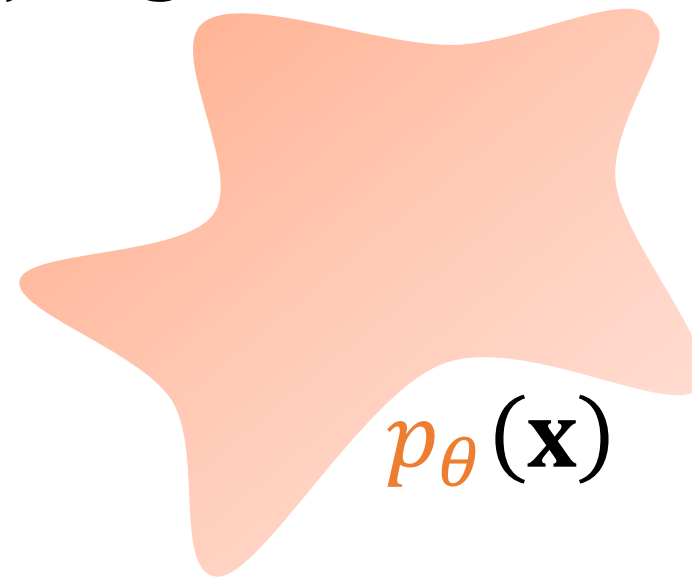
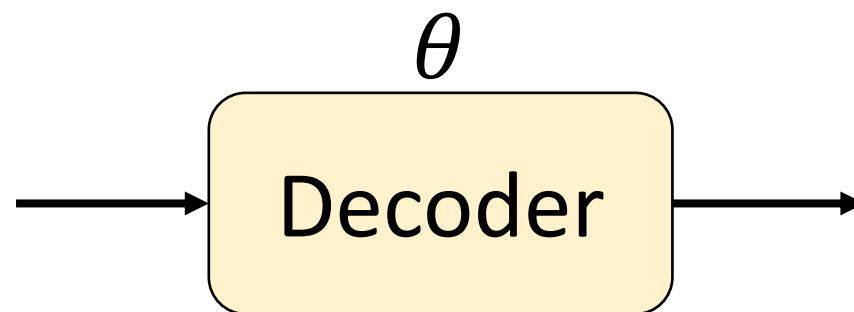
Dataset: $\{\mathbf{x}^1, \mathbf{x}^2, \dots, \mathbf{x}^m\} \sim p_{\text{data}}(\mathbf{x})$

Maximum Likelihood

$$\theta^* \approx \operatorname{argmax} \int p_{\text{data}}(\mathbf{x}) \log p_{\theta}(\mathbf{x}) d\mathbf{x} \\ - \int p_{\text{data}}(\mathbf{x}) \log p_{\text{data}}(\mathbf{x}) d\mathbf{x}$$



Gaussian
Distribution

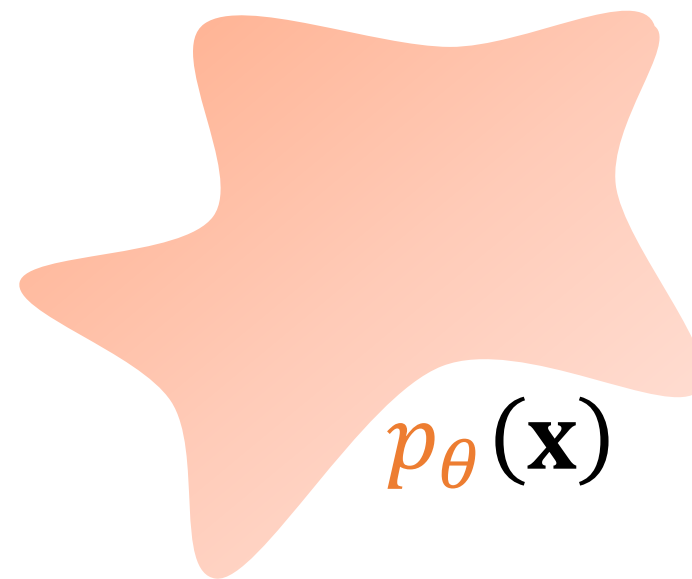
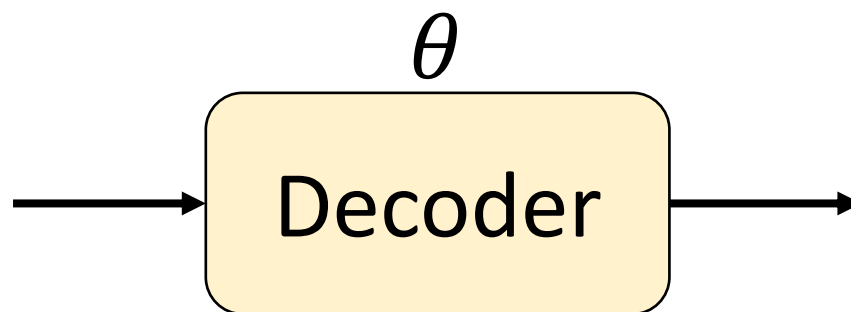




Dataset: $\{\mathbf{x}^1, \mathbf{x}^2, \dots, \mathbf{x}^m\} \sim p_{\text{data}}(\mathbf{x})$

Maximum Likelihood

$$\theta^* \approx \operatorname{argmax} \int p_{\text{data}}(\mathbf{x}) \log \frac{p_{\theta}(\mathbf{x})}{p_{\text{data}}(\mathbf{x})} d\mathbf{x}$$

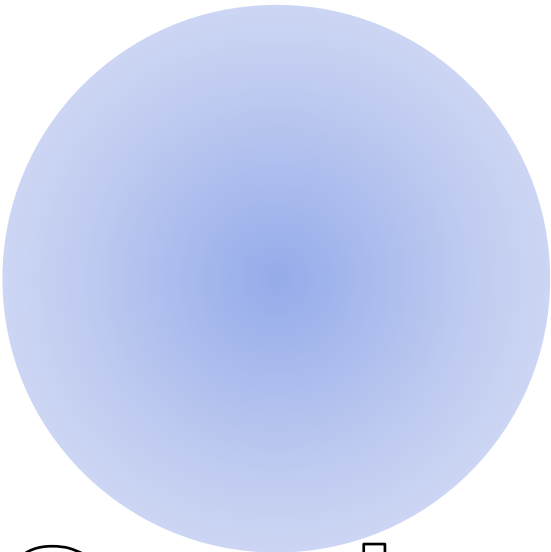




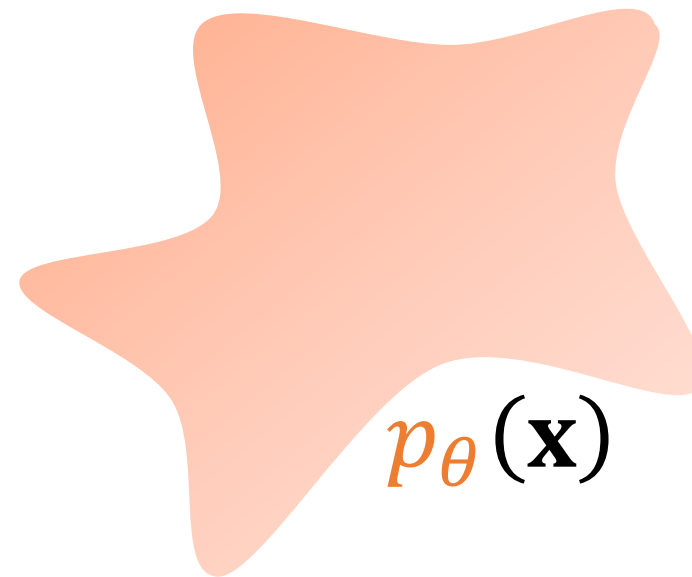
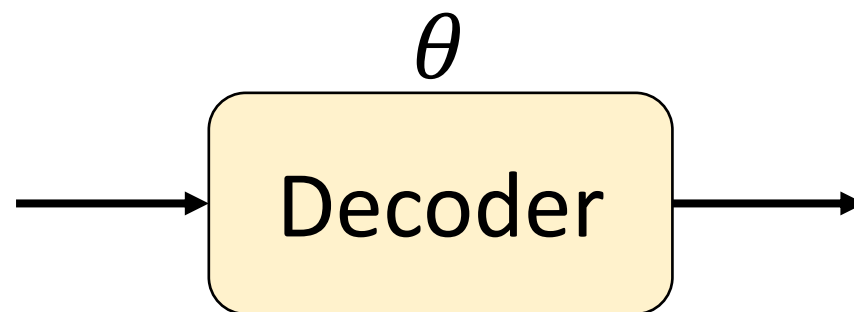
Dataset: $\{\mathbf{x}^1, \mathbf{x}^2, \dots, \mathbf{x}^m\} \sim p_{\text{data}}(\mathbf{x})$

Maximum Likelihood

$$\begin{aligned}\theta^* &\approx \operatorname{argmin} \int p_{\text{data}}(\mathbf{x}) \log \frac{p_{\text{data}}(\mathbf{x})}{p_{\theta}(\mathbf{x})} d\mathbf{x} \\ &= \operatorname{argmin} D_{\text{KL}}(p_{\text{data}} || p_{\theta})\end{aligned}$$

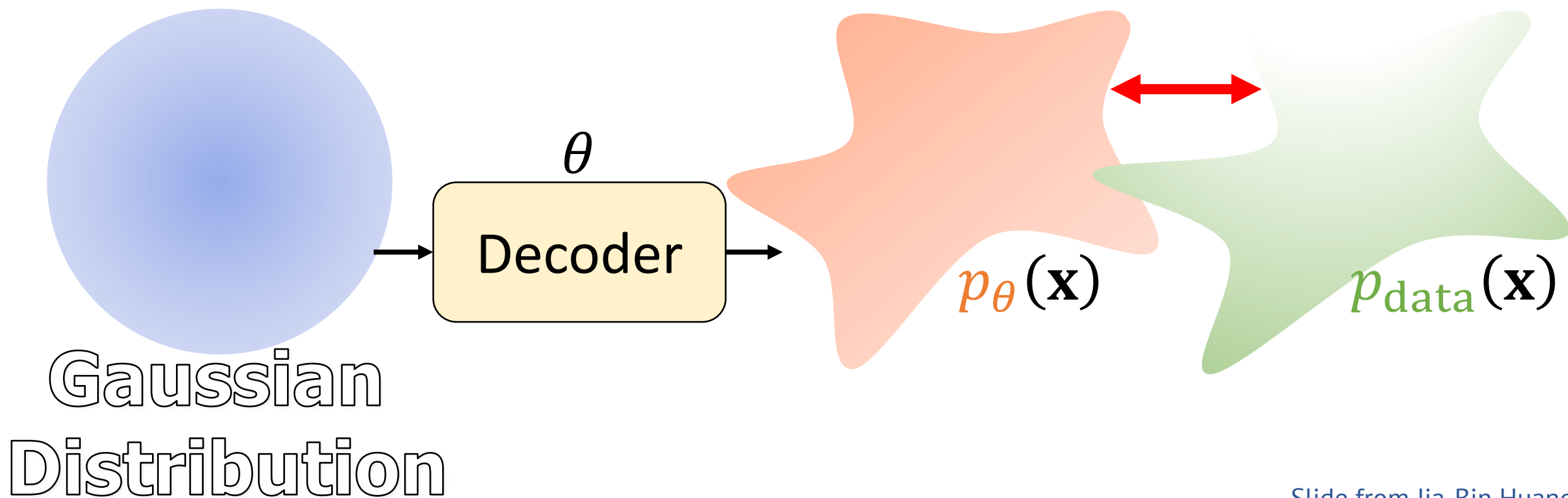


Gaussian
Distribution



Maximum Likelihood

$$\theta^* \approx \operatorname{argmin} \int p_{\text{data}}(\mathbf{x}) \log \frac{p_{\text{data}}(\mathbf{x})}{p_{\theta}(\mathbf{x})} d\mathbf{x}$$
$$= \operatorname{argmin} D_{\text{KL}}(p_{\text{data}} || p_{\theta})$$





$$\log p(\mathbf{x}) = \log \int p(\mathbf{x}, \mathbf{z}) d\mathbf{z}$$

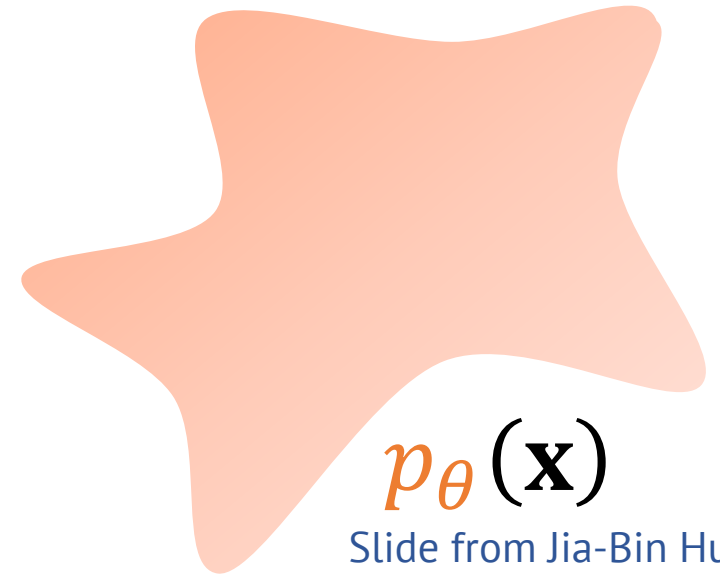
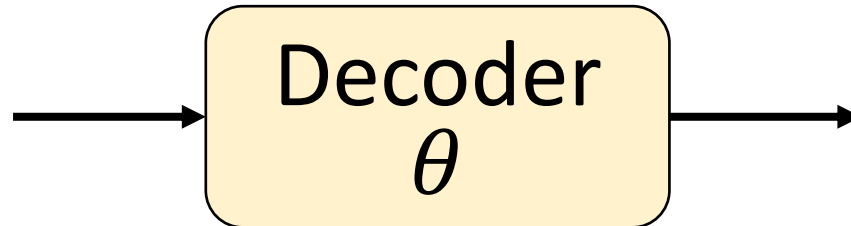
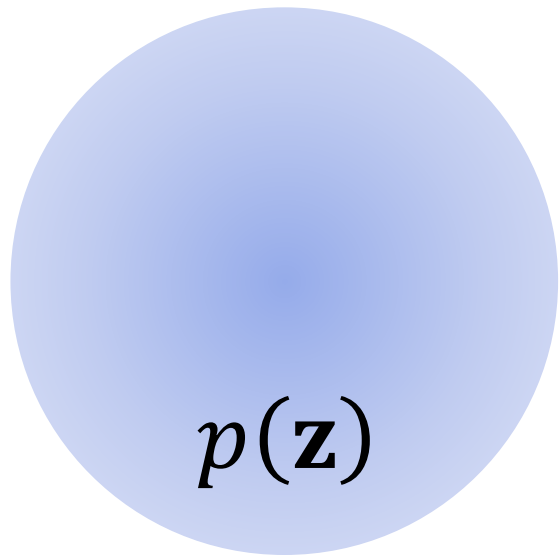


Integrating out all latent variables $\mathbf{z}$

$$\log p(\mathbf{x}) = \log \frac{p(\mathbf{x}, \mathbf{z})}{p(\mathbf{z}|\mathbf{x})}$$



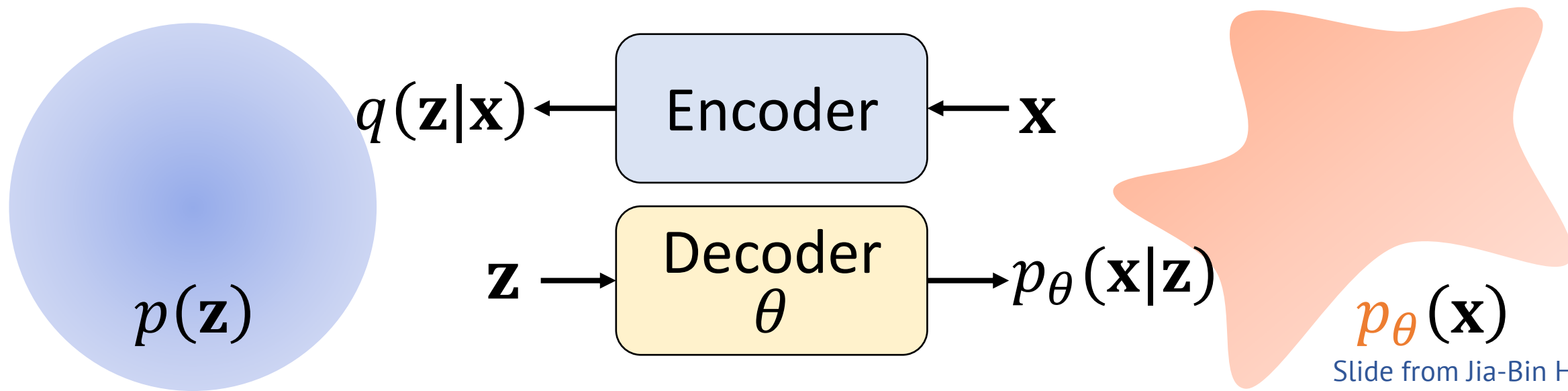
Assuming we know latent encoder $p(\mathbf{z}|\mathbf{x})$



$p_{\theta}(\mathbf{x})$



$$\log p(\mathbf{x}) = \log p(\mathbf{x}) \int q(\mathbf{z}|\mathbf{x}) d\mathbf{z}$$





$$\log p(\mathbf{x}) = \log p(\mathbf{x}) \int q(\mathbf{z}|\mathbf{x}) \, d\mathbf{z}$$



$$\log p(\mathbf{x}) = \int q(\mathbf{z}|\mathbf{x}) \log p(\mathbf{x}) \, d\mathbf{z}$$



$$\log p(\mathbf{x}) = \mathbb{E}_{q(\mathbf{z}|\mathbf{x})}[\log p(\mathbf{x})]$$



$$\log p(\mathbf{x}) = \mathbb{E}_{q(\mathbf{z}|\mathbf{x})} \left[\log \frac{p(\mathbf{x}, \mathbf{z})}{p(\mathbf{z}|\mathbf{x})} \right]$$



$$\log p(\mathbf{x}) = \mathbb{E}_{q(\mathbf{z}|\mathbf{x})} \left[\log \frac{p(\mathbf{x}, \mathbf{z})}{p(\mathbf{z}|\mathbf{x})} \frac{q(\mathbf{z}|\mathbf{x})}{q(\mathbf{z}|\mathbf{x})} \right]$$



$$\log p(\mathbf{x}) = \mathbb{E}_{q(\mathbf{z}|\mathbf{x})} \left[\log \frac{p(\mathbf{x}, \mathbf{z})}{q(\mathbf{z}|\mathbf{x})} \frac{q(\mathbf{z}|\mathbf{x})}{p(\mathbf{z}|\mathbf{x})} \right]$$



$$\log p(\mathbf{x}) = \mathbb{E}_{q(\mathbf{z}|\mathbf{x})} \left[\log \frac{p(\mathbf{x}, \mathbf{z})}{q(\mathbf{z}|\mathbf{x})} \right] + \mathbb{E}_{q(\mathbf{z}|\mathbf{x})} \left[\log \frac{q(\mathbf{z}|\mathbf{x})}{p(\mathbf{z}|\mathbf{x})} \right]$$



$$\log p(\mathbf{x}) = \mathbb{E}_{q(\mathbf{z}|\mathbf{x})} \left[\log \frac{p(\mathbf{x}, \mathbf{z})}{q(\mathbf{z}|\mathbf{x})} \right] + D_{\text{KL}}(q(\mathbf{z}|\mathbf{x}) || p(\mathbf{z}|\mathbf{x}))$$



$$\log p(\mathbf{x}) = \mathbb{E}_{q(\mathbf{z}|\mathbf{x})} \left[\log \frac{p(\mathbf{x}, \mathbf{z})}{q(\mathbf{z}|\mathbf{x})} \right] + \underbrace{D_{\text{KL}}(q(\mathbf{z}|\mathbf{x}) || p(\mathbf{z}|\mathbf{x}))}_{\geq 0}$$



$$\log p(\mathbf{x}) \geq \mathbb{E}_{q(\mathbf{z}|\mathbf{x})} \left[\log \frac{p(\mathbf{x}, \mathbf{z})}{q(\mathbf{z}|\mathbf{x})} \right]$$



$$\log p(\mathbf{x}) \geq \mathbb{E}_{q(\mathbf{z}|\mathbf{x})} \left[\log \frac{p(\mathbf{x}, \mathbf{z})}{q(\mathbf{z}|\mathbf{x})} \right]$$

Evidence Evidence Lower Bound



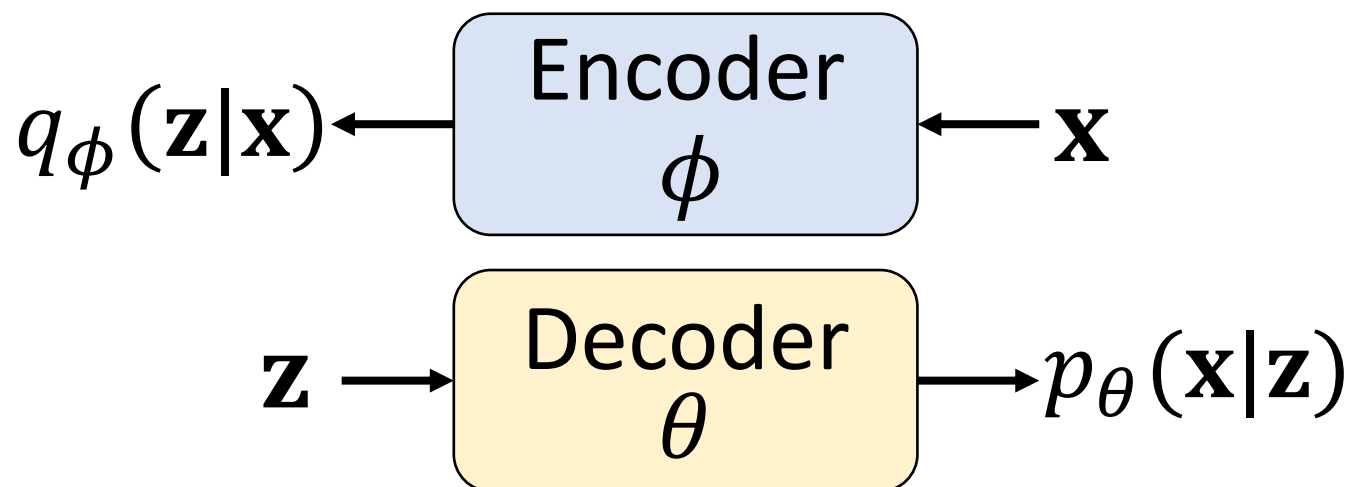
$$\log p(\mathbf{x}) \geq \mathbb{E}_{q(\mathbf{z}|\mathbf{x})} \left[\log \frac{p(\mathbf{x}, \mathbf{z})}{q(\mathbf{z}|\mathbf{x})} \right]$$

Evidence Evidence Lower Bound (ELBO)



$$\log p(\mathbf{x}) \geq \mathbb{E}_{q(\mathbf{z}|\mathbf{x})} \left[\log \frac{p(\mathbf{x}, \mathbf{z})}{q(\mathbf{z}|\mathbf{x})} \right]$$

Evidence Evidence Lower Bound (ELBO)





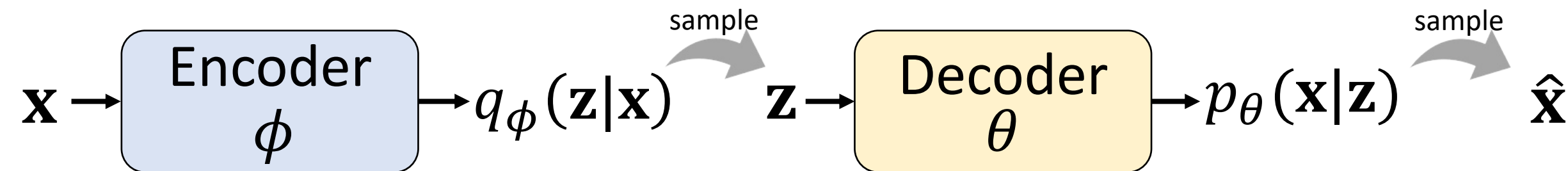
$$\log p(\mathbf{x}) \geq \mathbb{E}_{q(\mathbf{z}|\mathbf{x})} \left[\log \frac{p(\mathbf{x}, \mathbf{z})}{q(\mathbf{z}|\mathbf{x})} \right] \quad (\text{ELBO})$$

$$\begin{aligned} \mathbb{E}_{q_\phi(\mathbf{z}|\mathbf{x})} \left[\log \frac{p(\mathbf{x}, \mathbf{z})}{q_\phi(\mathbf{z}|\mathbf{x})} \right] &= \mathbb{E}_{q_\phi(\mathbf{z}|\mathbf{x})} \left[\log \frac{p_\theta(\mathbf{x}|\mathbf{z})p(\mathbf{z})}{q_\phi(\mathbf{z}|\mathbf{x})} \right] \\ &= \mathbb{E}_{q_\phi(\mathbf{z}|\mathbf{x})} [\log p_\theta(\mathbf{x}|\mathbf{z})] + \mathbb{E}_{q_\phi(\mathbf{z}|\mathbf{x})} \left[\log \frac{p(\mathbf{z})}{q_\phi(\mathbf{z}|\mathbf{x})} \right] \\ &= \underbrace{\mathbb{E}_{q_\phi(\mathbf{z}|\mathbf{x})} [\log p_\theta(\mathbf{x}|\mathbf{z})]}_{\text{Reconstruction term}} - \underbrace{D_{\text{KL}}(q_\phi(\mathbf{z}|\mathbf{x}) \parallel p(\mathbf{z}))}_{\text{Regularization term}} \end{aligned}$$

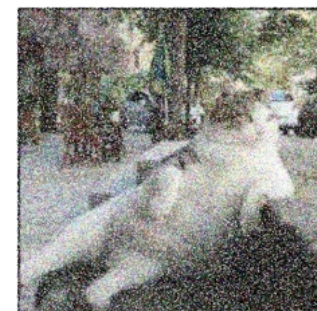
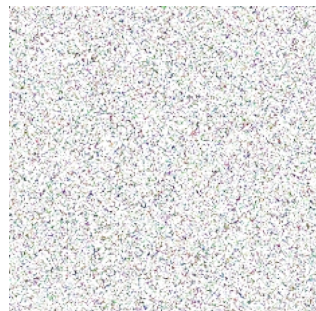
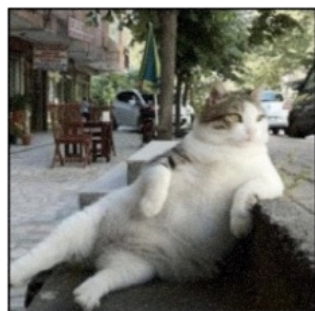
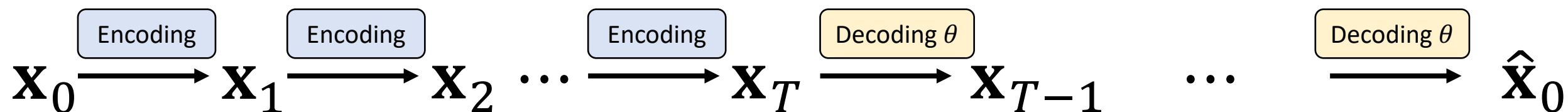
$$\|\mathbf{x} - \hat{\mathbf{x}}\|_2 = \|\mathbf{x} - DE(EN(\mathbf{z}))\|_2 - \frac{1}{2} \sum_{j=0}^{k-1} (\sigma_j + \mu_j^2 - 1 - \log \sigma_j)$$



Variational Autoencoder (VAE)

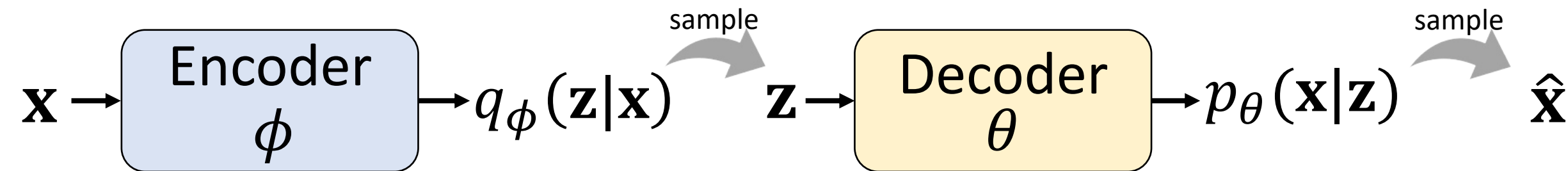


Diffusion models





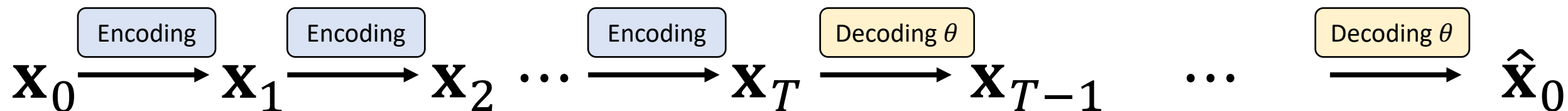
Variational Autoencoder (VAE)



Observed $\mathbf{x}$
Latent $\mathbf{z}$

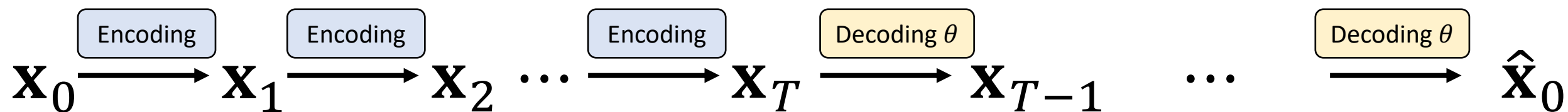
Maximize $\mathbb{E}_{q(\mathbf{z}|\mathbf{x})} \left[\log \frac{p(\mathbf{x}, \mathbf{z})}{q(\mathbf{z}|\mathbf{x})} \right]$

Diffusion models



Observed $\mathbf{x}_0$
Latent $\mathbf{x}_1, \dots, \mathbf{x}_T$

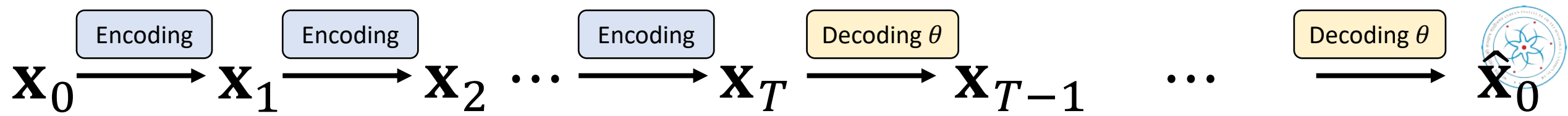
Maximize $\mathbb{E}_{q(\mathbf{x}_1:\mathbf{x}_T|\mathbf{x}_0)} \left[\log \frac{p(\mathbf{x}_0:\mathbf{x}_T)}{q(\mathbf{x}_1:\mathbf{x}_T|\mathbf{x}_0)} \right]$



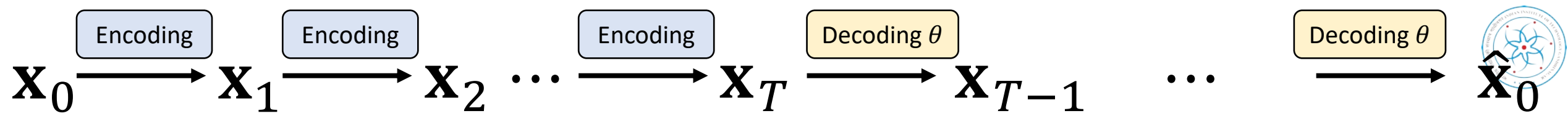
Observed $\mathbf{x}_0$

Latent $\mathbf{x}_1, \dots, \mathbf{x}_T$

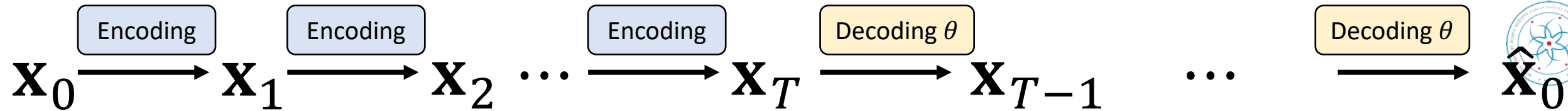
Maximize $\mathbb{E}_{q(\mathbf{x}_1:\mathbf{x}_T|\mathbf{x}_0)} \left[\log \frac{p(\mathbf{x}_0:\mathbf{x}_T)}{q(\mathbf{x}_1:\mathbf{x}_T|\mathbf{x}_0)} \right]$



$$\text{Maximize } \mathbb{E}_{q(\mathbf{x}_1:\mathbf{x}_T|\mathbf{x}_0)} \left[\log \frac{p(\mathbf{x}_0:\mathbf{x}_T)}{q(\mathbf{x}_1:\mathbf{x}_T|\mathbf{x}_0)} \right]$$



$$\text{Maximize } \mathbb{E}_{q(\mathbf{x}_1:\mathbf{x}_T|\mathbf{x}_0)} \left[\log \frac{p(\mathbf{x}_0:\mathbf{x}_T)}{q(\mathbf{x}_1:\mathbf{x}_T|\mathbf{x}_0)} \right]$$



Maximize $\mathbb{E}_{q(\mathbf{x}_1:\mathbf{x}_T|\mathbf{x}_0)} \left[\log \frac{p(\mathbf{x}_0:\mathbf{x}_T)}{q(\mathbf{x}_1:\mathbf{x}_T|\mathbf{x}_0)} \right]$

$q(\mathbf{x}_1:\mathbf{x}_T|\mathbf{x}_0) = \prod_{t=1}^T q(\mathbf{x}_t|\mathbf{x}_{t-1})$

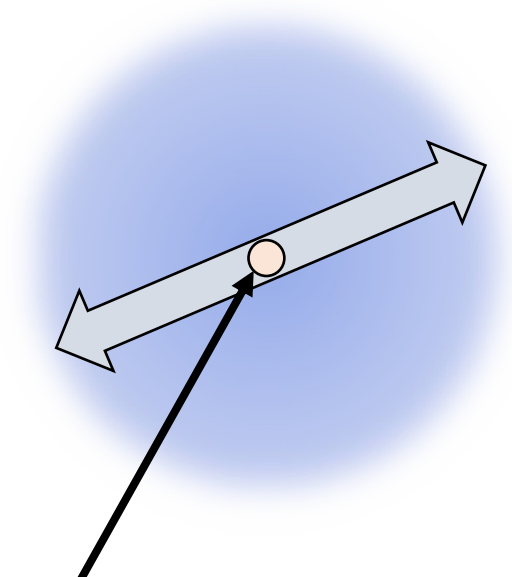
Encoding

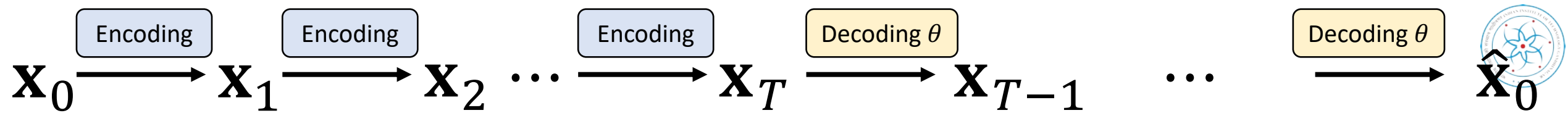


$q(\mathbf{x}_t|\mathbf{x}_{t-1})$

Encoding

$= \mathcal{N}(\mathbf{x}_t; \underbrace{\sqrt{\alpha_t} \mathbf{x}_{t-1}}_{\text{Mean}}, \underbrace{(1 - \alpha_t) \mathbf{I}}_{\text{Variance}})$



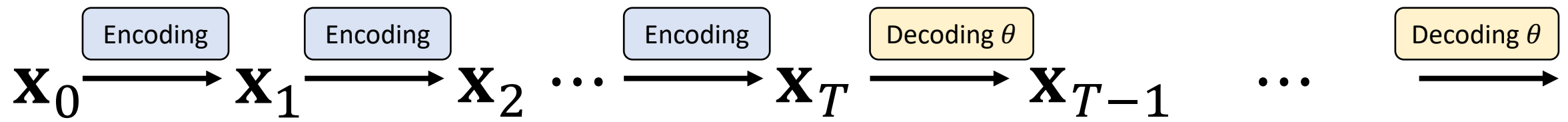


$$\mathbb{E}_{q(\mathbf{x}_1:\mathbf{x}_T|\mathbf{x}_0)} \left[\log \frac{p(\mathbf{x}_0:\mathbf{x}_T)}{q(\mathbf{x}_1:\mathbf{x}_T|\mathbf{x}_0)} \right]$$

① $-D_{\text{KL}}(q(\mathbf{x}_T|\mathbf{x}_0)||p(\mathbf{x}_T))$ **Prior matching**

② $\mathbb{E}_{q(\mathbf{x}_1|\mathbf{x}_0)} [\log p_\theta(\mathbf{x}_0|\mathbf{x}_1)]$ **Reconstruction**

③ $-\sum_{t=2}^T \mathbb{E}_{q(\mathbf{x}_t|\mathbf{x}_0)} [D_{\text{KL}}(q(\mathbf{x}_{t-1}|\mathbf{x}_t, \mathbf{x}_0)||p_\theta(\mathbf{x}_{t-1}|\mathbf{x}_t))] \mathbf{Denoising matching}$

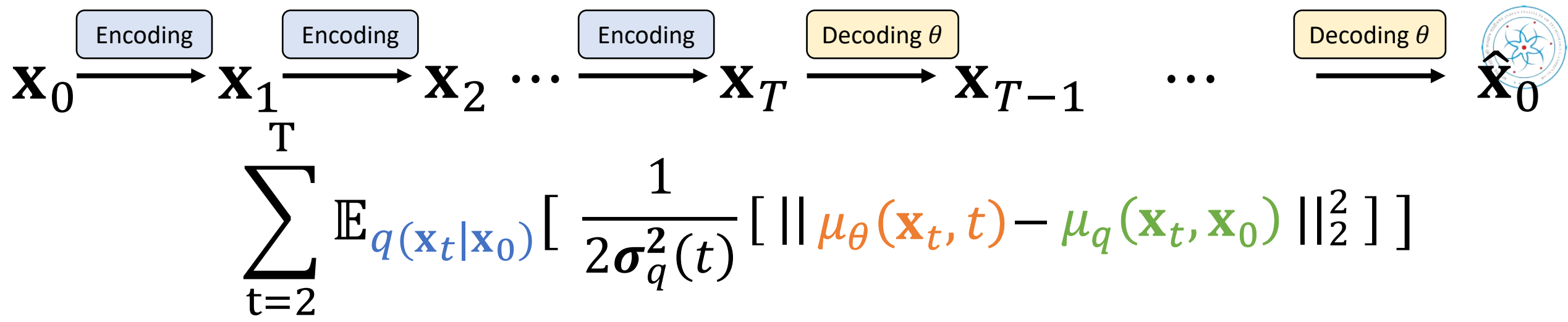


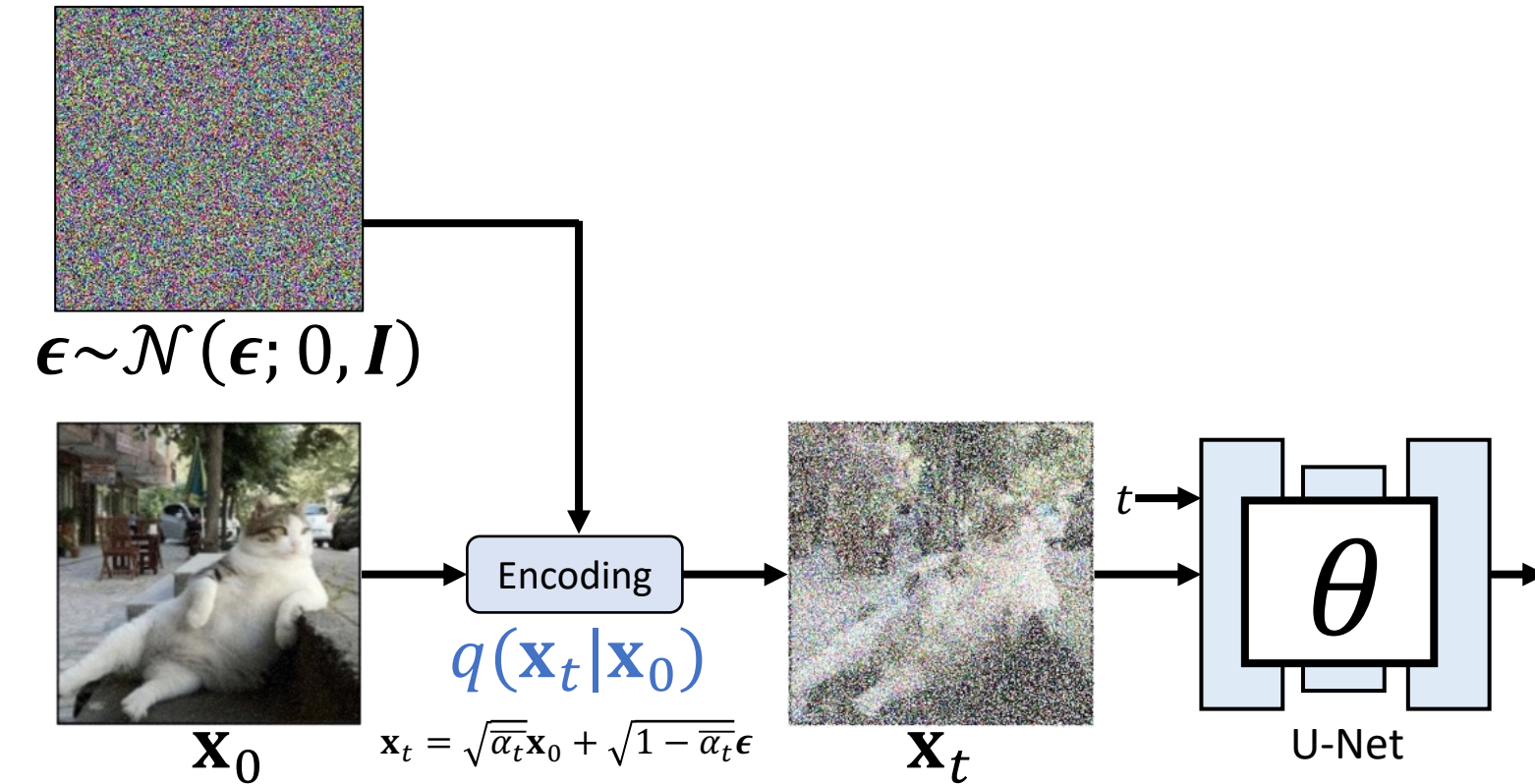
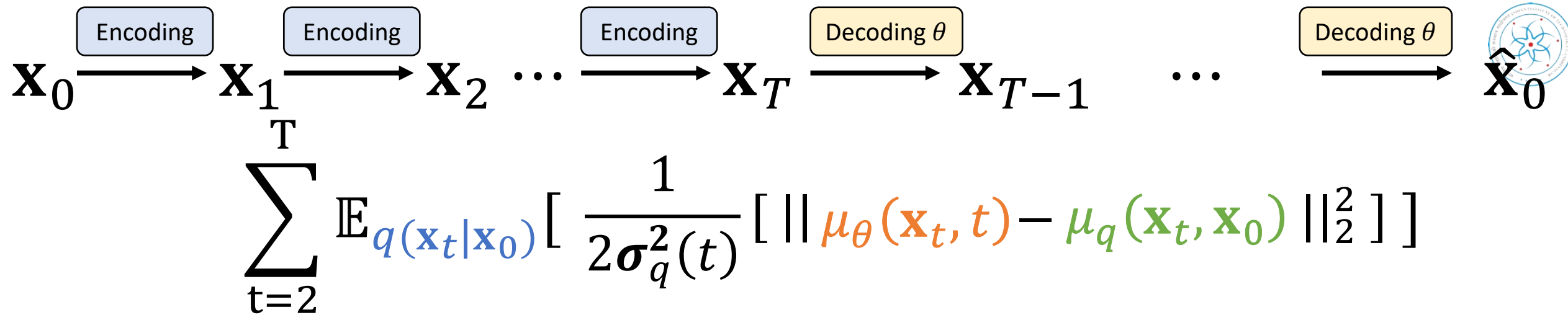
$$\mathbb{E}_{q(\mathbf{x}_1:\mathbf{x}_T|\mathbf{x}_0)} \left[\log \frac{p(\mathbf{x}_0:\mathbf{x}_T)}{q(\mathbf{x}_1:\mathbf{x}_T|\mathbf{x}_0)} \right]$$

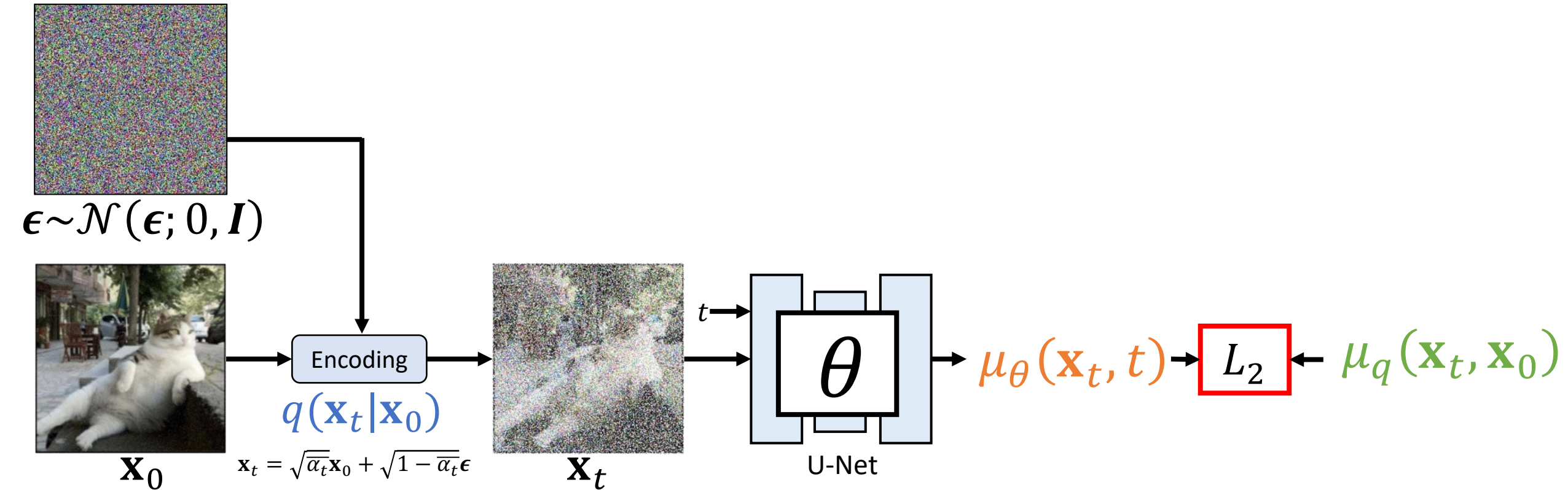
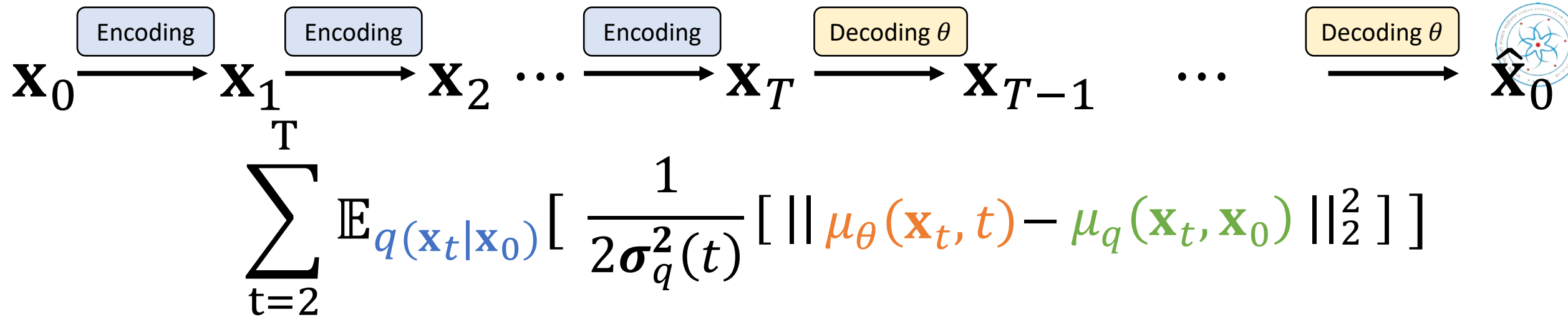
① $-D_{\text{KL}}(q(\mathbf{x}_T|\mathbf{x}_0)||p(\mathbf{x}_T))$ **Prior matching**

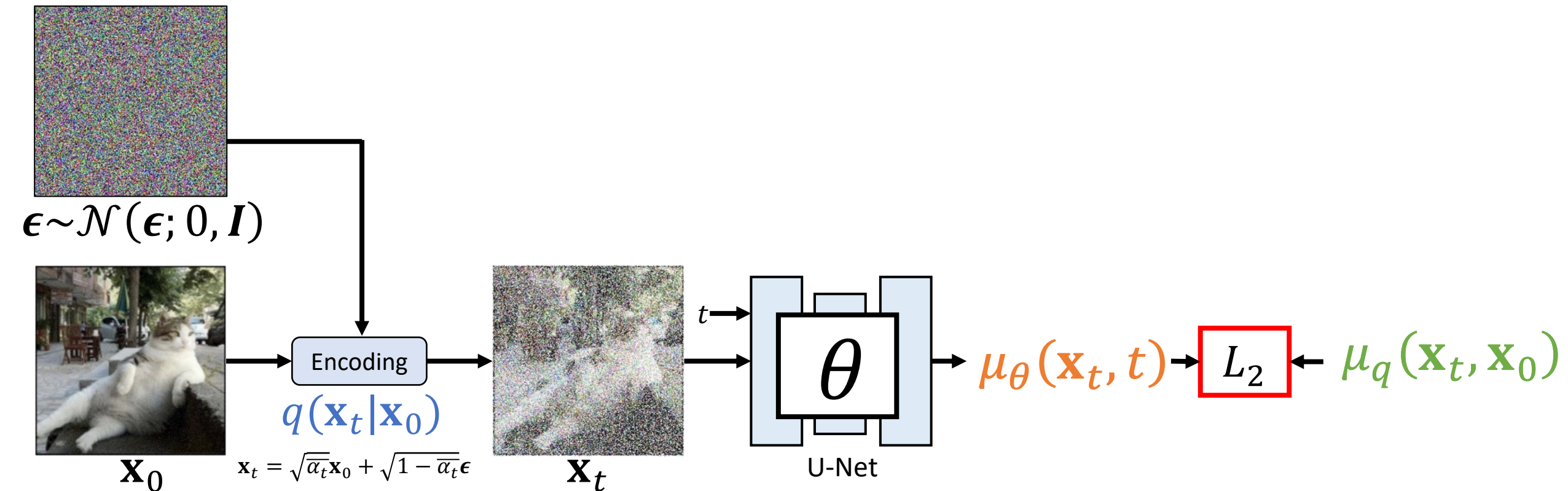
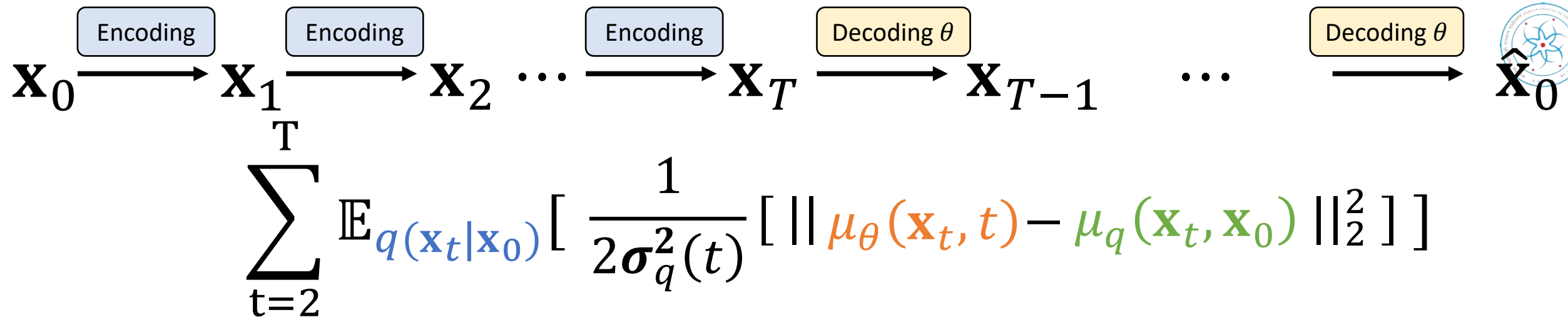
② $\mathbb{E}_{q(\mathbf{x}_1|\mathbf{x}_0)} [\log p_{\theta}(\mathbf{x}_0|\mathbf{x}_1)]$ **Reconstruction**

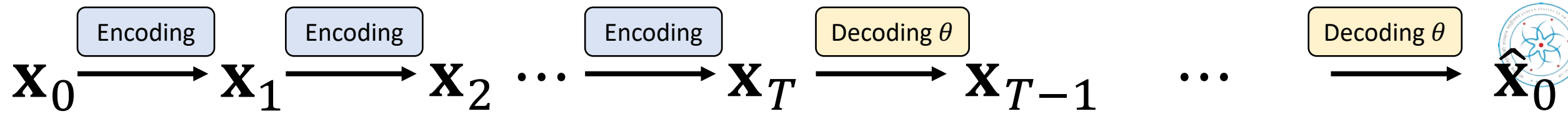
③ $-\sum_{t=2}^T \mathbb{E}_{q(\mathbf{x}_t|\mathbf{x}_0)} [D_{\text{KL}}(q(\mathbf{x}_{t-1}|\mathbf{x}_t, \mathbf{x}_0)||p_{\theta}(\mathbf{x}_{t-1}|\mathbf{x}_t))] \mathbf{Denoising matching}$





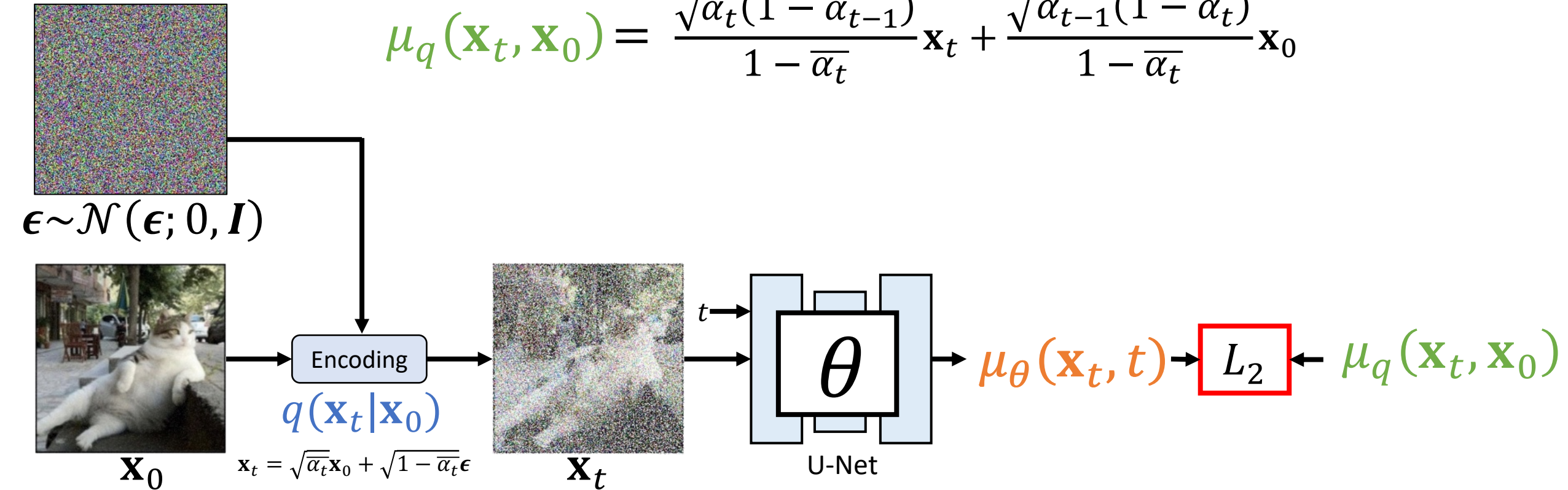


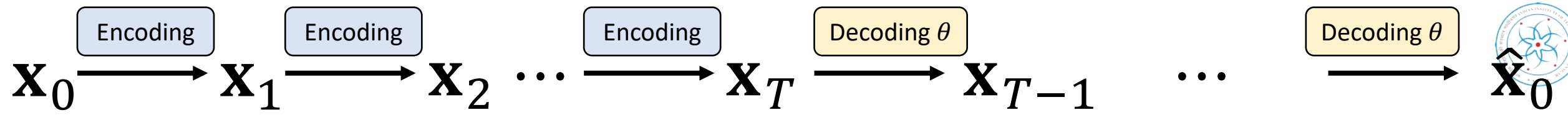




$$\sum_{t=2}^T \mathbb{E}_{q(\mathbf{x}_t|\mathbf{x}_0)} \left[\frac{1}{2\sigma_q^2(t)} \left[\|\mu_{\theta}(\mathbf{x}_t, t) - \mu_q(\mathbf{x}_t, \mathbf{x}_0)\|_2^2 \right] \right]$$

$$\mu_q(\mathbf{x}_t, \mathbf{x}_0) = \frac{\sqrt{\alpha_t}(1 - \bar{\alpha}_{t-1})}{1 - \bar{\alpha}_t} \mathbf{x}_t + \frac{\sqrt{\bar{\alpha}_{t-1}}(1 - \alpha_t)}{1 - \bar{\alpha}_t} \mathbf{x}_0$$

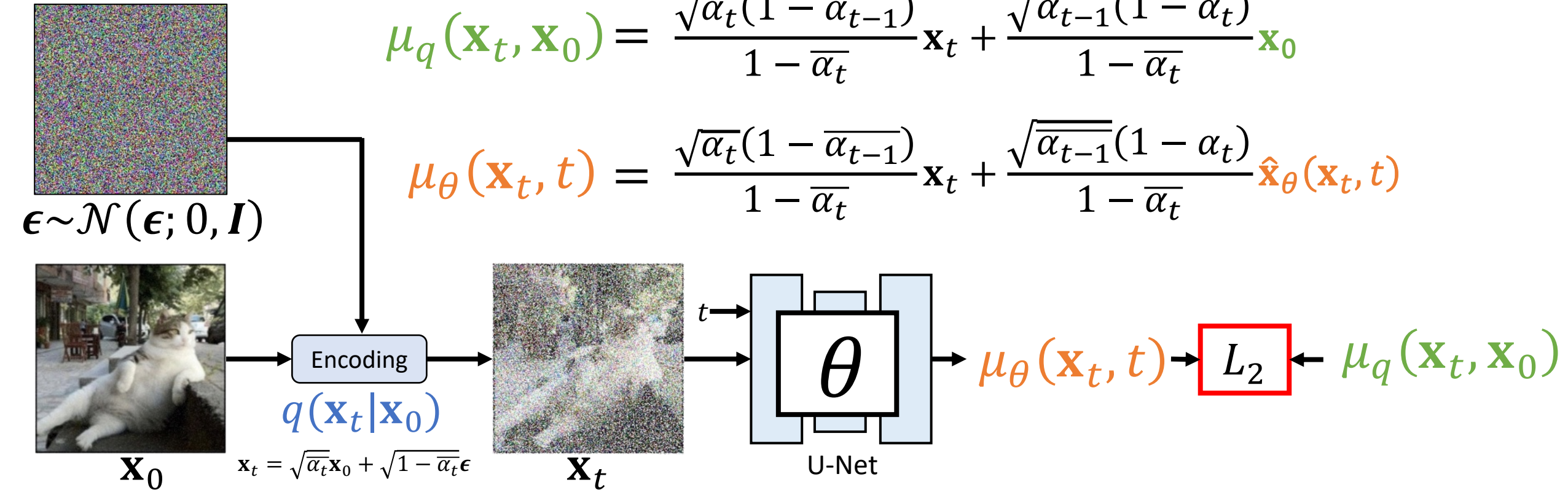


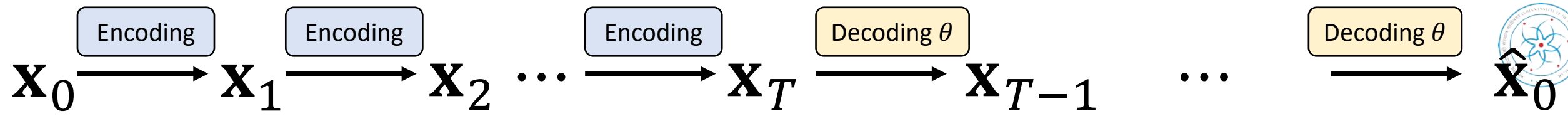


$$\sum_{t=2}^T \mathbb{E}_{q(\mathbf{x}_t|\mathbf{x}_0)} \left[\frac{1}{2\sigma_q^2(t)} \left[\|\mu_\theta(\mathbf{x}_t, t) - \mu_q(\mathbf{x}_t, \mathbf{x}_0)\|_2^2 \right] \right]$$

$$\mu_q(\mathbf{x}_t, \mathbf{x}_0) = \frac{\sqrt{\alpha_t}(1 - \bar{\alpha}_{t-1})}{1 - \bar{\alpha}_t} \mathbf{x}_t + \frac{\sqrt{\bar{\alpha}_{t-1}}(1 - \alpha_t)}{1 - \bar{\alpha}_t} \mathbf{x}_0$$

$$\mu_\theta(\mathbf{x}_t, t) = \frac{\sqrt{\alpha_t}(1 - \bar{\alpha}_{t-1})}{1 - \bar{\alpha}_t} \mathbf{x}_t + \frac{\sqrt{\bar{\alpha}_{t-1}}(1 - \alpha_t)}{1 - \bar{\alpha}_t} \hat{\mathbf{x}}_\theta(\mathbf{x}_t, t)$$

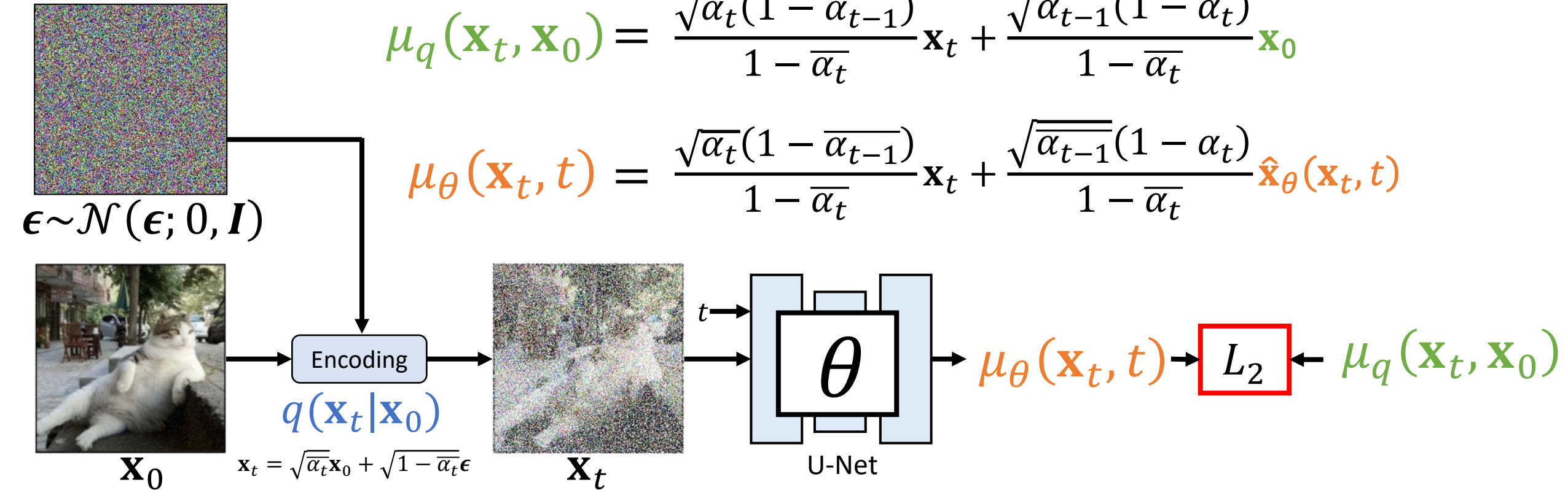


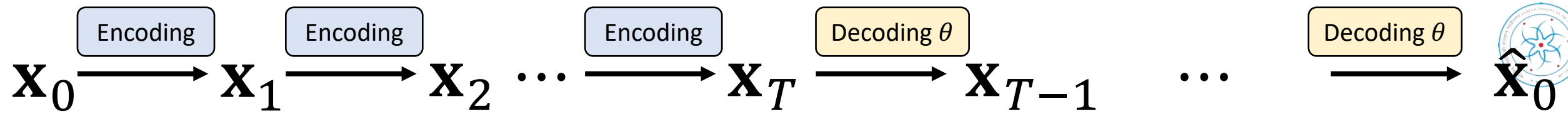


$$\sum_{t=2}^T \mathbb{E}_{q(\mathbf{x}_t|\mathbf{x}_0)} \left[\frac{1}{2\sigma_q^2(t)} \left[\|\mu_{\theta}(\mathbf{x}_t, t) - \mu_q(\mathbf{x}_t, \mathbf{x}_0)\|_2^2 \right] \right]$$

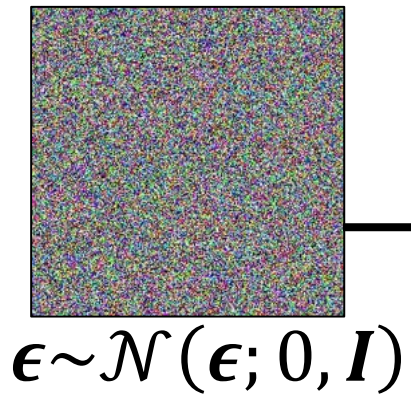
$$\mu_q(\mathbf{x}_t, \mathbf{x}_0) = \frac{\sqrt{\alpha_t}(1 - \bar{\alpha}_{t-1})}{1 - \bar{\alpha}_t} \mathbf{x}_t + \frac{\sqrt{\bar{\alpha}_{t-1}}(1 - \alpha_t)}{1 - \bar{\alpha}_t} \mathbf{x}_0$$

$$\mu_{\theta}(\mathbf{x}_t, t) = \frac{\sqrt{\alpha_t}(1 - \bar{\alpha}_{t-1})}{1 - \bar{\alpha}_t} \mathbf{x}_t + \frac{\sqrt{\bar{\alpha}_{t-1}}(1 - \alpha_t)}{1 - \bar{\alpha}_t} \hat{\mathbf{x}}_{\theta}(\mathbf{x}_t, t)$$



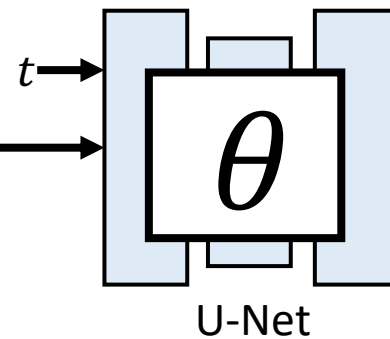
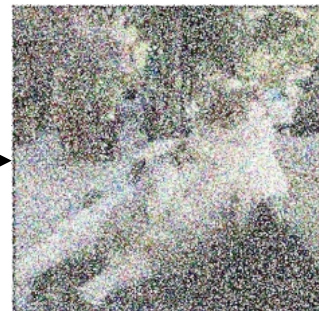
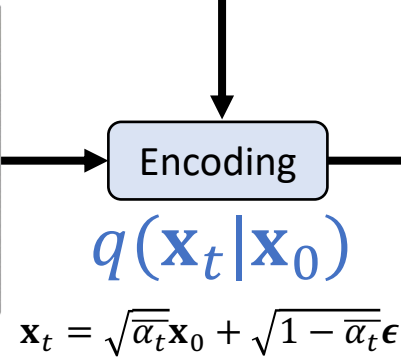


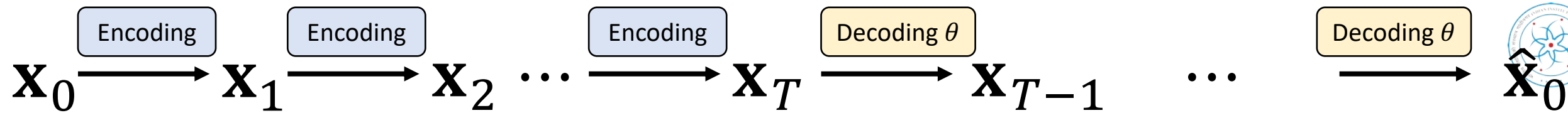
$$\sum_{t=2}^T \mathbb{E}_{q(\mathbf{x}_t|\mathbf{x}_0)} [w(t) [|| \hat{\mathbf{x}}_{\theta}(\mathbf{x}_t, t) - \mathbf{x}_0 ||_2^2]]$$



$$\mu_q(\mathbf{x}_t, \mathbf{x}_0) = \frac{\sqrt{\alpha_t}(1 - \bar{\alpha}_{t-1})}{1 - \bar{\alpha}_t} \mathbf{x}_t + \frac{\sqrt{\bar{\alpha}_{t-1}}(1 - \alpha_t)}{1 - \bar{\alpha}_t} \mathbf{x}_0$$

$$\mu_{\theta}(\mathbf{x}_t, t) = \frac{\sqrt{\alpha_t}(1 - \bar{\alpha}_{t-1})}{1 - \bar{\alpha}_t} \mathbf{x}_t + \frac{\sqrt{\bar{\alpha}_{t-1}}(1 - \alpha_t)}{1 - \bar{\alpha}_t} \hat{\mathbf{x}}_{\theta}(\mathbf{x}_t, t)$$

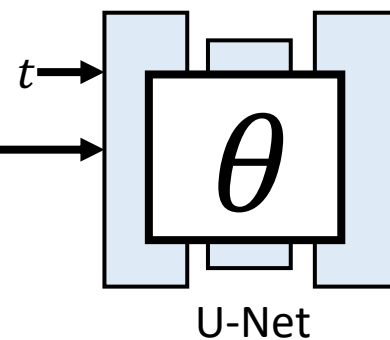
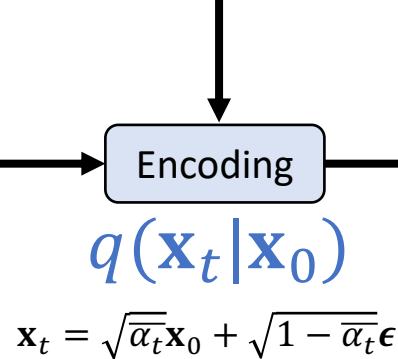
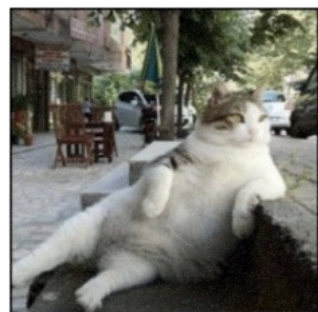
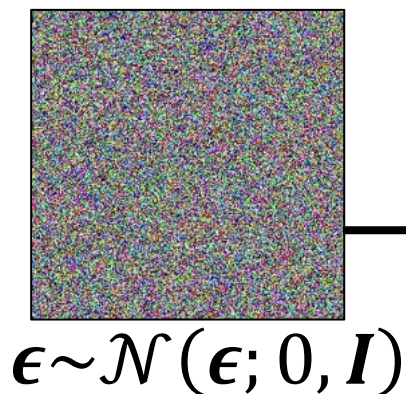




$$\sum_{t=2}^T \mathbb{E}_{q(\mathbf{x}_t|\mathbf{x}_0)} [w(t) [|| \hat{\mathbf{x}}_{\theta}(\mathbf{x}_t, t) - \mathbf{x}_0 ||_2^2]]$$

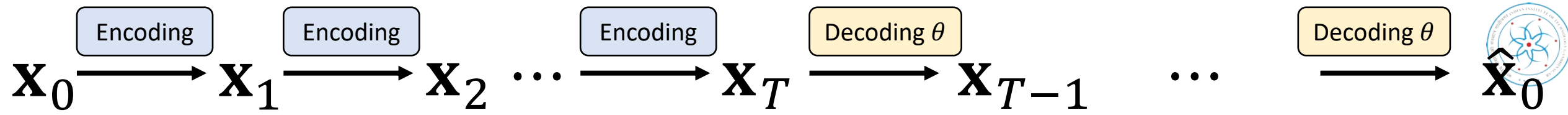
$$\mu_q(\mathbf{x}_t, \mathbf{x}_0) = \frac{\sqrt{\alpha_t}(1 - \bar{\alpha}_{t-1})}{1 - \bar{\alpha}_t} \mathbf{x}_t + \frac{\sqrt{\bar{\alpha}_{t-1}}(1 - \alpha_t)}{1 - \bar{\alpha}_t} \mathbf{x}_0$$

$$\mu_{\theta}(\mathbf{x}_t, t) = \frac{\sqrt{\alpha_t}(1 - \bar{\alpha}_{t-1})}{1 - \bar{\alpha}_t} \mathbf{x}_t + \frac{\sqrt{\bar{\alpha}_{t-1}}(1 - \alpha_t)}{1 - \bar{\alpha}_t} \hat{\mathbf{x}}_{\theta}(\mathbf{x}_t, t)$$



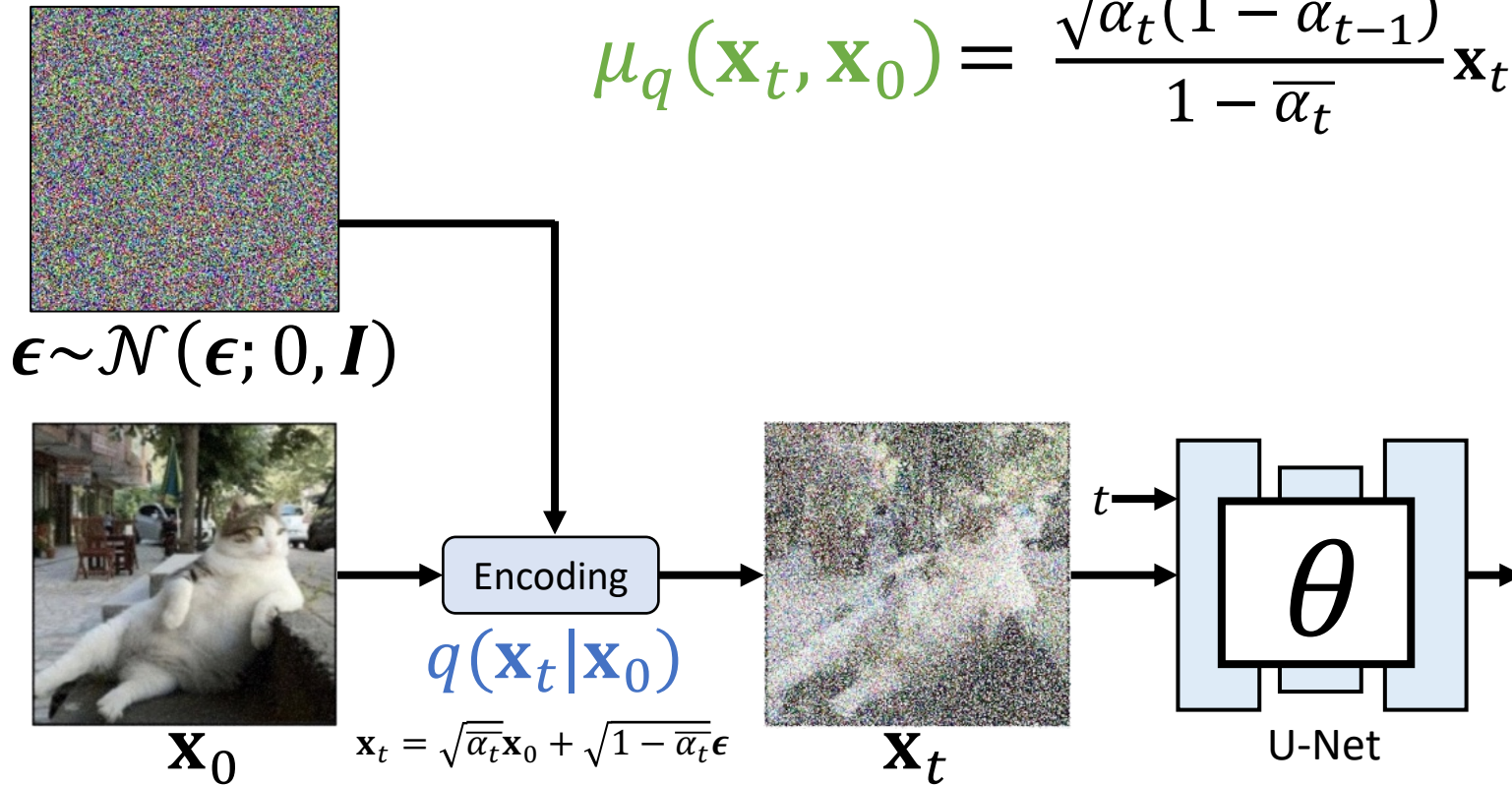
$$\hat{\mathbf{x}}_{\theta}(\mathbf{x}_t, t)$$

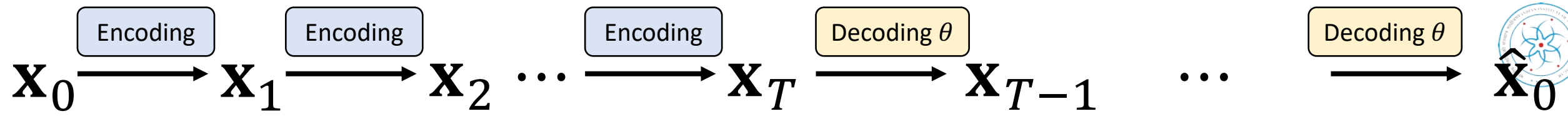
$$L_2$$



$$\sum_{t=2}^T \mathbb{E}_{q(\mathbf{x}_t|\mathbf{x}_0)} [w(t) [|| \mu_{\theta}(\mathbf{x}_t, t) - \mu_q(\mathbf{x}_t, \mathbf{x}_0) ||_2^2]]$$

$$\mu_q(\mathbf{x}_t, \mathbf{x}_0) = \frac{\sqrt{\alpha_t}(1 - \bar{\alpha}_{t-1})}{1 - \bar{\alpha}_t} \mathbf{x}_t + \frac{\sqrt{\bar{\alpha}_{t-1}}(1 - \alpha_t)}{1 - \bar{\alpha}_t} \mathbf{x}_0$$

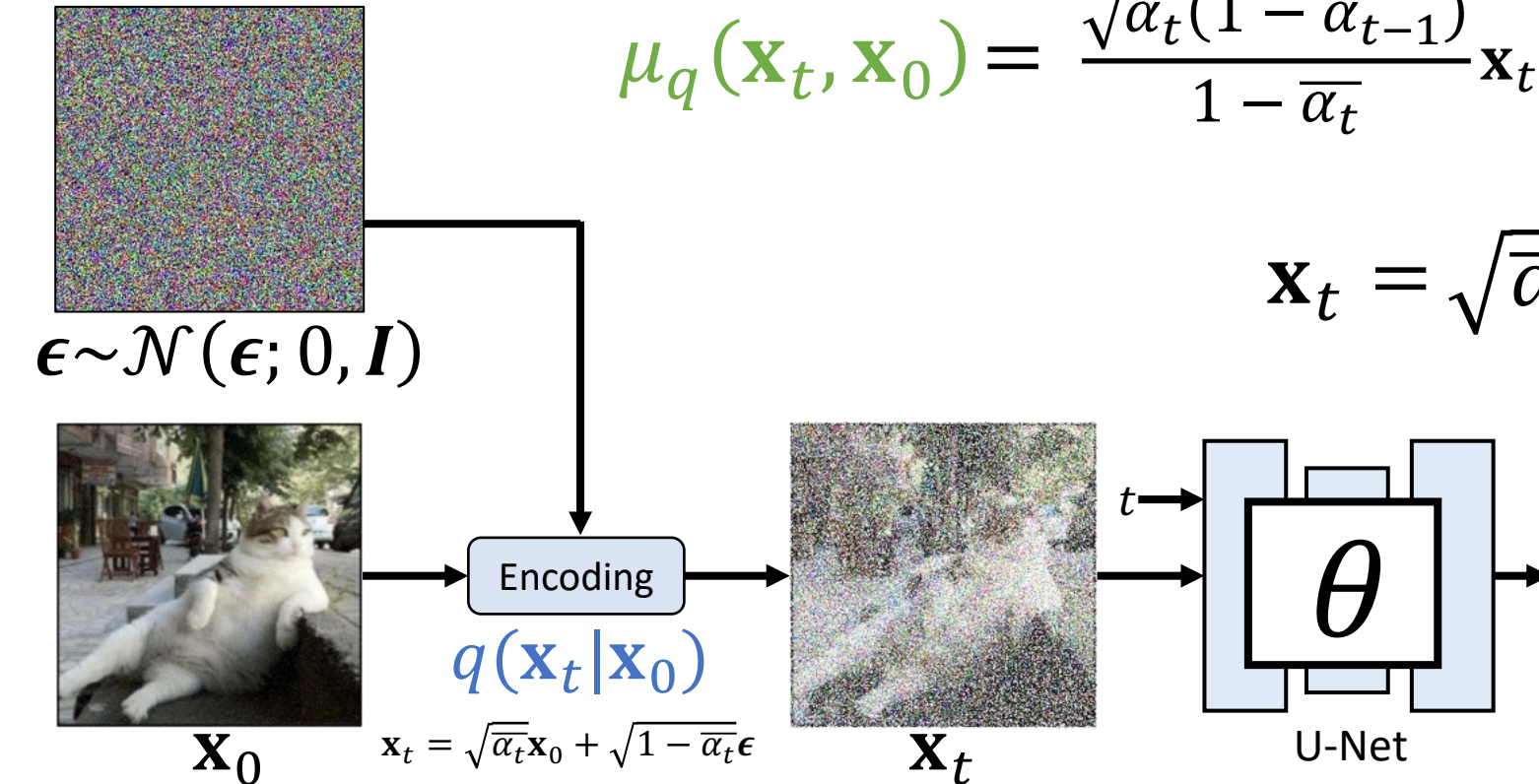


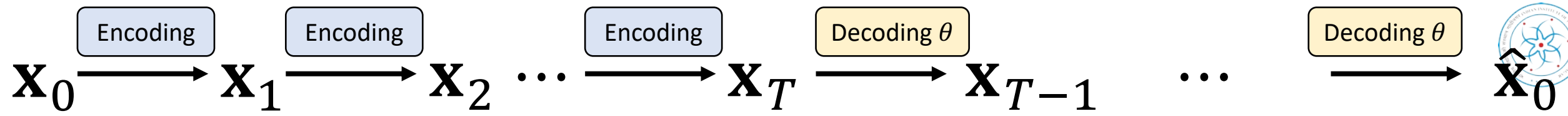


$$\sum_{t=2}^T \mathbb{E}_{q(\mathbf{x}_t|\mathbf{x}_0)} [w(t) [|| \mu_{\theta}(\mathbf{x}_t, t) - \mu_q(\mathbf{x}_t, \mathbf{x}_0) ||_2^2]]$$

$$\mu_q(\mathbf{x}_t, \mathbf{x}_0) = \frac{\sqrt{\alpha_t}(1 - \bar{\alpha}_{t-1})}{1 - \bar{\alpha}_t} \mathbf{x}_t + \frac{\sqrt{\bar{\alpha}_{t-1}}(1 - \alpha_t)}{1 - \bar{\alpha}_t} \mathbf{x}_0$$

$$\mathbf{x}_t = \sqrt{\bar{\alpha}_t} \mathbf{x}_0 + \sqrt{1 - \bar{\alpha}_t} \epsilon$$

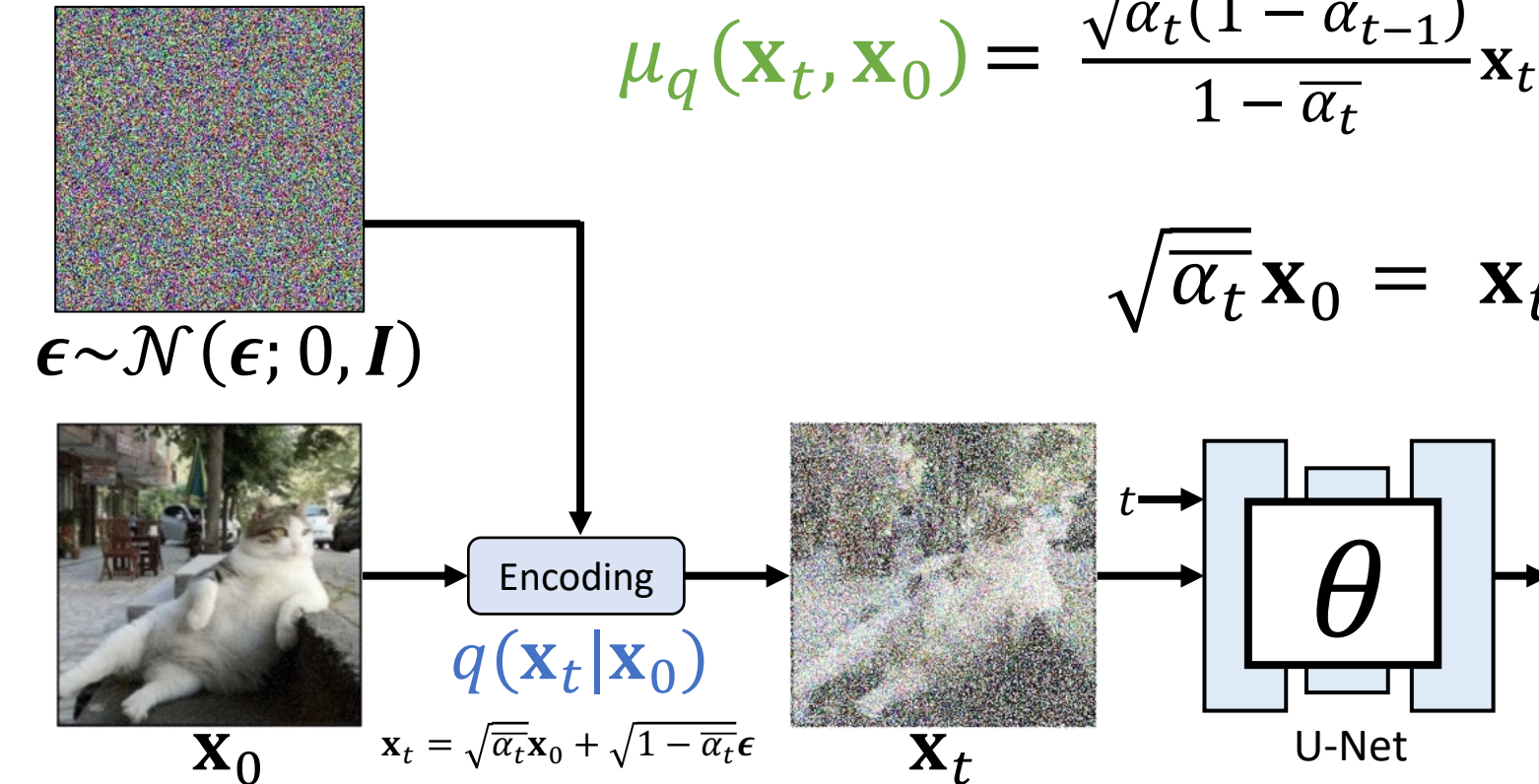


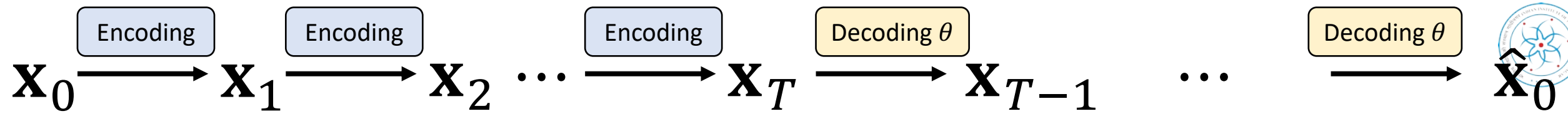


$$\sum_{t=2}^T \mathbb{E}_{q(\mathbf{x}_t|\mathbf{x}_0)} \left[w(t) \left[\|\mu_{\theta}(\mathbf{x}_t, t) - \mu_q(\mathbf{x}_t, \mathbf{x}_0)\|_2^2 \right] \right]$$

$$\mu_q(\mathbf{x}_t, \mathbf{x}_0) = \frac{\sqrt{\alpha_t}(1 - \bar{\alpha}_{t-1})}{1 - \bar{\alpha}_t} \mathbf{x}_t + \frac{\sqrt{\bar{\alpha}_{t-1}}(1 - \alpha_t)}{1 - \bar{\alpha}_t} \mathbf{x}_0$$

$$\sqrt{\bar{\alpha}_t} \mathbf{x}_0 = \mathbf{x}_t - \sqrt{1 - \bar{\alpha}_t} \epsilon$$

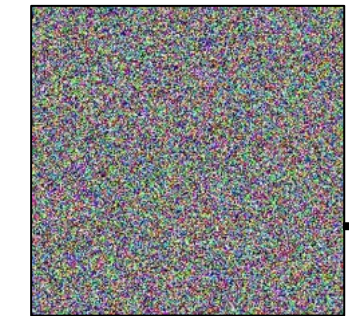




$$\sum_{t=2}^T \mathbb{E}_{q(\mathbf{x}_t|\mathbf{x}_0)} [w(t) [|| \mu_{\theta}(\mathbf{x}_t, t) - \mu_q(\mathbf{x}_t, \mathbf{x}_0) ||_2^2]]$$

$$\mu_q(\mathbf{x}_t, \mathbf{x}_0) = \frac{\sqrt{\alpha_t}(1 - \bar{\alpha}_{t-1})}{1 - \bar{\alpha}_t} \mathbf{x}_t + \frac{\sqrt{\bar{\alpha}_{t-1}}(1 - \alpha_t)}{1 - \bar{\alpha}_t} \mathbf{x}_0$$

$$\mathbf{x}_0 = \frac{\mathbf{x}_t - \sqrt{1 - \bar{\alpha}_t} \epsilon}{\sqrt{\alpha_t}}$$



$$\epsilon \sim \mathcal{N}(\epsilon; 0, I)$$



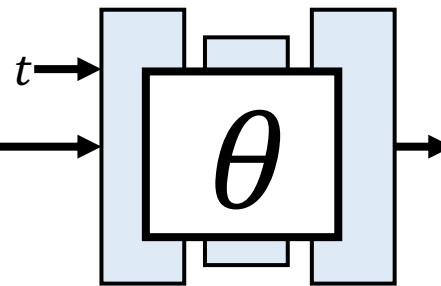
$\mathbf{x}_0$

Encoding
 $q(\mathbf{x}_t|\mathbf{x}_0)$

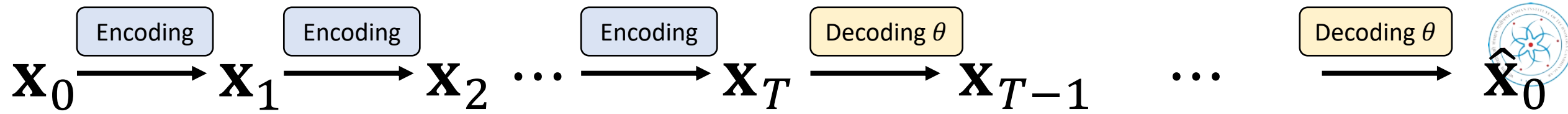
$$\mathbf{x}_t = \sqrt{\alpha_t} \mathbf{x}_0 + \sqrt{1 - \alpha_t} \epsilon$$



$\mathbf{x}_t$

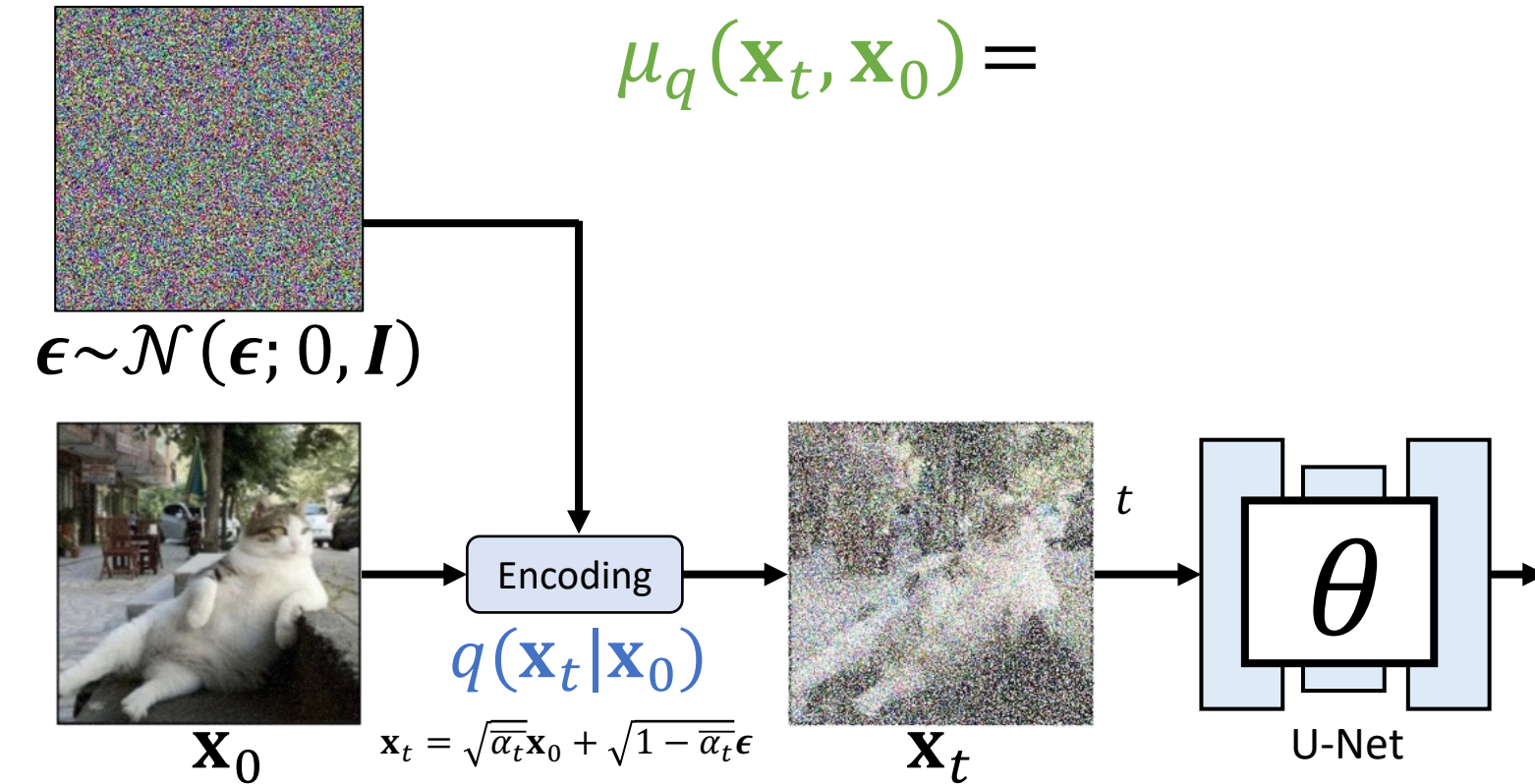


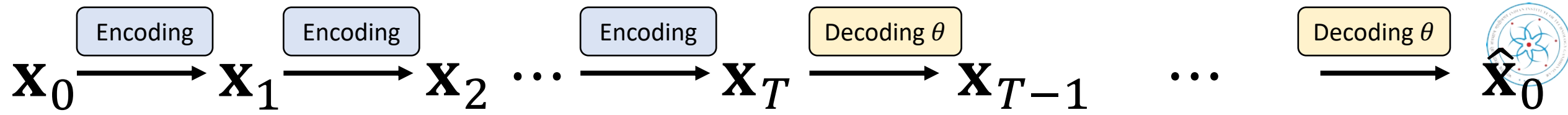
U-Net



$$\sum_{t=2}^T \mathbb{E}_{q(\mathbf{x}_t|\mathbf{x}_0)} [w(t) [|| \mu_{\theta}(\mathbf{x}_t, t) - \mu_q(\mathbf{x}_t, \mathbf{x}_0) ||_2^2]]$$

$$\mu_q(\mathbf{x}_t, \mathbf{x}_0) =$$

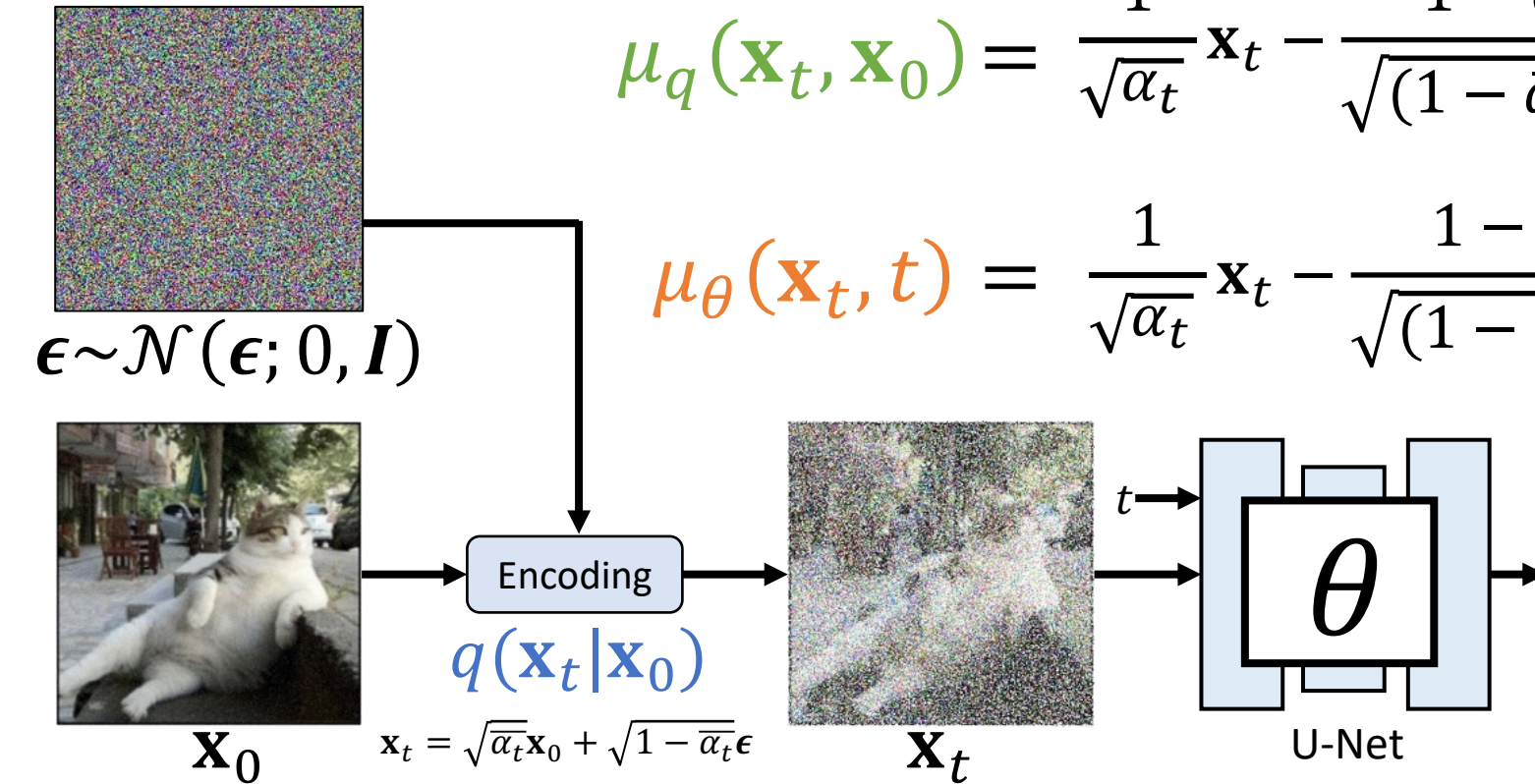


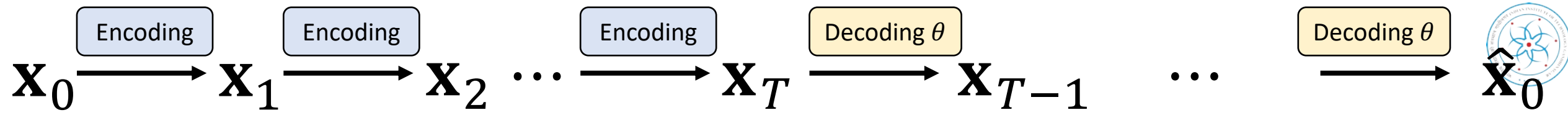


$$\sum_{t=2}^T \mathbb{E}_{q(\mathbf{x}_t|\mathbf{x}_0)} [w(t) [|| \mu_{\theta}(\mathbf{x}_t, t) - \mu_q(\mathbf{x}_t, \mathbf{x}_0) ||_2^2]]$$

$$\mu_q(\mathbf{x}_t, \mathbf{x}_0) = \frac{1}{\sqrt{\alpha_t}} \mathbf{x}_t - \frac{1 - \alpha_t}{\sqrt{(1 - \bar{\alpha}_t)\alpha_t}} \epsilon$$

$$\mu_{\theta}(\mathbf{x}_t, t) = \frac{1}{\sqrt{\alpha_t}} \mathbf{x}_t - \frac{1 - \alpha_t}{\sqrt{(1 - \bar{\alpha}_t)\alpha_t}} \hat{\epsilon}_{\theta}(\mathbf{x}_t, t)$$

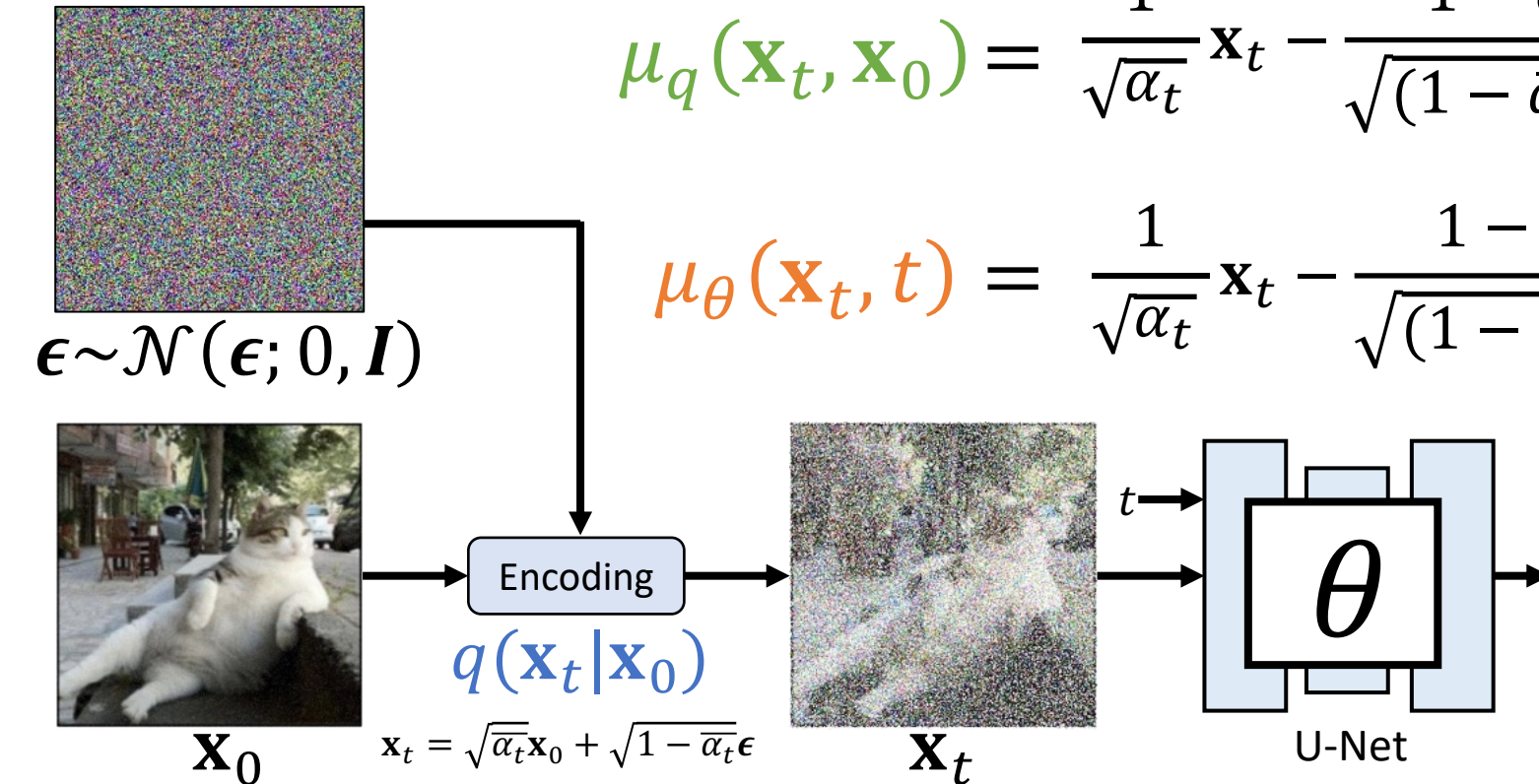


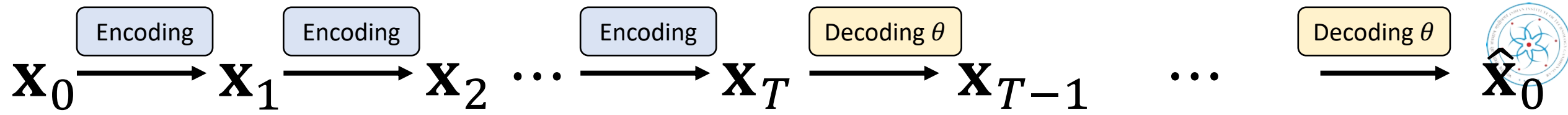


$$\sum_{t=2}^T \mathbb{E}_{q(\mathbf{x}_t|\mathbf{x}_0)} [w(t) [|| \mu_{\theta}(\mathbf{x}_t, t) - \mu_q(\mathbf{x}_t, \mathbf{x}_0) ||_2^2]]$$

$$\mu_q(\mathbf{x}_t, \mathbf{x}_0) = \frac{1}{\sqrt{\alpha_t}} \mathbf{x}_t - \frac{1 - \alpha_t}{\sqrt{(1 - \bar{\alpha}_t)\alpha_t}} \epsilon$$

$$\mu_{\theta}(\mathbf{x}_t, t) = \frac{1}{\sqrt{\alpha_t}} \mathbf{x}_t - \frac{1 - \alpha_t}{\sqrt{(1 - \bar{\alpha}_t)\alpha_t}} \hat{\epsilon}_{\theta}(\mathbf{x}_t, t)$$

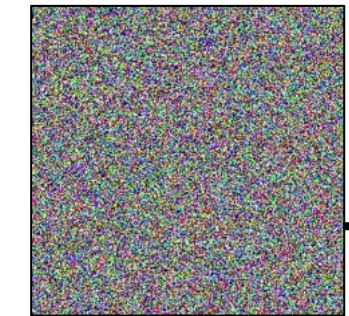




$$\sum_{t=2}^T \mathbb{E}_{q(\mathbf{x}_t|\mathbf{x}_0)} [w(t) [|| \hat{\epsilon}_{\theta}(\mathbf{x}_t, t) - \epsilon ||_2^2]]$$

$$\mu_q(\mathbf{x}_t, \mathbf{x}_0) = \frac{1}{\sqrt{\alpha_t}} \mathbf{x}_t - \frac{1 - \alpha_t}{\sqrt{(1 - \bar{\alpha}_t)\alpha_t}} \epsilon$$

$$\mu_{\theta}(\mathbf{x}_t, t) = \frac{1}{\sqrt{\alpha_t}} \mathbf{x}_t - \frac{1 - \alpha_t}{\sqrt{(1 - \bar{\alpha}_t)\alpha_t}} \hat{\epsilon}_{\theta}(\mathbf{x}_t, t)$$



$$\epsilon \sim \mathcal{N}(\epsilon; 0, I)$$



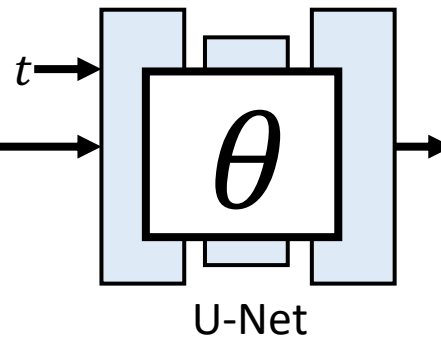
$\mathbf{x}_0$

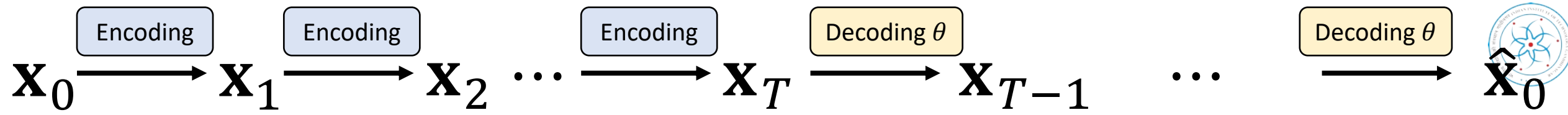
Encoding
 $q(\mathbf{x}_t|\mathbf{x}_0)$

$$\mathbf{x}_t = \sqrt{\bar{\alpha}_t} \mathbf{x}_0 + \sqrt{1 - \bar{\alpha}_t} \epsilon$$



$\mathbf{x}_t$

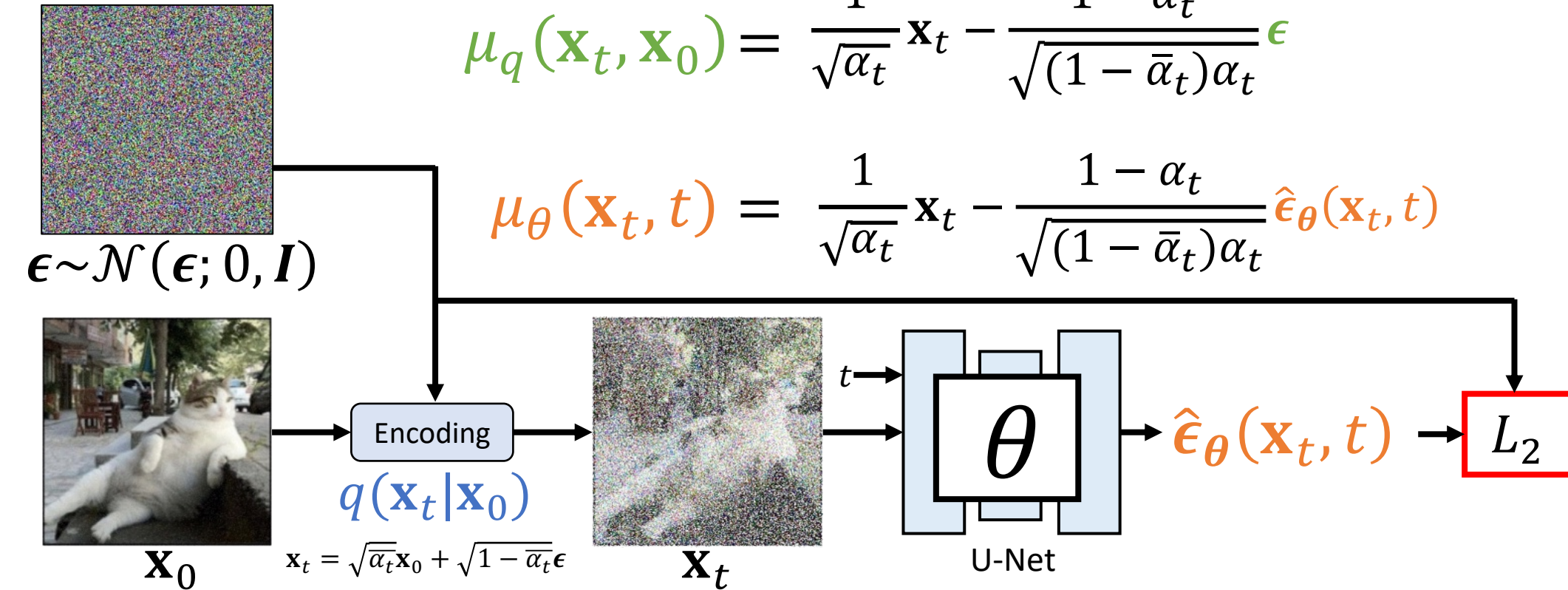


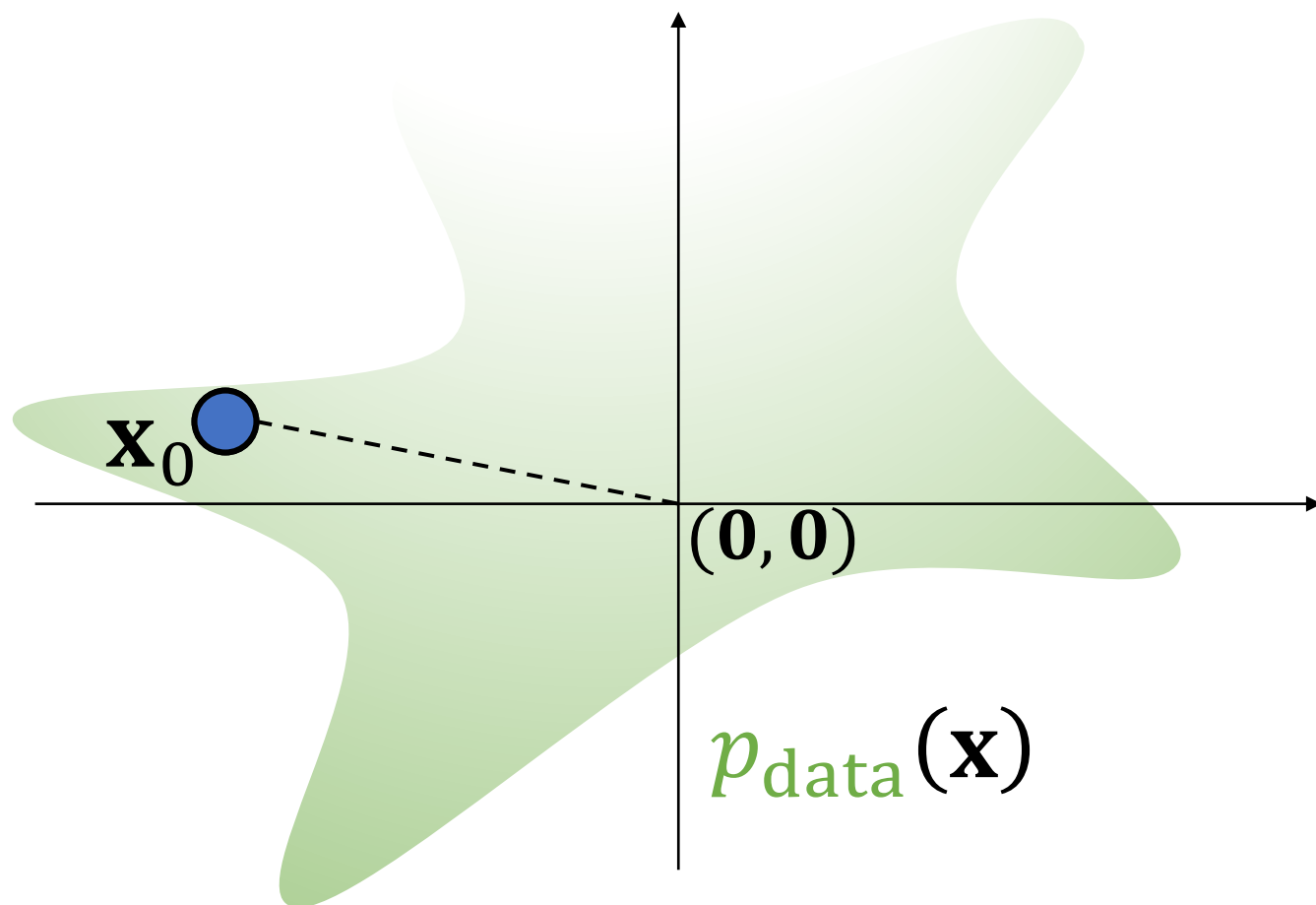


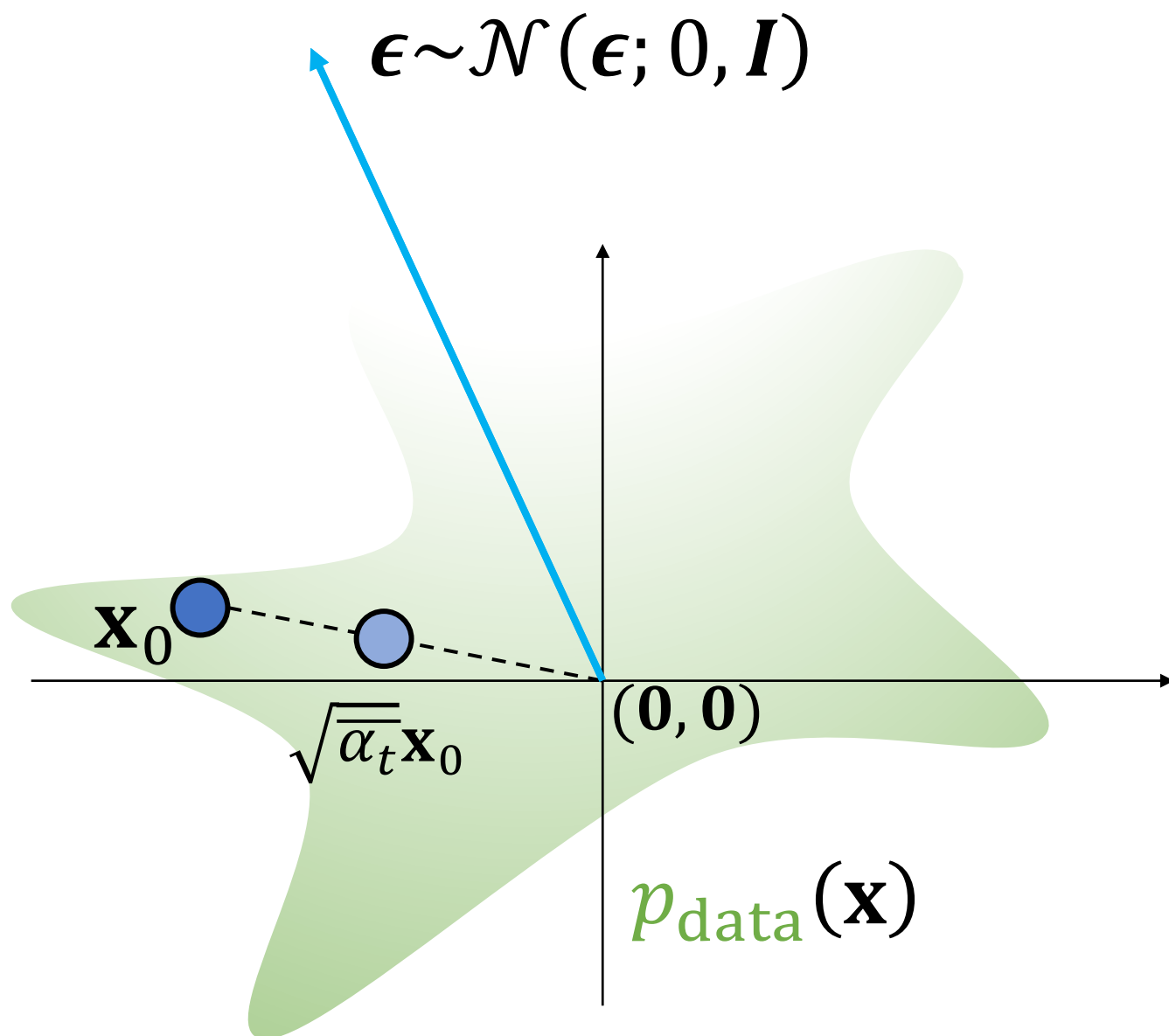
$$\sum_{t=2}^T \mathbb{E}_{q(\mathbf{x}_t|\mathbf{x}_0)} [w(t) [|| \hat{\epsilon}_{\theta}(\mathbf{x}_t, t) - \epsilon ||_2^2]]$$

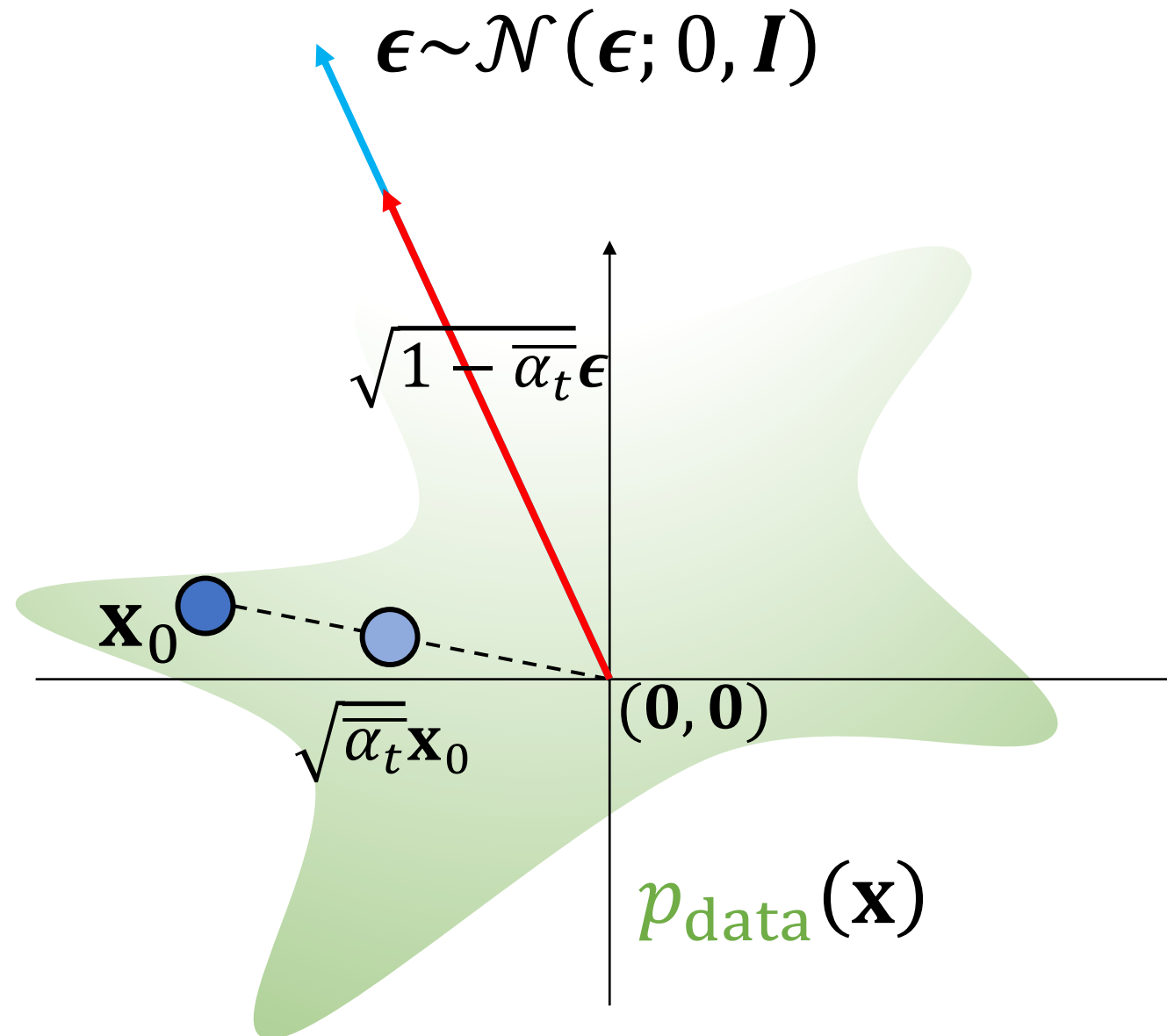
$$\mu_q(\mathbf{x}_t, \mathbf{x}_0) = \frac{1}{\sqrt{\alpha_t}} \mathbf{x}_t - \frac{1 - \alpha_t}{\sqrt{(1 - \bar{\alpha}_t)\alpha_t}} \epsilon$$

$$\mu_{\theta}(\mathbf{x}_t, t) = \frac{1}{\sqrt{\alpha_t}} \mathbf{x}_t - \frac{1 - \alpha_t}{\sqrt{(1 - \bar{\alpha}_t)\alpha_t}} \hat{\epsilon}_{\theta}(\mathbf{x}_t, t)$$



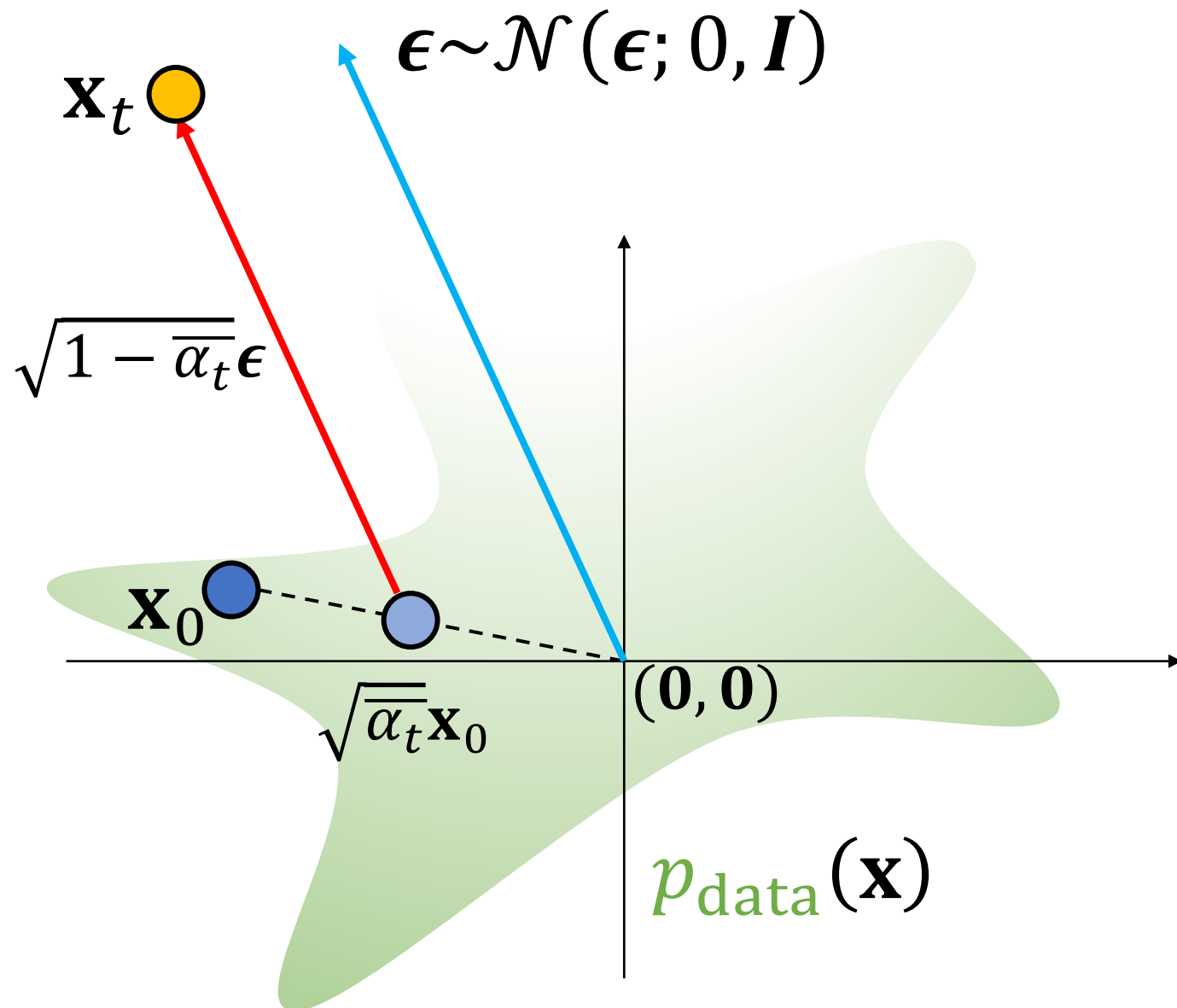




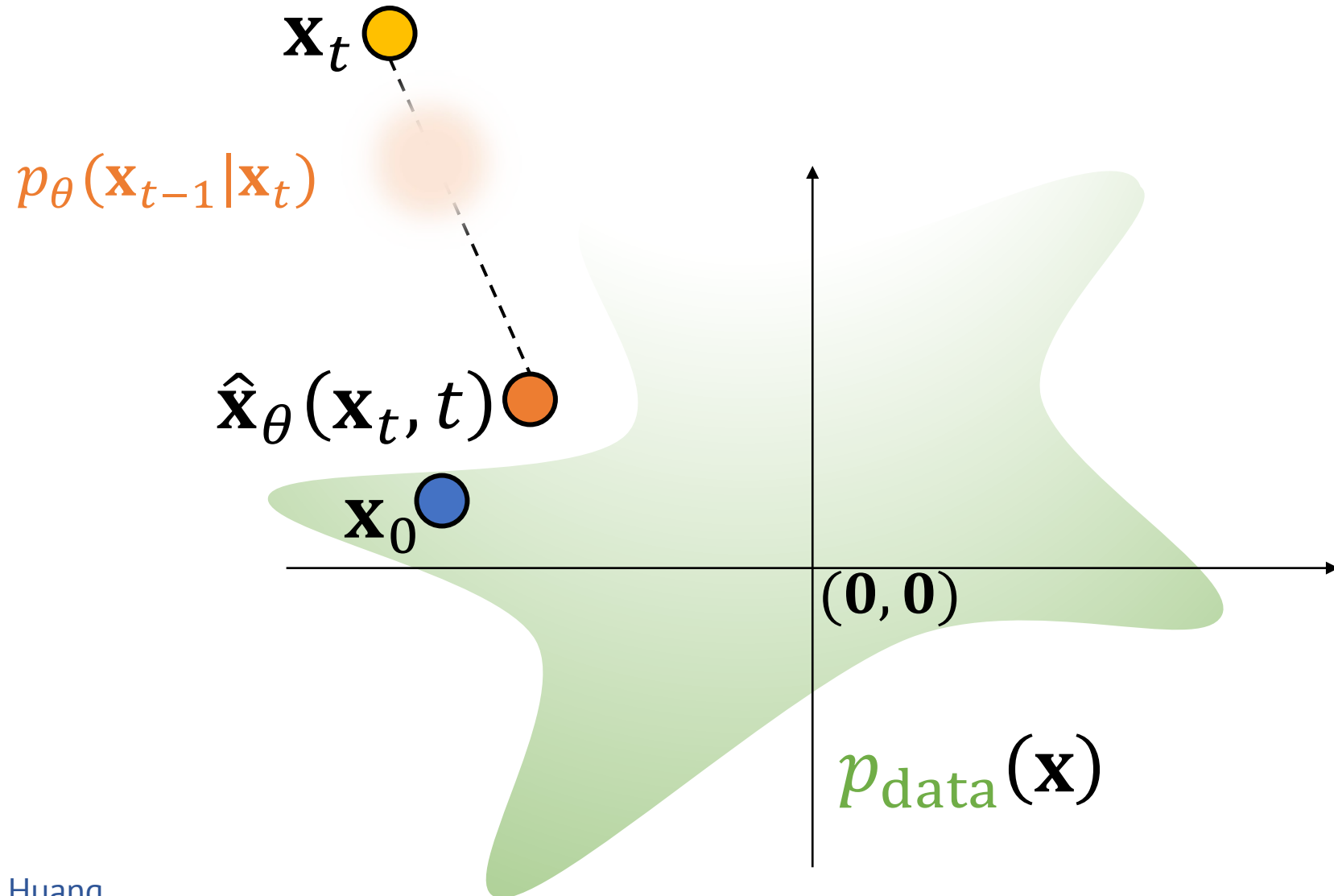




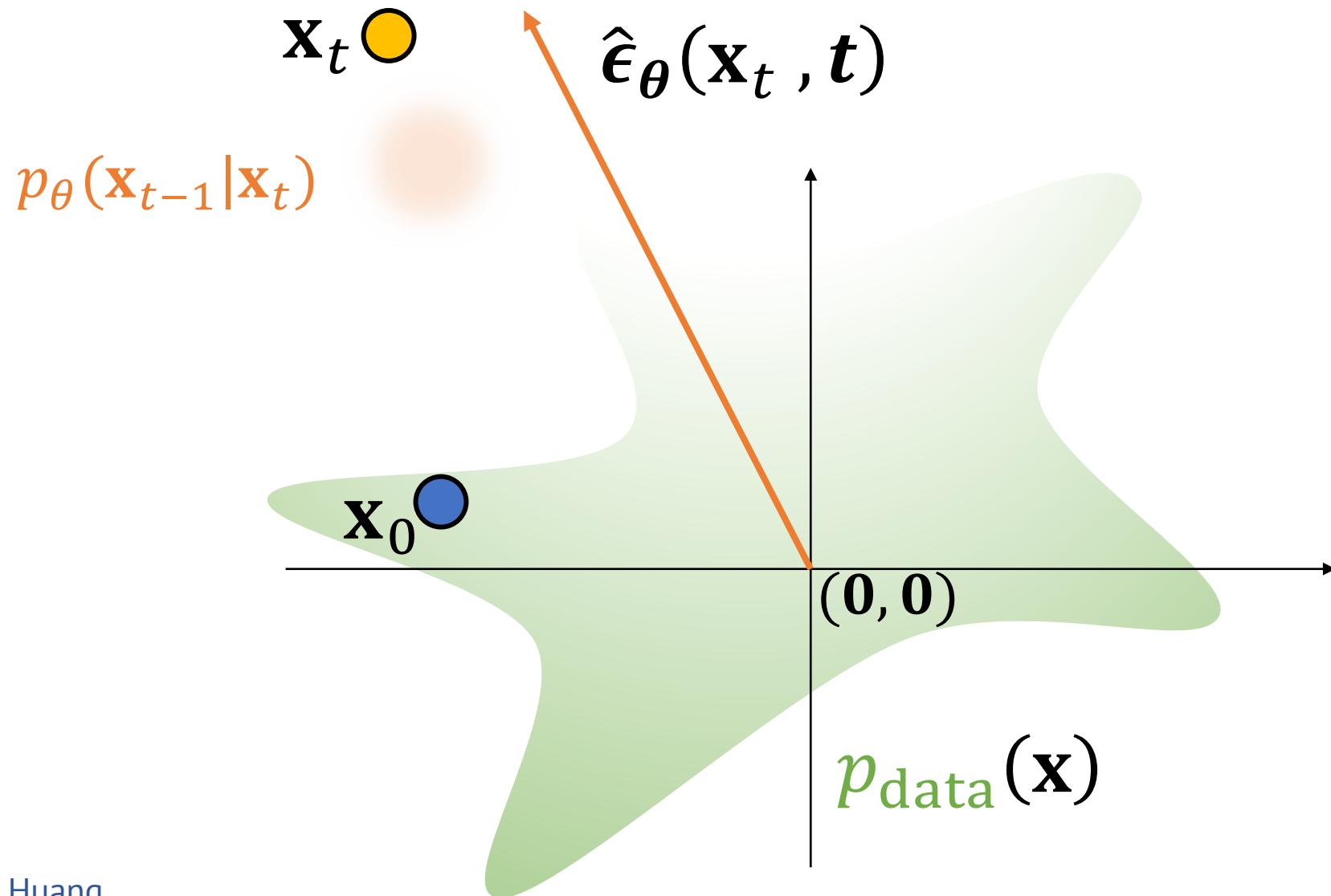
$$\mathbf{x}_t = \sqrt{\alpha_t} \mathbf{x}_0 + \sqrt{1 - \alpha_t} \boldsymbol{\epsilon}$$



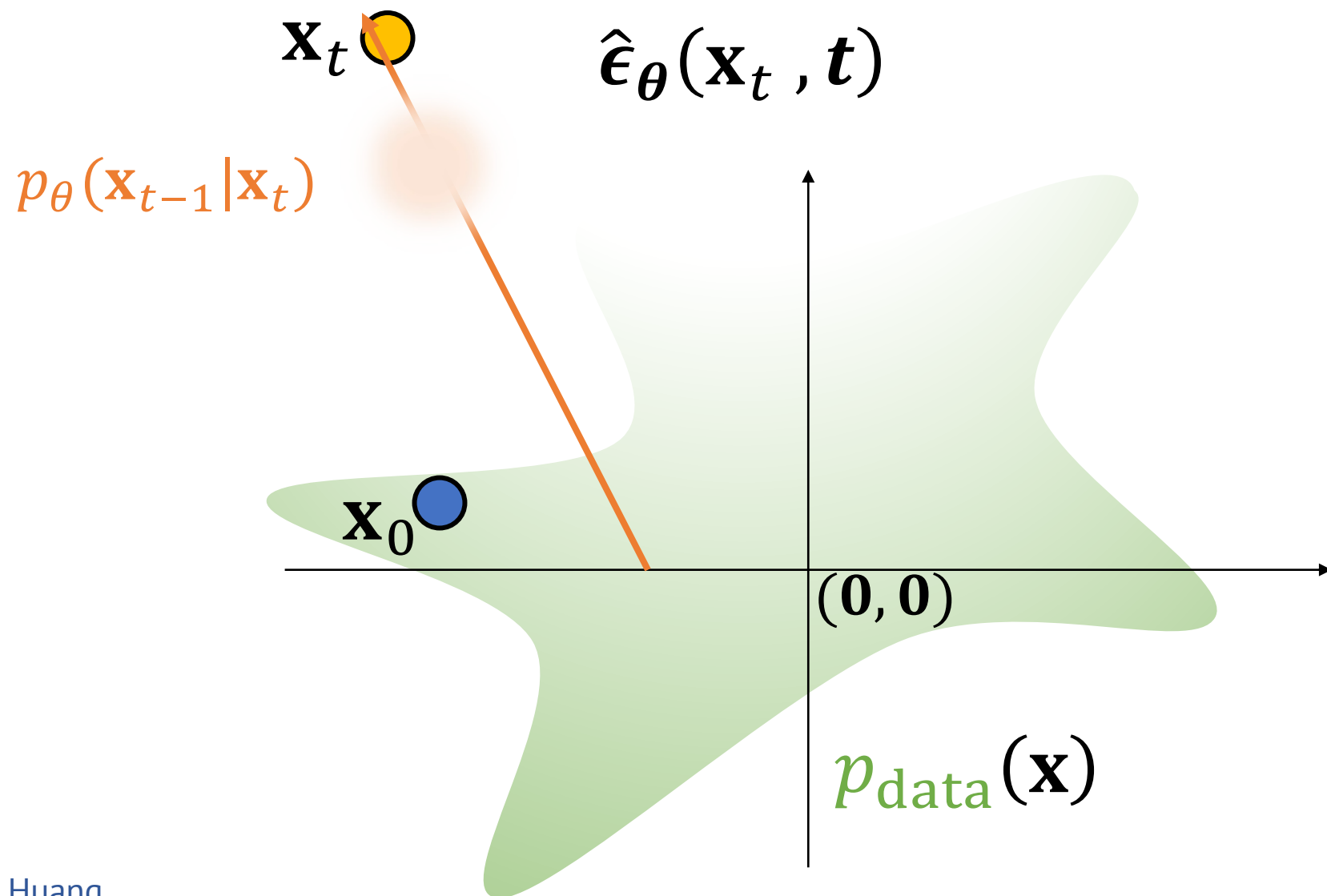
$$\mu_{\theta}(\mathbf{x}_t, t) = \frac{\sqrt{\alpha_t}(1 - \bar{\alpha}_{t-1})}{1 - \bar{\alpha}_t} \mathbf{x}_t + \frac{\sqrt{\bar{\alpha}_{t-1}}(1 - \alpha_t)}{1 - \bar{\alpha}_t} \hat{\mathbf{x}}_{\theta}(\mathbf{x}_t, t)$$



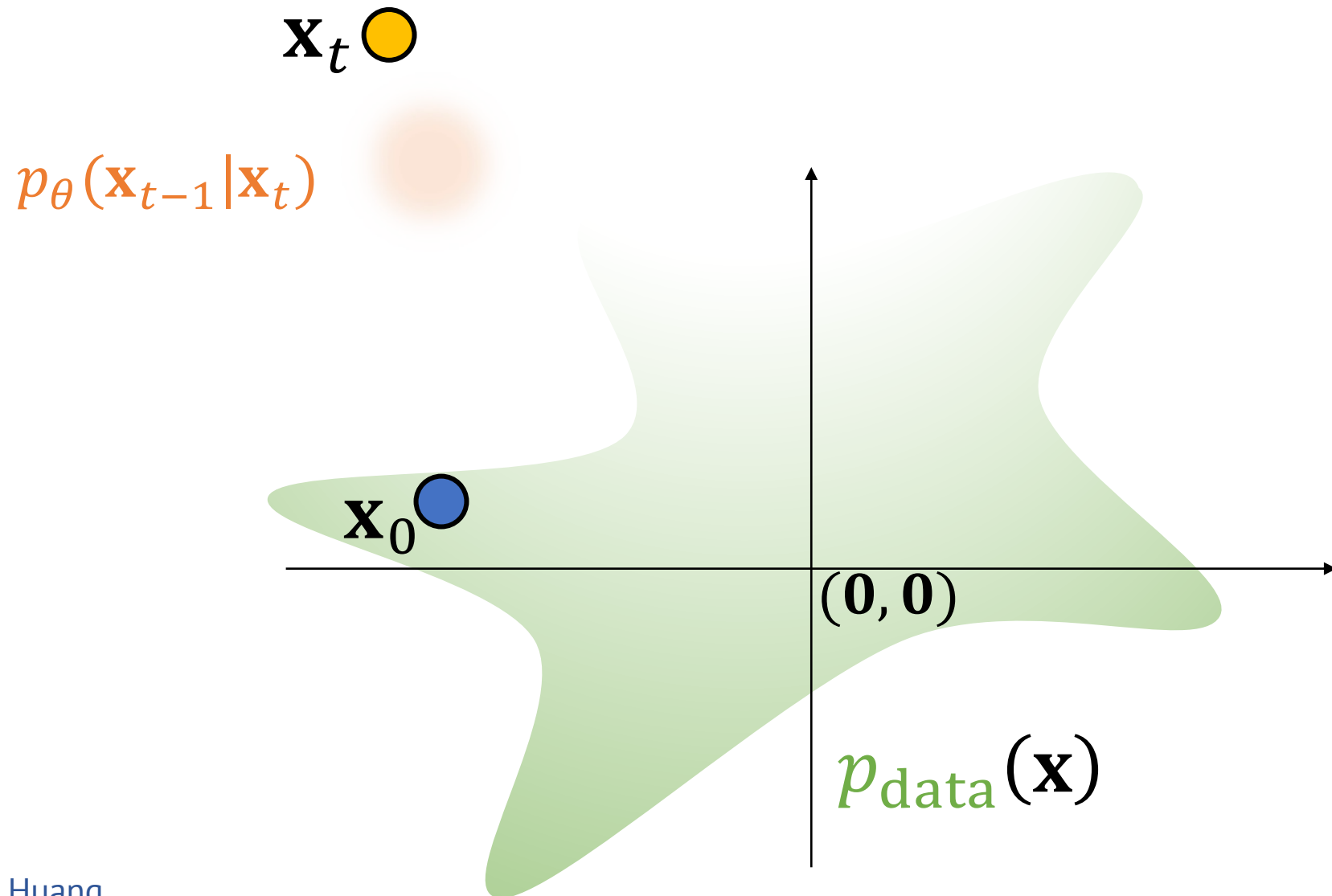
$$\mu_{\theta}(\mathbf{x}_t, t) = \frac{1}{\sqrt{\alpha_t}} \mathbf{x}_t - \frac{1 - \alpha_t}{\sqrt{(1 - \bar{\alpha}_t)\alpha_t}} \hat{\epsilon}_{\theta}(\mathbf{x}_t, t)$$



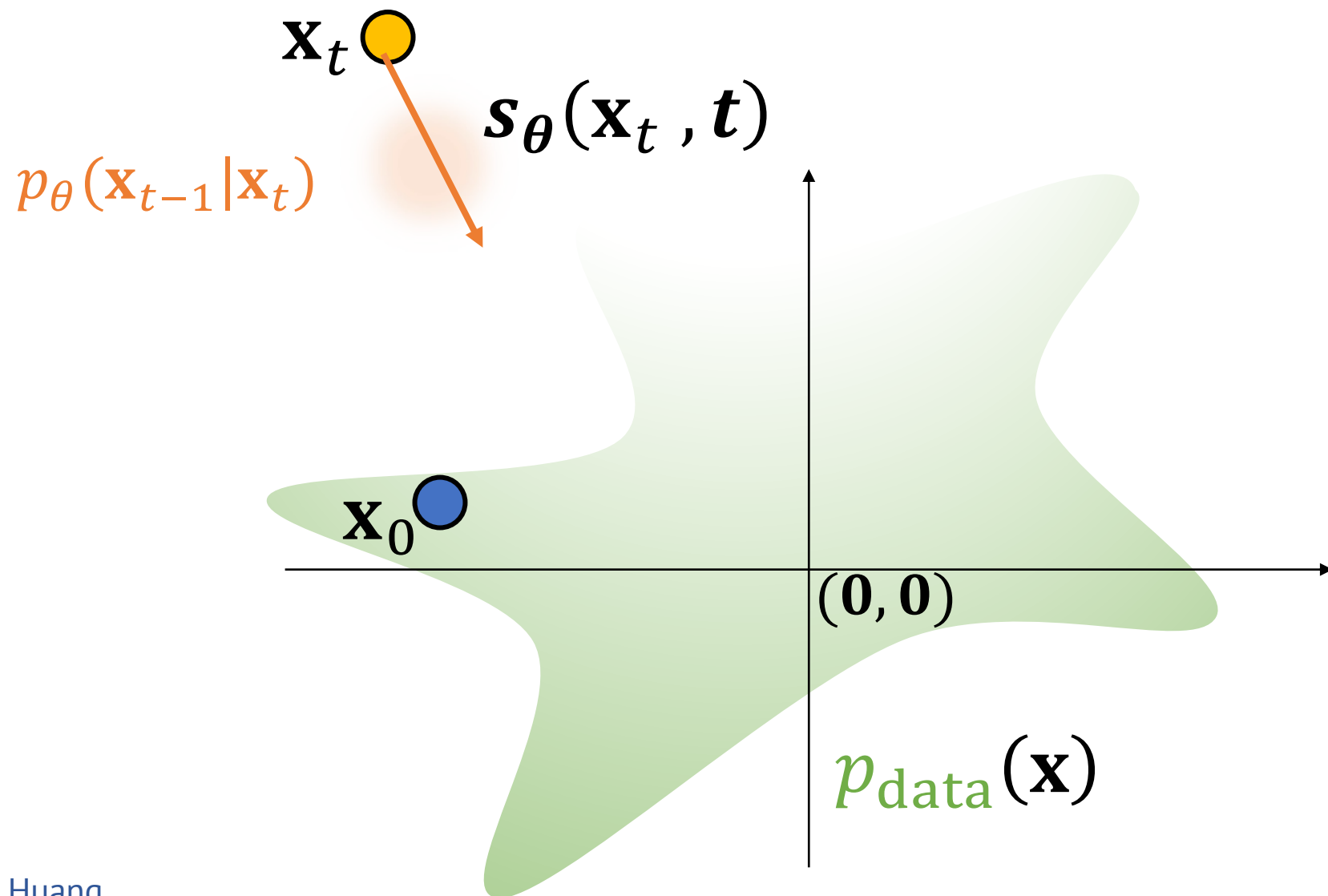
$$\mu_{\theta}(\mathbf{x}_t, t) = \frac{1}{\sqrt{\alpha_t}} \mathbf{x}_t - \frac{1 - \alpha_t}{\sqrt{(1 - \bar{\alpha}_t) \alpha_t}} \hat{\epsilon}_{\theta}(\mathbf{x}_t, t)$$



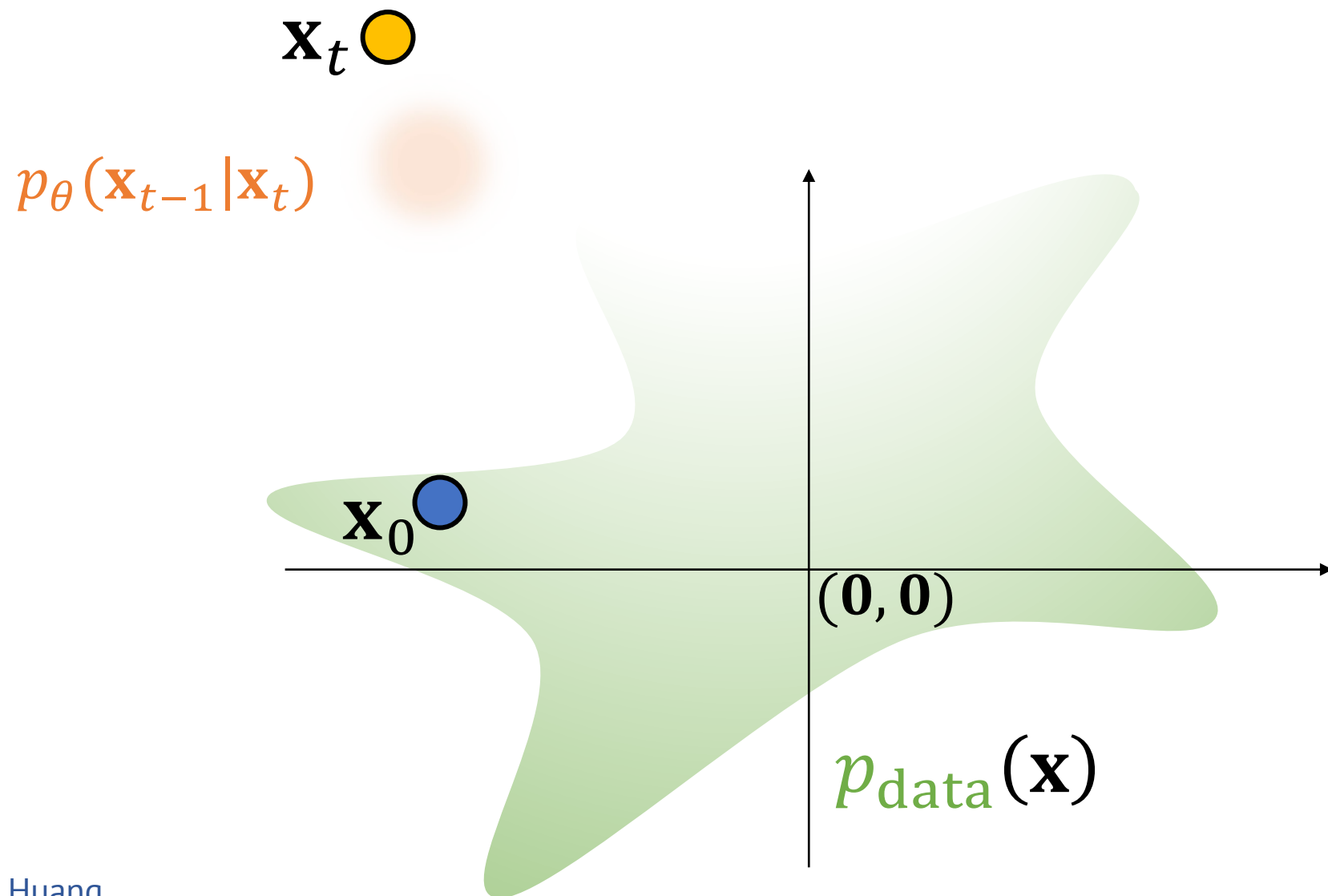
$$\mu_{\theta}(\mathbf{x}_t, t) =$$



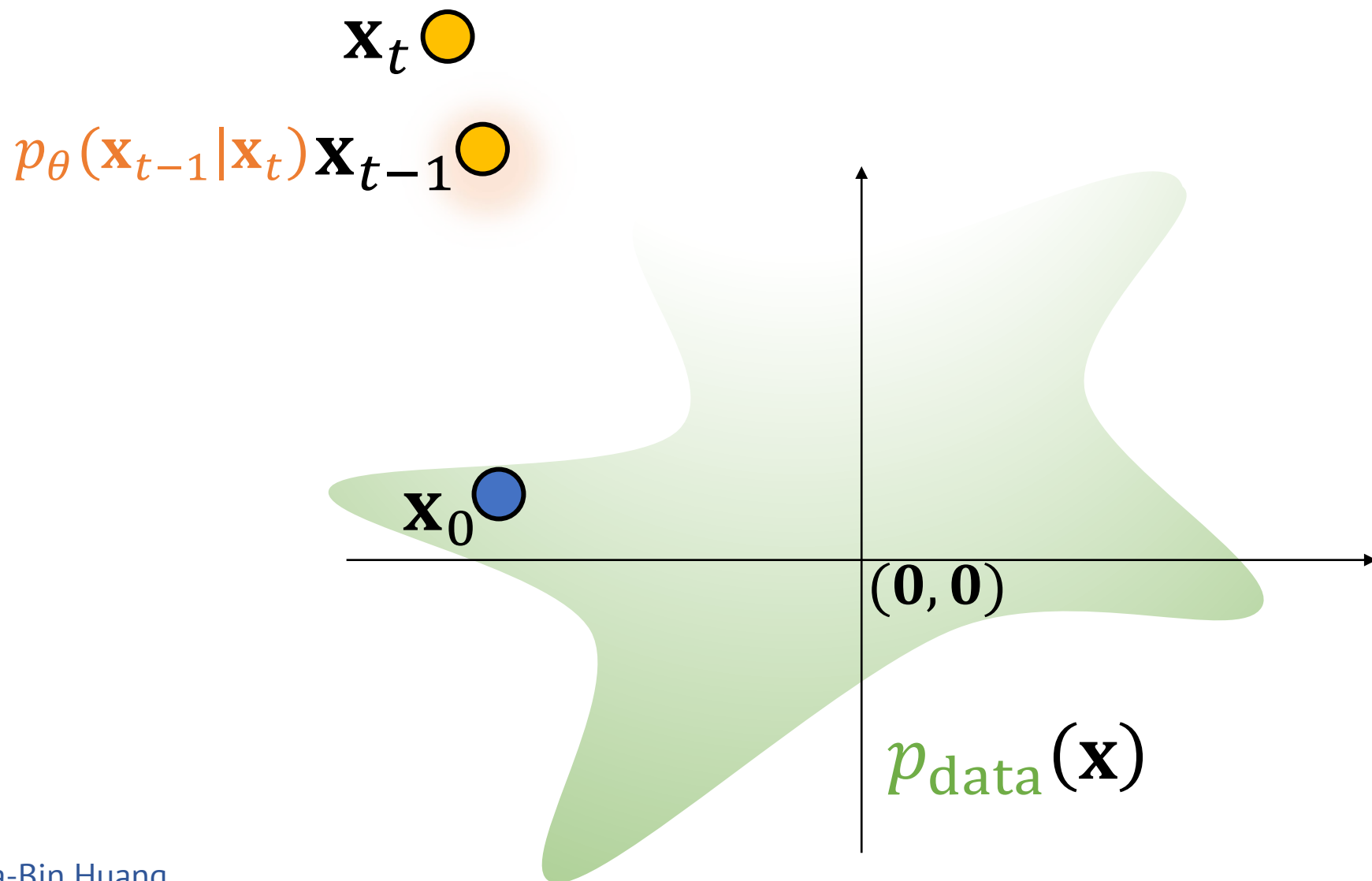
$$\mu_{\theta}(\mathbf{x}_t, t) = \frac{1}{\sqrt{\alpha_t}} \mathbf{x}_t + \frac{1 - \alpha_t}{\sqrt{\alpha_t}} \mathbf{s}_{\theta}(\mathbf{x}_t, t)$$



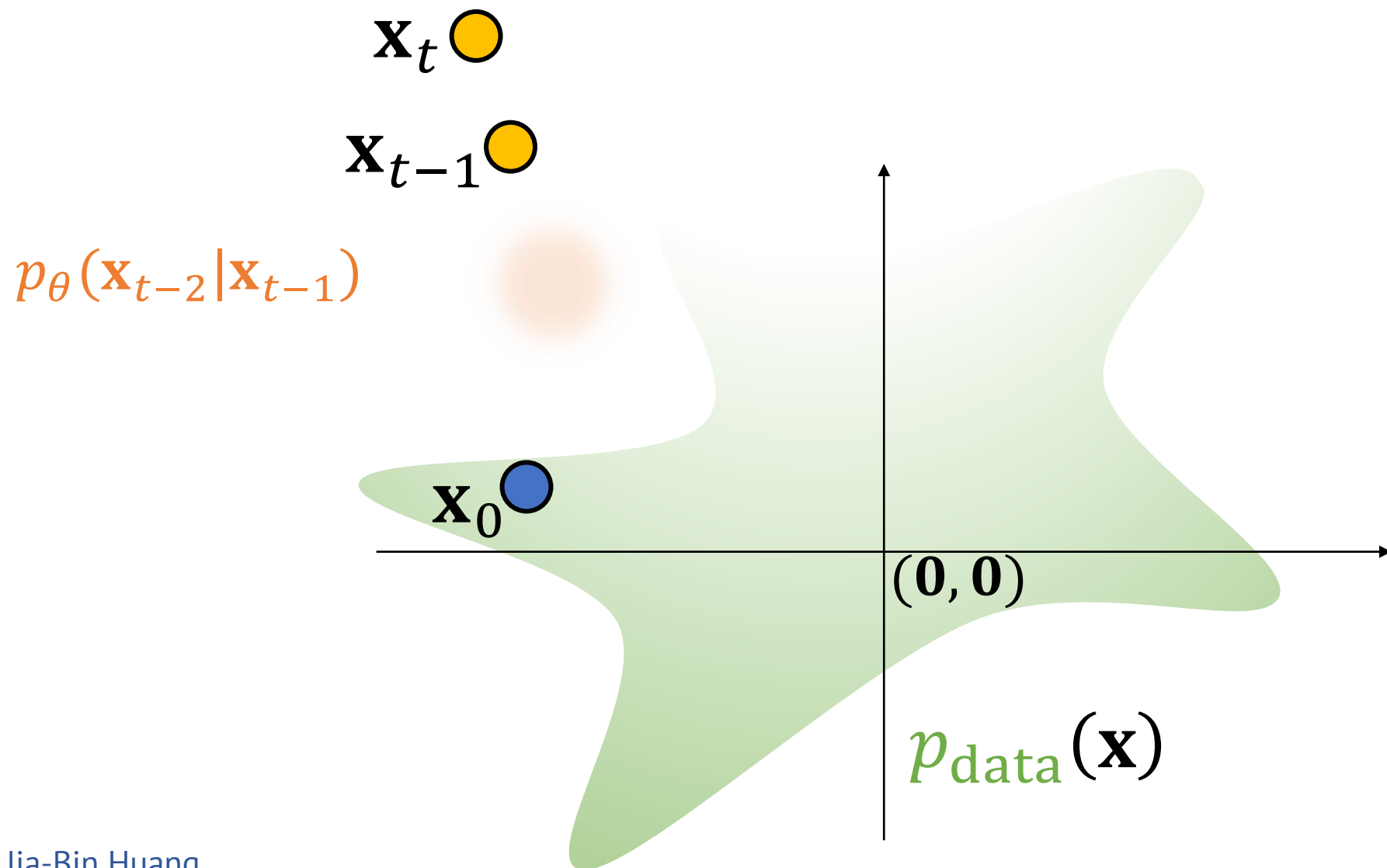
$$\mu_{\theta}(\mathbf{x}_t, t) = \frac{1}{\sqrt{\alpha_t}} \mathbf{x}_t + \frac{1 - \alpha_t}{\sqrt{\alpha_t}} \mathbf{s}_{\theta}(\mathbf{x}_t, t)$$



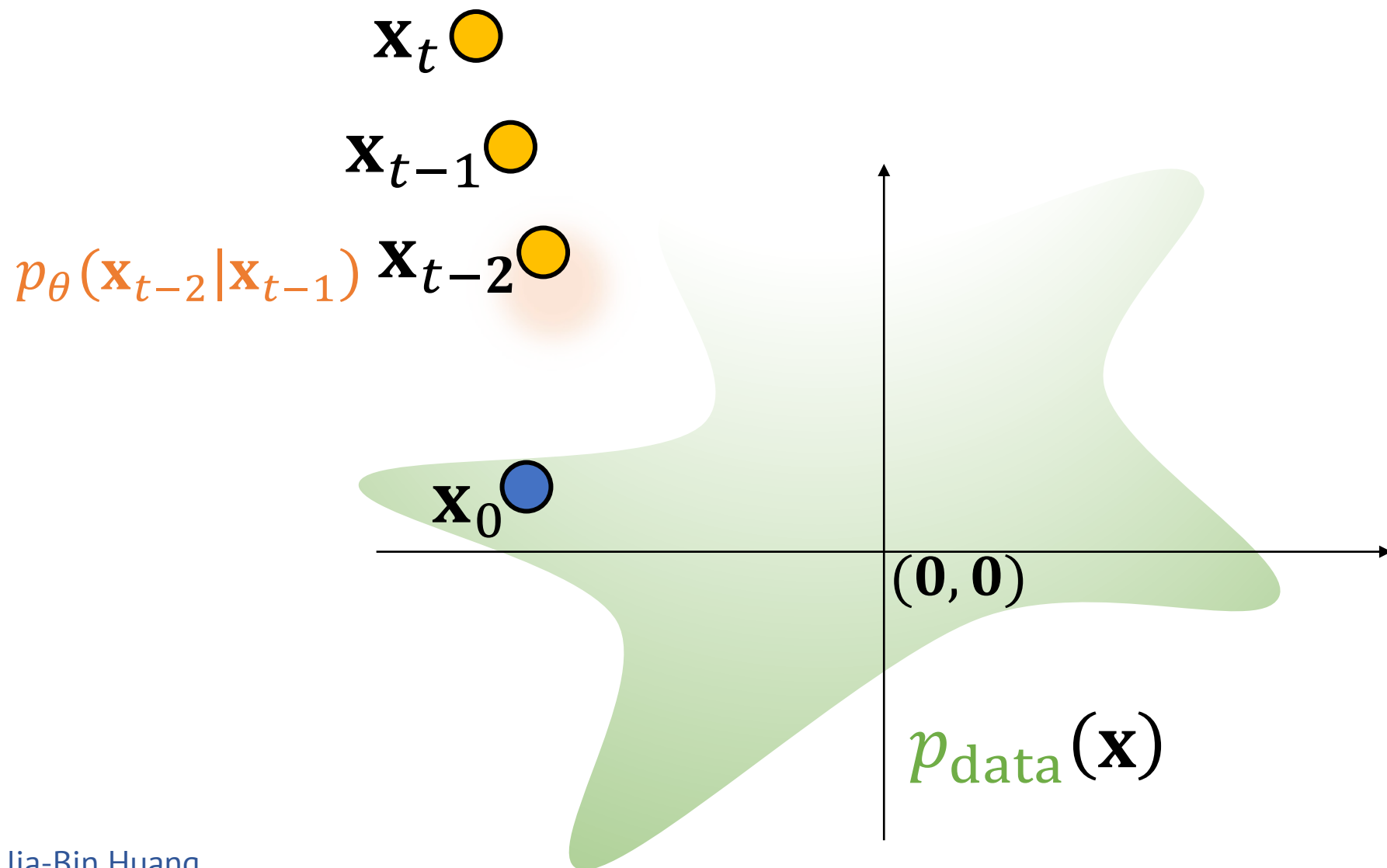
$$\mu_{\theta}(\mathbf{x}_t, t) = \frac{1}{\sqrt{\alpha_t}} \mathbf{x}_t + \frac{1 - \alpha_t}{\sqrt{\alpha_t}} \mathbf{s}_{\theta}(\mathbf{x}_t, t)$$



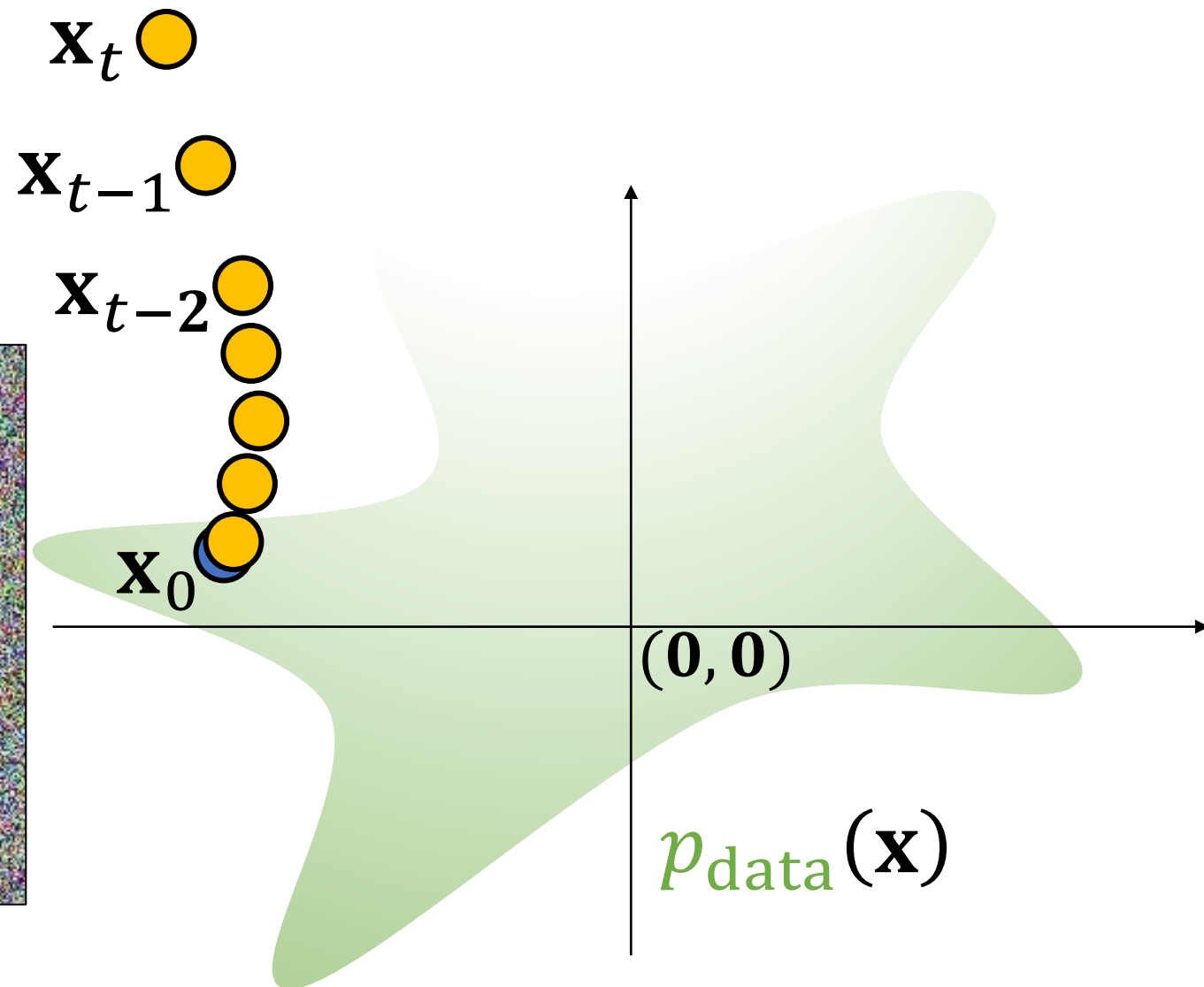
$$\mu_{\theta}(\mathbf{x}_t, t) = \frac{1}{\sqrt{\alpha_t}} \mathbf{x}_t + \frac{1 - \alpha_t}{\sqrt{\alpha_t}} \mathbf{s}_{\theta}(\mathbf{x}_t, t)$$



$$\mu_{\theta}(\mathbf{x}_t, t) = \frac{1}{\sqrt{\alpha_t}} \mathbf{x}_t + \frac{1 - \alpha_t}{\sqrt{\alpha_t}} \mathbf{s}_{\theta}(\mathbf{x}_t, t)$$



$$\mu_{\theta}(\mathbf{x}_t, t) = \frac{1}{\sqrt{\alpha_t}} \mathbf{x}_t + \frac{1 - \alpha_t}{\sqrt{\alpha_t}} \mathbf{s}_{\theta}(\mathbf{x}_t, t)$$





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