Generative AI for medical imaging

Recent advances and potential benefits

Olivier Bernard

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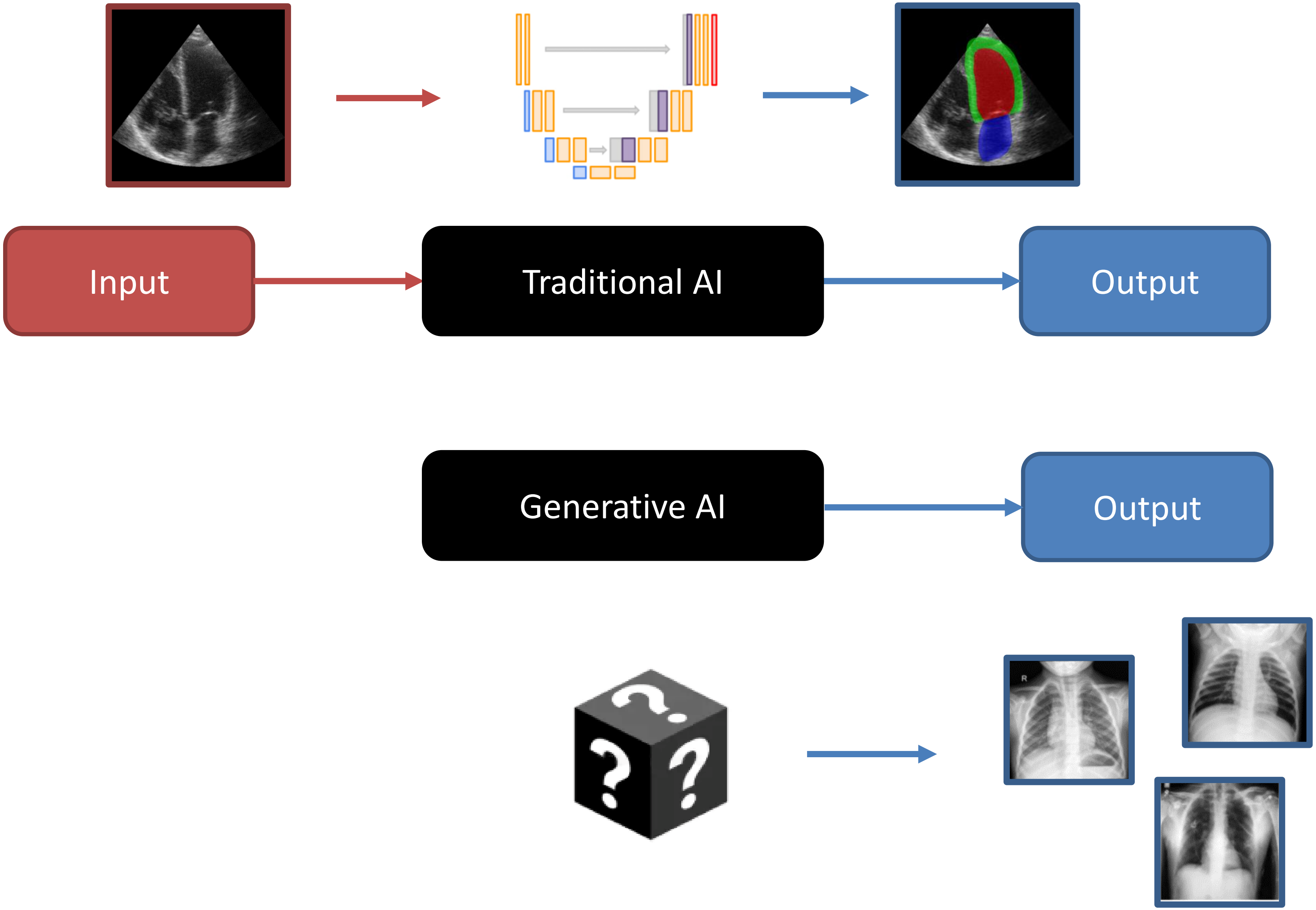
Generative AI for imaging

Generative AI for medical imaging

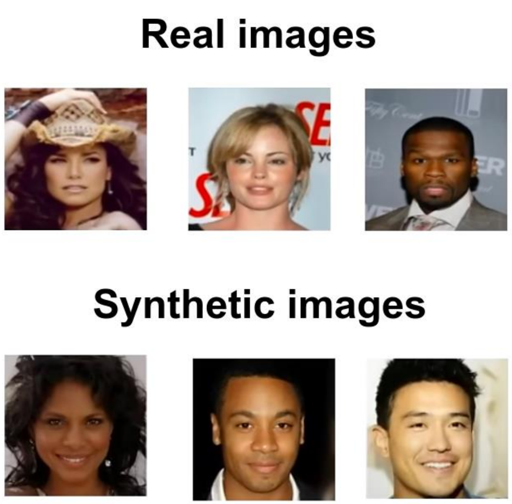


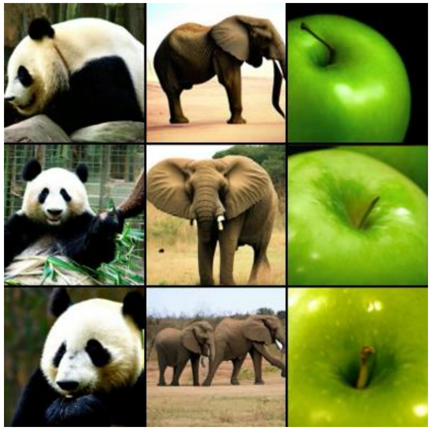
- Key challenges

Generative ability

Conditioning

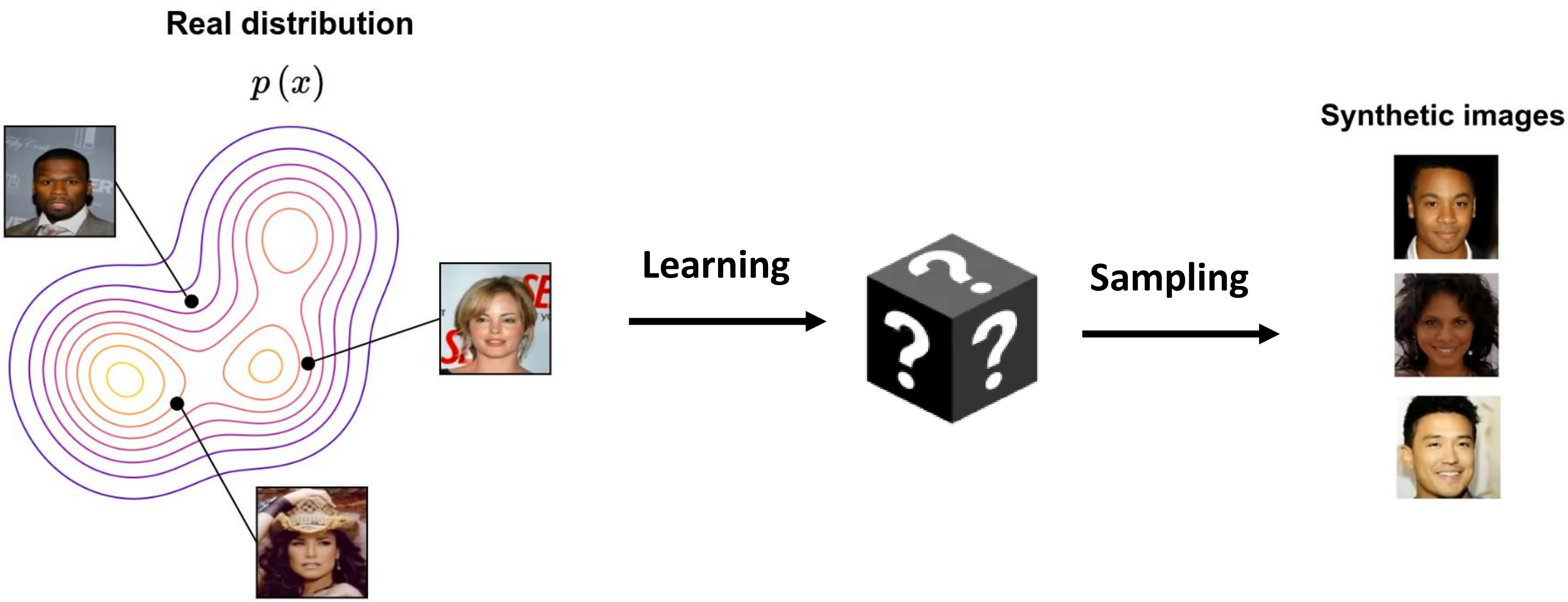
Multimodality



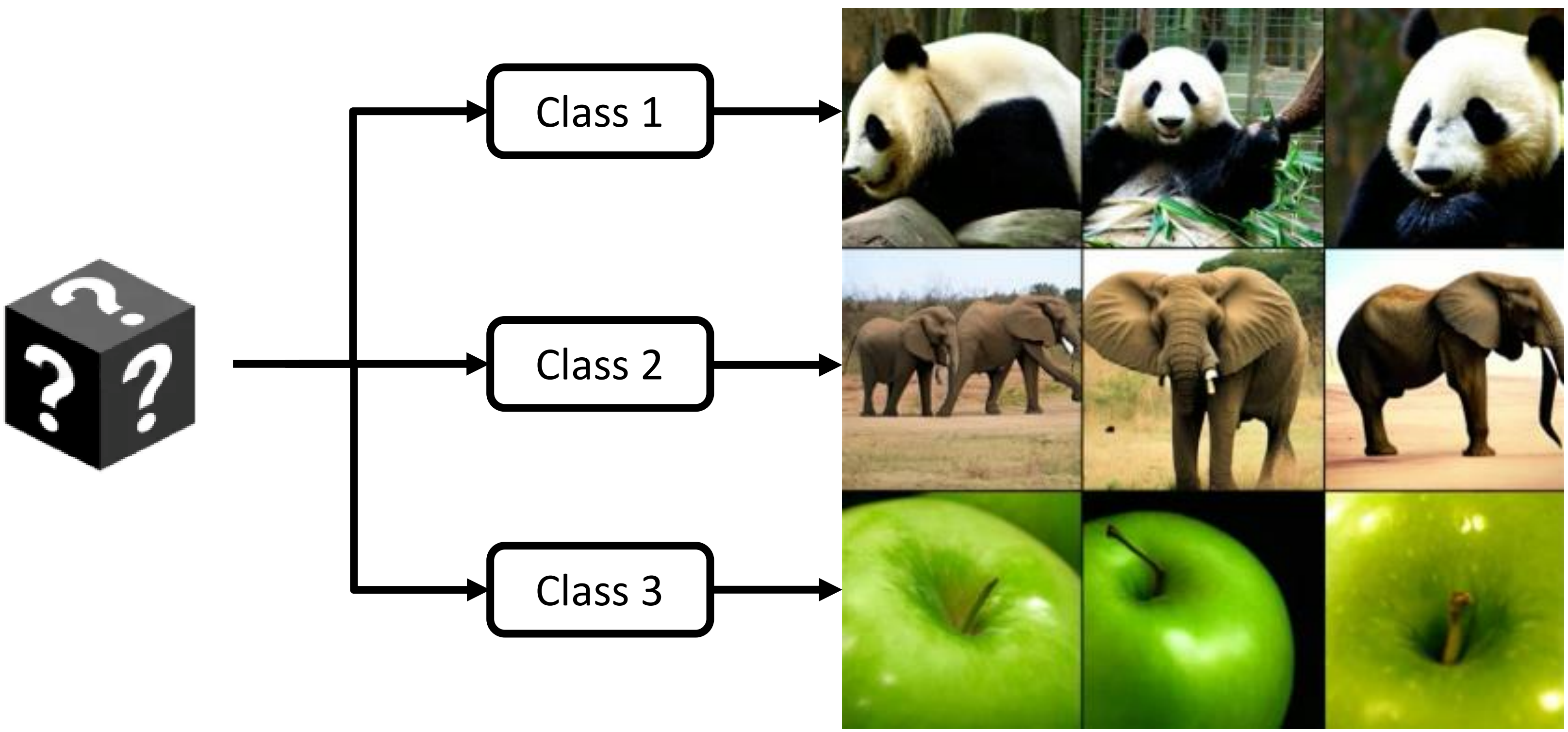


An Asian girl in ancient rides a giant panda

Generative ability



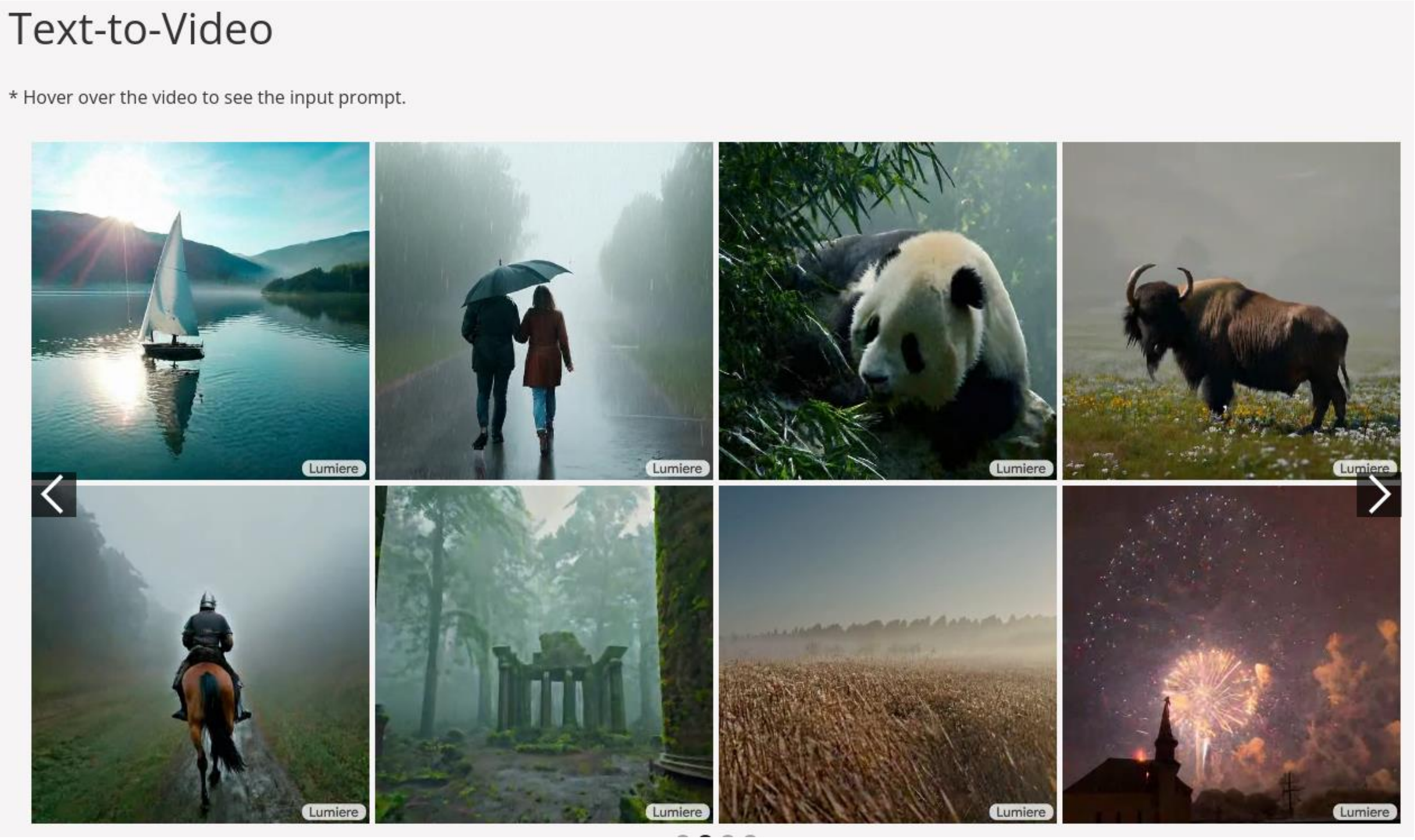
Conditioning



Multimodality

An Asian girl in ancient coarse linen clothes rides a giant panda and carries a wooden cage. A chubby little girl with two buns walks on the snow. High-precision clothing texture, real tactile skin, foggy white tone, low saturation, retro film texture, tranquil atmosphere, minimalism, long-range view, telephoto lens

Multimodality



https://lumiere-video.github.io/#section_image_to_video

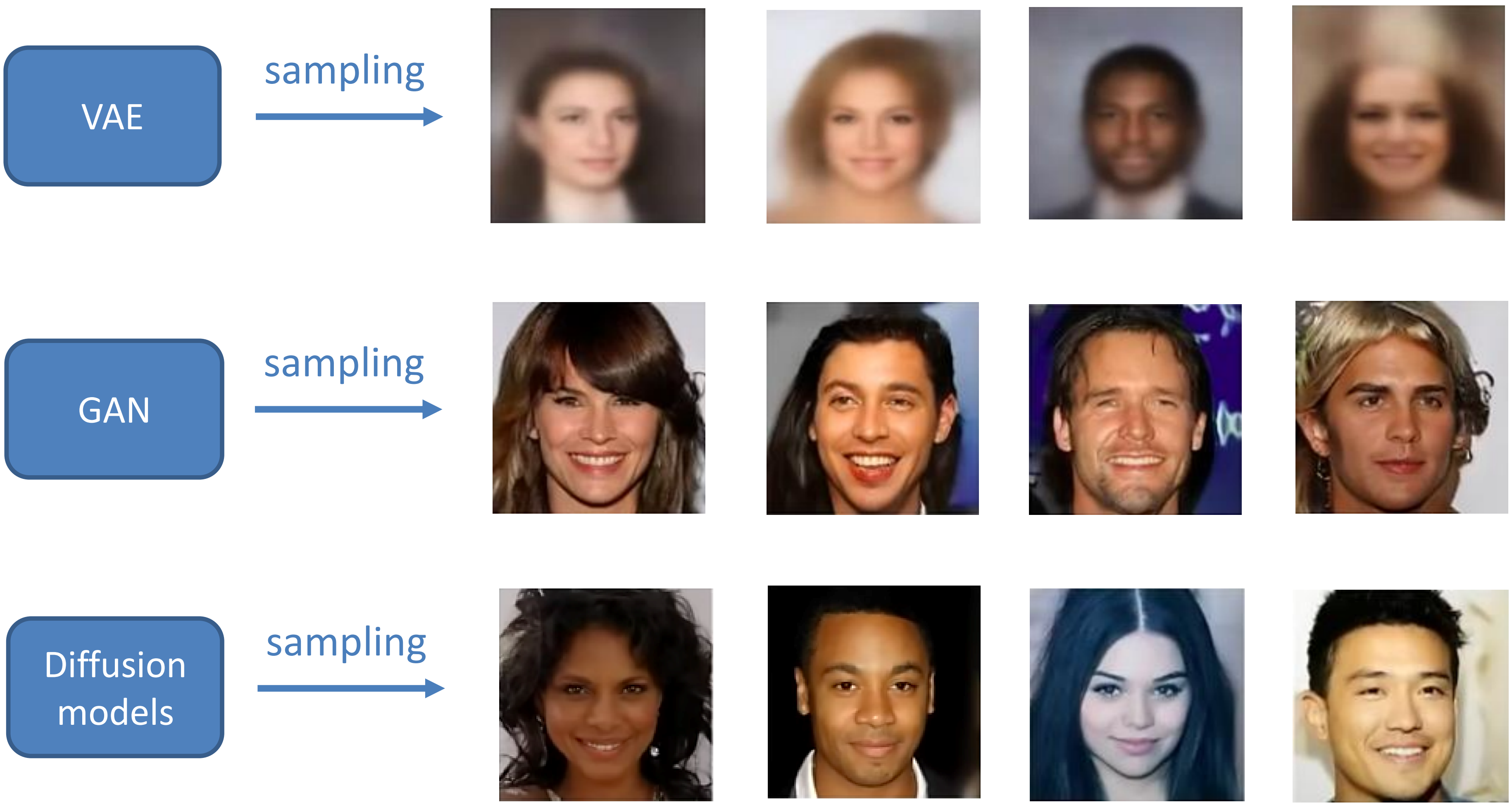
Multimodality

Image-to-Video

* Hover over the video to see the input image and prompt.

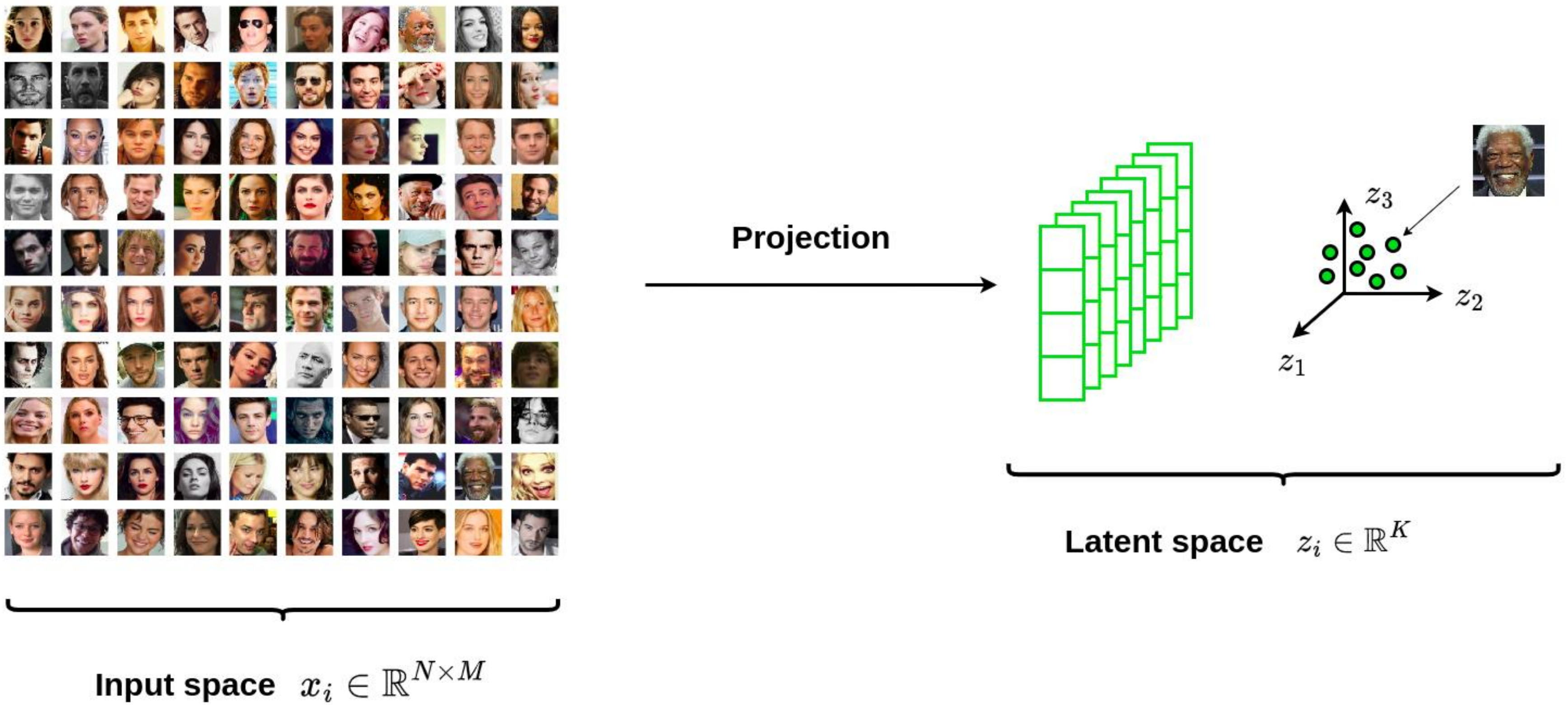
https://lumiere-video.github.io/#section_image_to_video

- Family of networks

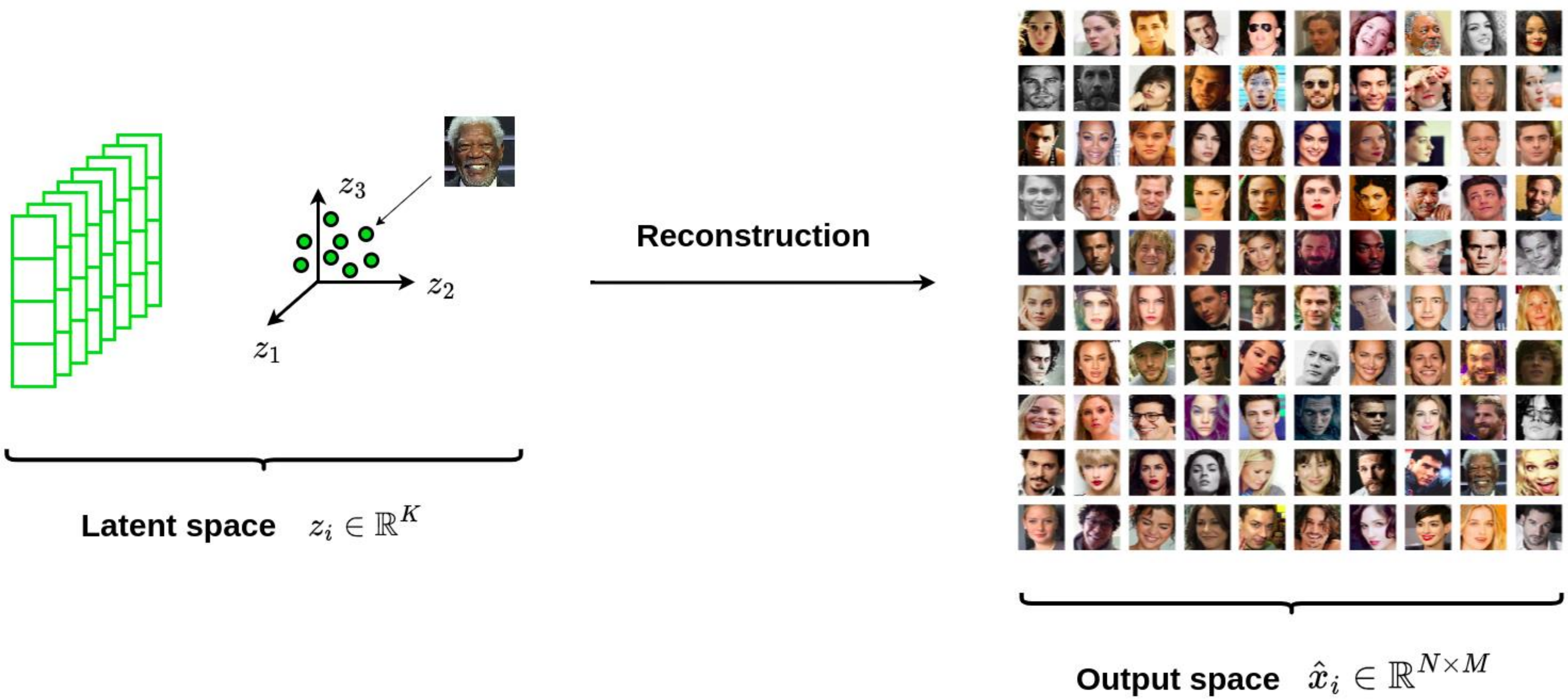


Variational auto-encoders

- Projection of the data into a lower dimensional space called latent space
- Interest: generating a more compact and interpretable representation

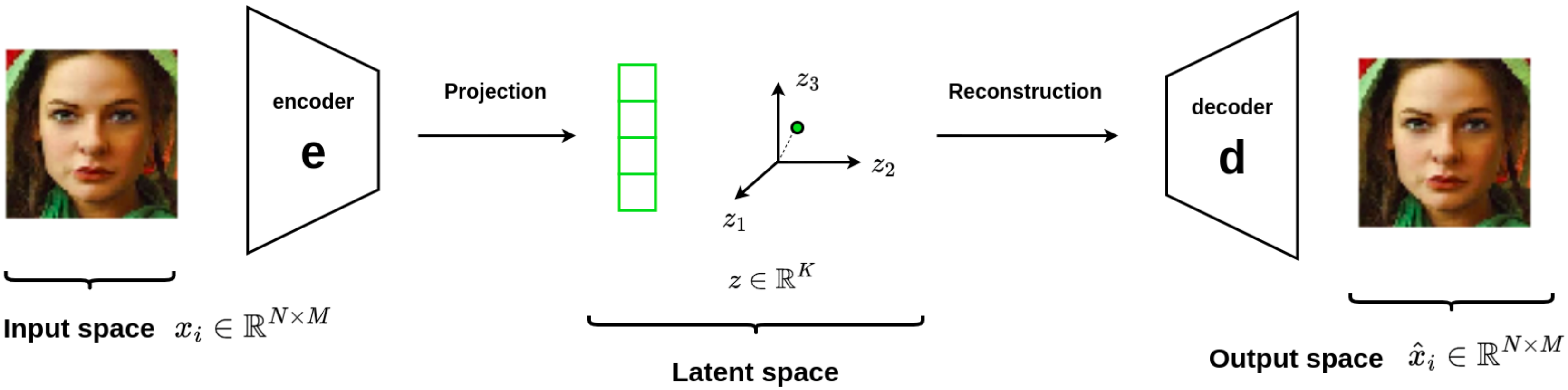


- How to learn a relevant latent representation ?



Auto-encoder framework

- Standard encoder / decoder architecture

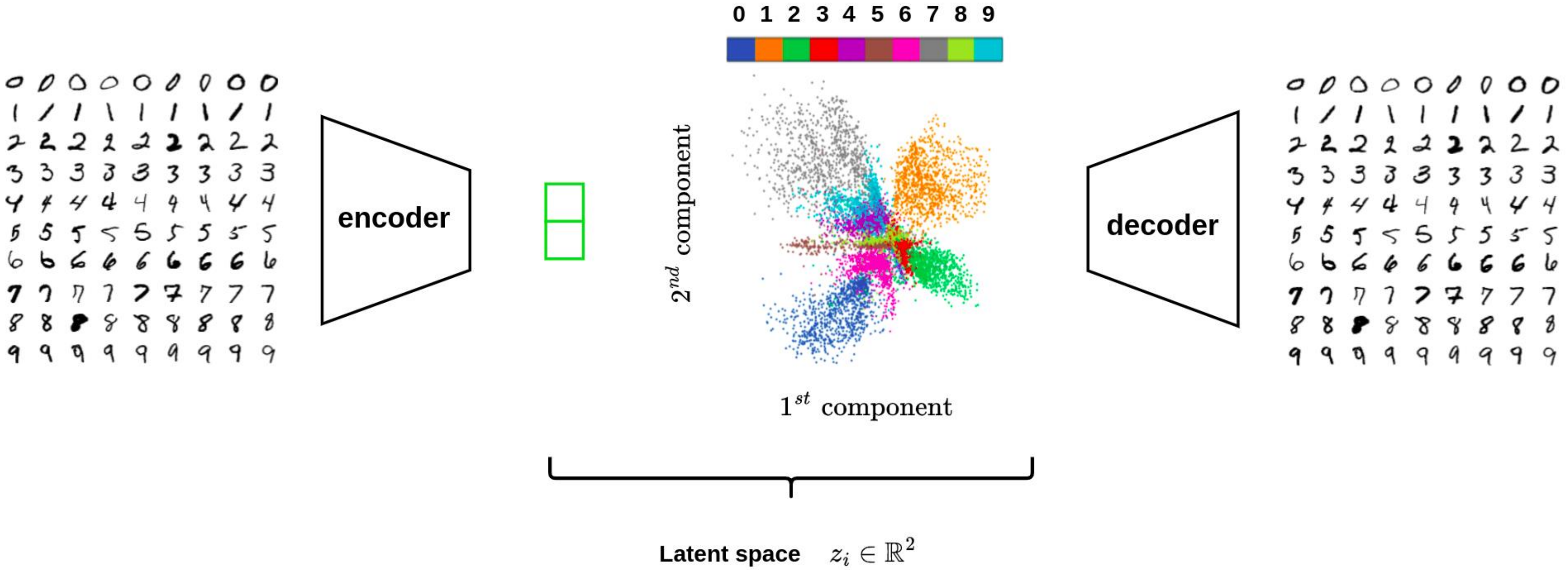


- Deep learning loss function

loss = $\|x - \hat{x}\|^2$

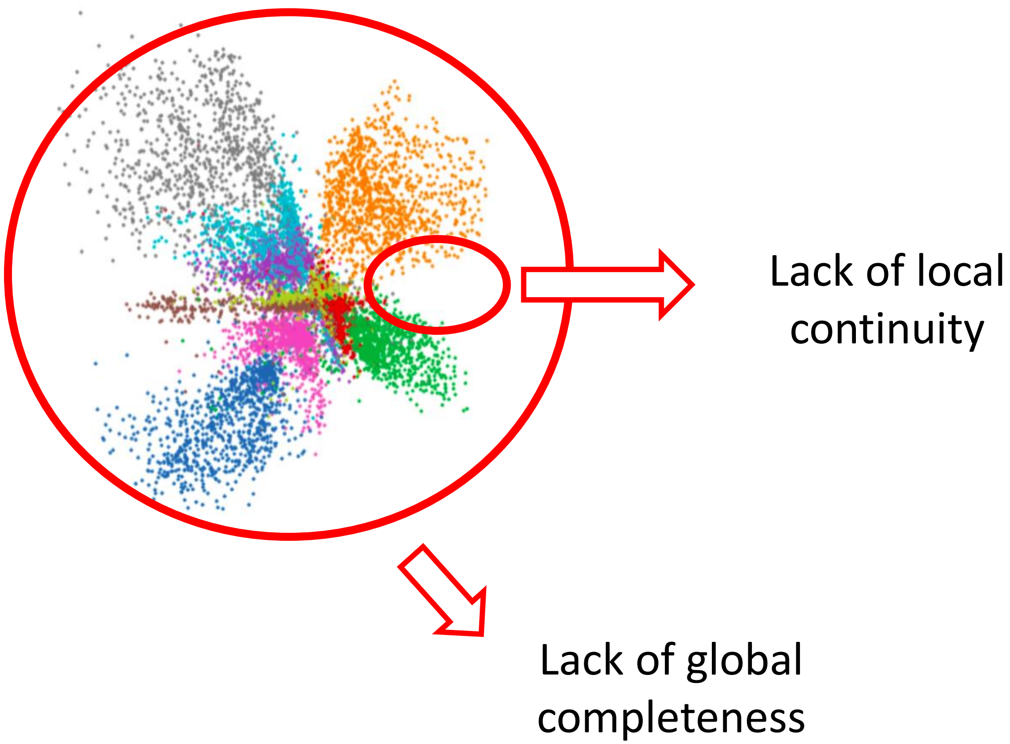
loss = $\|x - d(e(x))\|^2$

- Illustration from MNIST dataset
  - (train,test) = (60 000, 10 000)
  - Input image size: 32x32 / latent space K=16 (compression factor around 64)



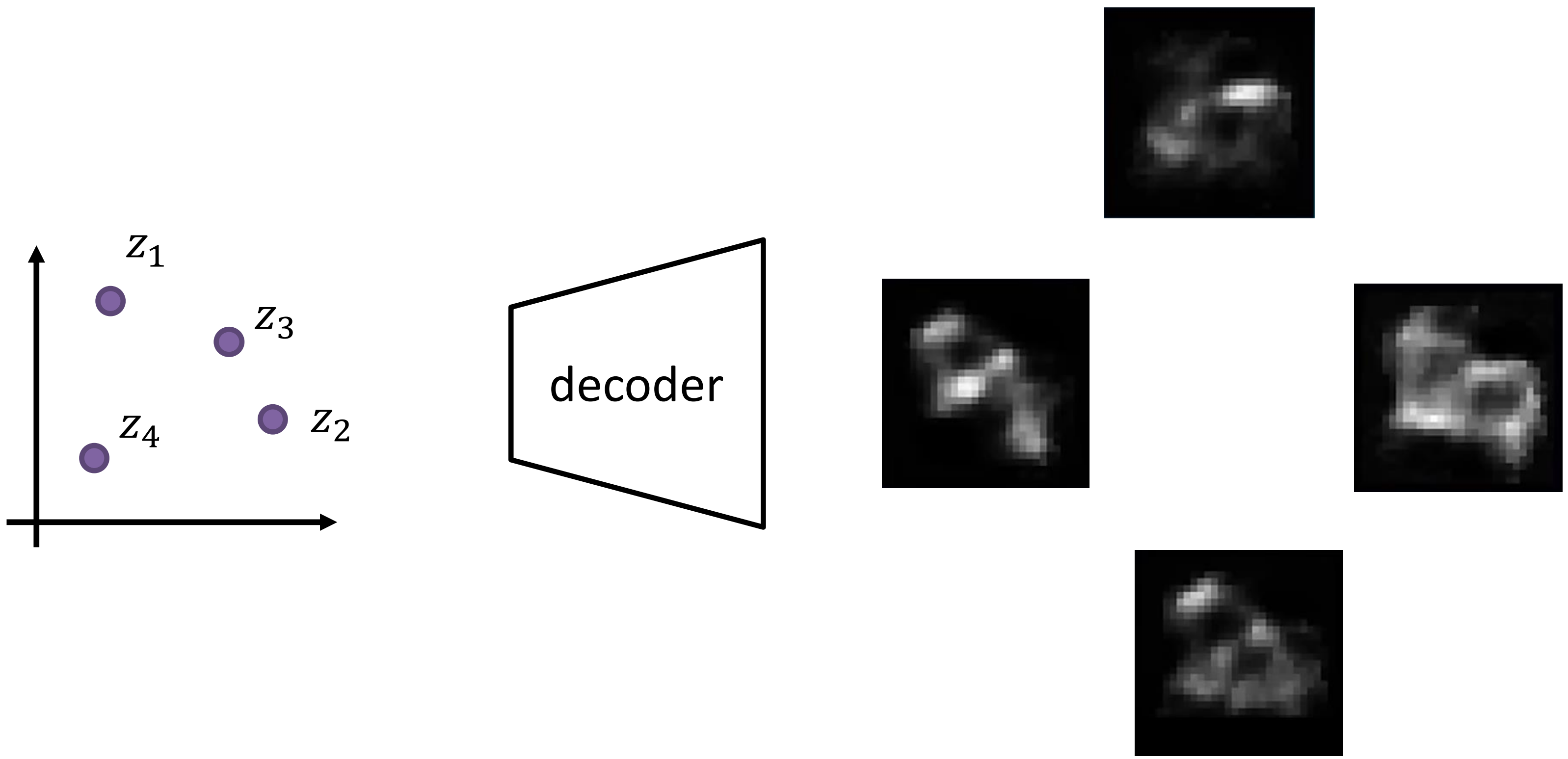
Auto-encoder weaknesses

- Needs to better control the structure of the latent space



Auto-encoder weaknesses

- Sampling random latent vector

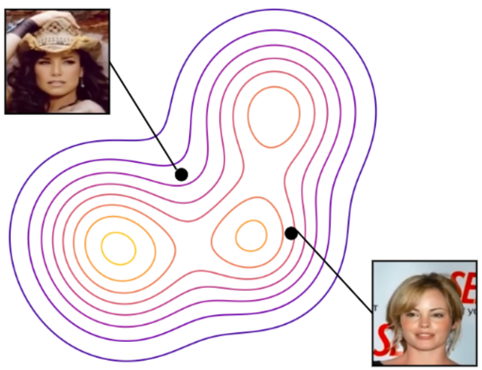


Variation Auto Encoder framework

- Starting point

Intractable distribution

$$p(x)$$

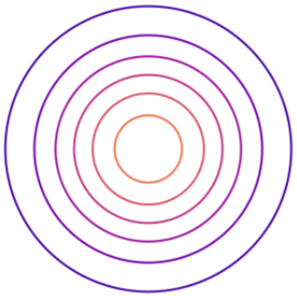


Data distribution

$$x \sim p(X) \in \mathbb{R}^{N \times M}$$

Controlled distribution

$$p(z)$$

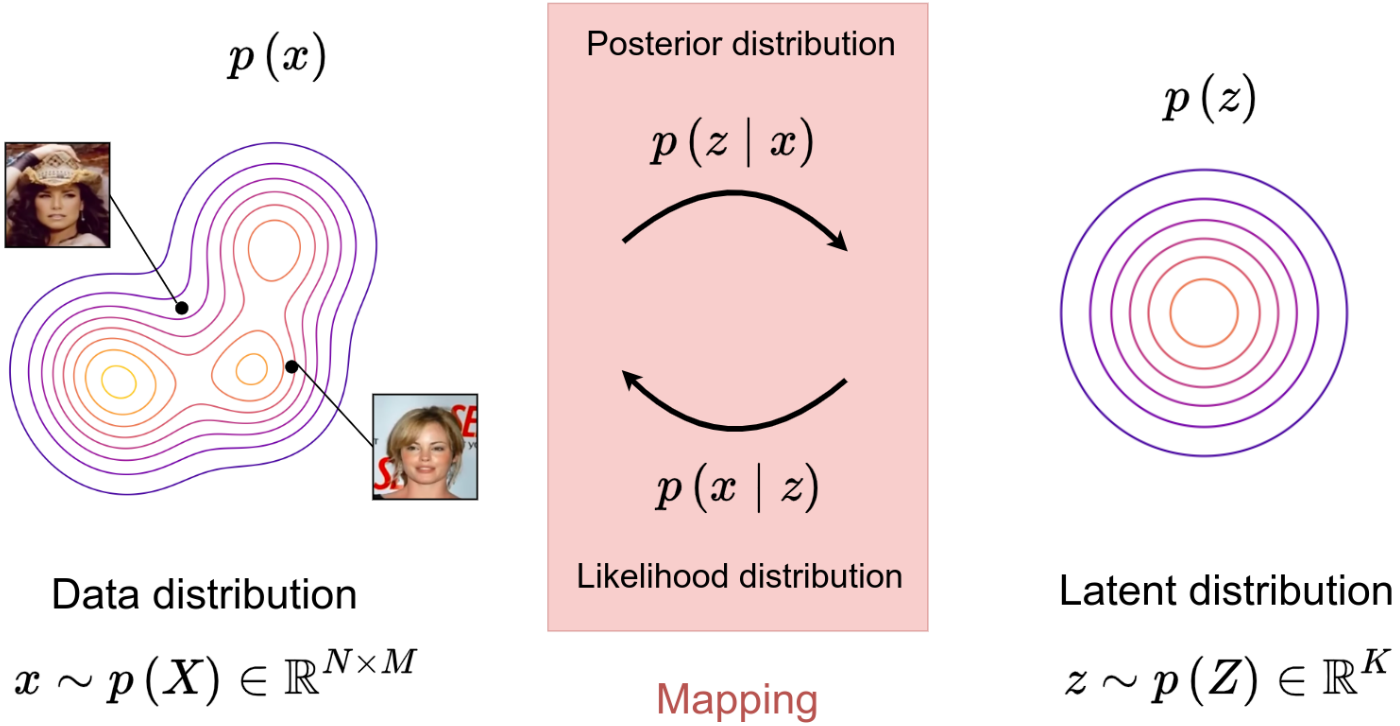


Latent distribution

$$z \sim p(Z) \in \mathbb{R}^{K}$$

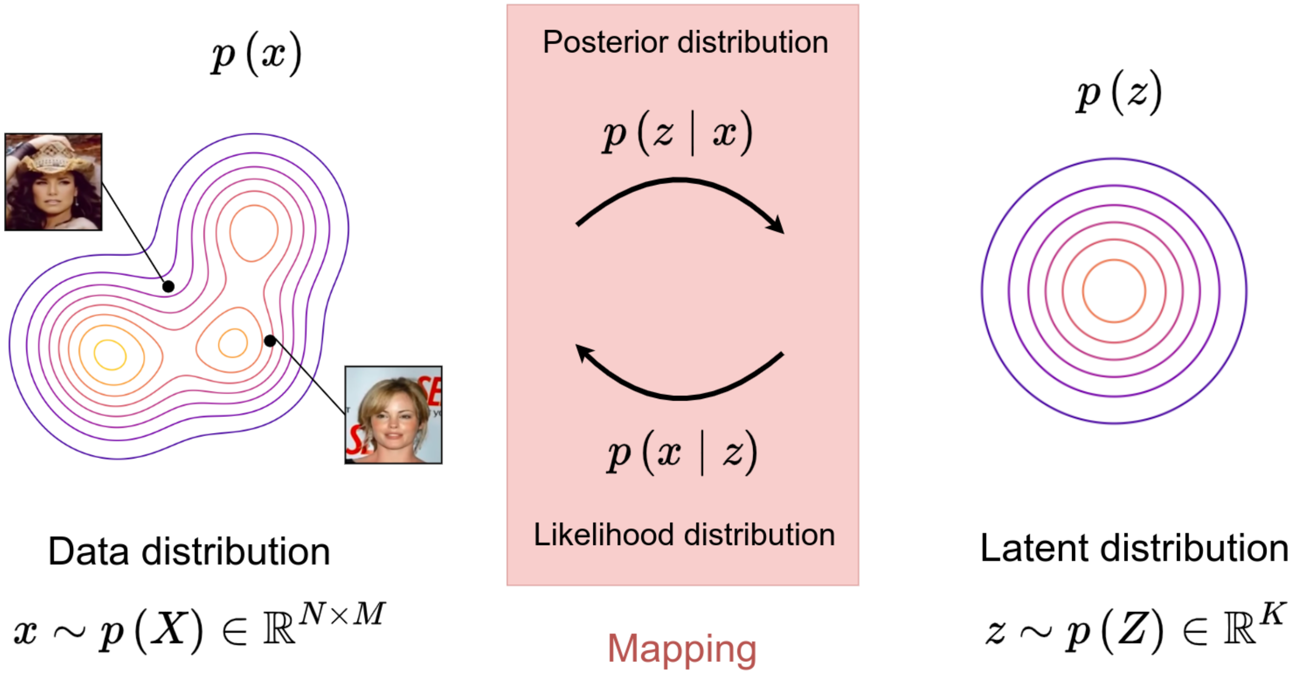
Variation Auto Encoder framework

- Creating a mapping between the two distributions
  - ➔ Through Bayesian statistics



Variation Auto Encoder framework

- Strong assumptions
  - → Latent distribution $p(z)$ is assumed to be a normal distribution
  - → The likelihood distribution is $p(x|z)$ assumed to be a Gaussian distribution whose parameters need to be learned
  - → The posterior distribution $p(z|x)$ is intractable and needs to be approximated



- Approximation of the posterior through variational inference
  - ➔ Statistical approximation technique for complex distributions, here $p(z|x)$
  - ➔ Definition of a parameterized family of distributions
    - e.g., family of Gaussian distributions with parameters μ_x, σ_x modeled by functions to be determined
  - ➔ Find the best approximation of the target distribution in this family
  - ➔ The best element of the family minimizes an approximation error measure between two distributions
    - Kullback-Leibler divergence function is often used

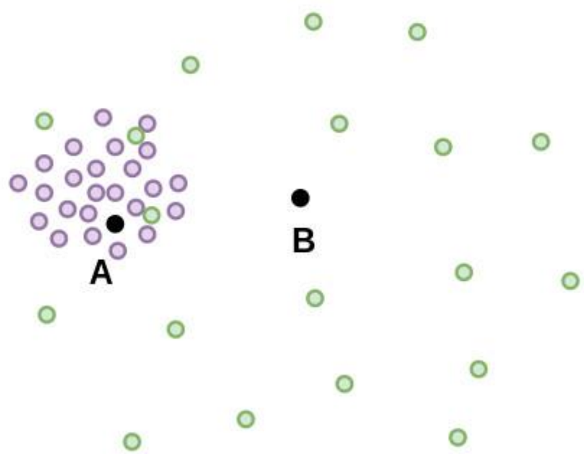
- Kullback-Leibler divergence function

→ Distance measure between two distributions via relative entropy

$$D_{KL}(p \parallel q) = \int p(x) \cdot \log\left(\frac{p(x)}{q(x)}\right) dx$$

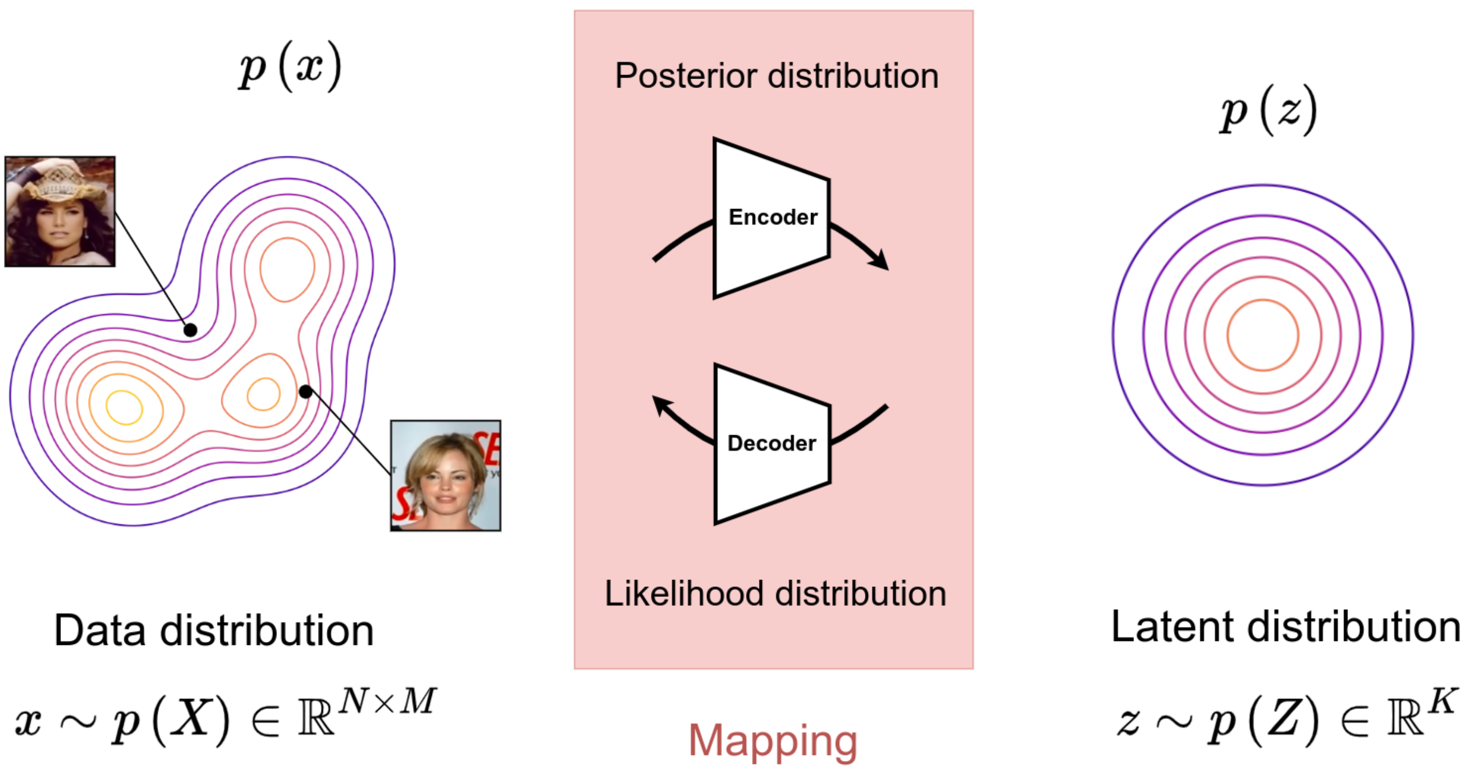
→ D_{KL} is a measure that is always positive $D_{KL}(p||q) \geq 0$

→ D_{KL} is a nonsymmetric measure $D_{KL}(p||q) \neq D_{KL}(q||p)$



- For the purple distribution, the distance AB is large
- For the green distribution, the distance AB is moderate
- The notion of distance differs depending on the distributions

- Enforce a structured latent space with reduced dimensionalities
  - ➔ Through Bayesian statistics



- The prior is modeled through a Gaussian distribution

$$p(z) = \mathcal{N}(0, I)$$

- The likelihood is modeled through a Gaussian distribution

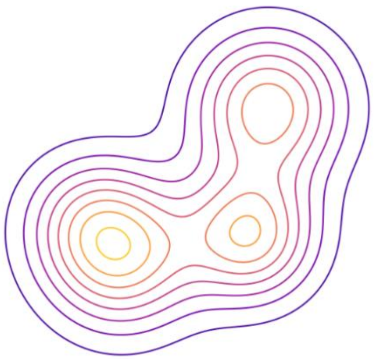
$$p(x \mid z) = \mathcal{N}(\mu_z, \sigma_z) = \mathcal{N}\left(f(z), cI\right)$$

- The posterior is approximated by an axis-aligned Gaussian distribution

$$q(z \mid x) = \mathcal{N}(\mu_x, \sigma_x) = \mathcal{N}\left(g(x), diag(h(x))\right)$$

- Optimization process
  - ➔ Sample a new data from the original data distribution
  - ➔ Pick a sample x that maximize $p(x)$, or $\log(p(x))$

$p(x)$



$$\log(p(x))$$

$$\log(p(x)) = \log\left(\int p(x,z)dz\right)$$

← Marginal distribution

$$\log(p(x)) = \log\left(\int \frac{q(z \mid x)}{q(z \mid x)} p(x,z)dz\right)$$

Expectation reformulation

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

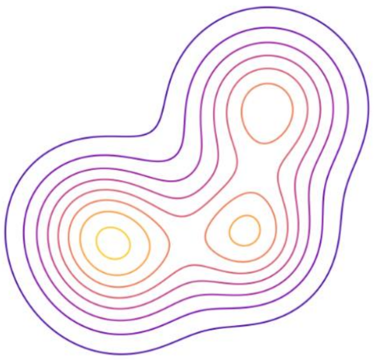
Jensen's inequality

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

- Evidence lower bound (ELBO)

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

ELBO



→ Maximization of the ELBO

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

Bayes' formula
$p(x,z) = p(x|z)\,p(z)$

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

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

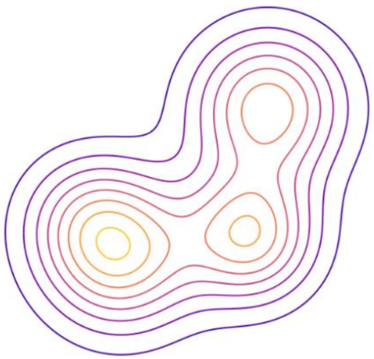
Kullback-Liebler divergence D_{KL}

$$\mathcal{L}(x) = \mathbb{E}_{q(z|x)}\left[\log\left(p(x\mid z)\right)\right] - D_{KL}\left(q(z\mid x)\,\|\,p(z)\right)$$

- ELBO maximization

$$\mathcal{L} = \mathbb{E}_{z\sim q_x}\left[log\left(p(x|z)\right)\right] - D_{KL}\left(q(z|x) \parallel p(z)\right)$$

$p\left(x\right)$

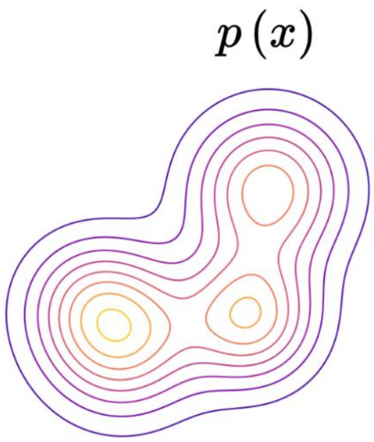


➔ Exploitation of the Gaussian assumption of the likelihood

$$p(x|z) = \mathcal{N}\left(f(z), cI\right)$$

$$\mathcal{L} \propto \mathbb{E}_{z\sim q_x}\left[-\alpha\|x - f(z)\|^2\right] - D_{KL}\left(q(z|x) \parallel p(z)\right)$$

Variation Auto Encoder framework



- Optimization process

$$(f^*, g^*, h^*) = \underset{(f,g,h)}{\arg\min} \left(\mathbb{E}_{z \sim q_x} \left[\alpha \|x - f(z)\|^2 \right] + D_{KL} \left(q(z|x) \parallel p(z) \right) \right)$$

- Deep learning loss function

$$\text{loss} = \alpha \|x - f(z)\|^2 + D_{KL} \left(\mathcal{N} \left(g(x), diag\left(h(x) \right) \right), \mathcal{N} \left(0, I \right) \right)$$

→ $g(\cdot)$ and $h(\cdot)$ are modeled through an encoder

→ $f(\cdot)$ is modeled through a decoder

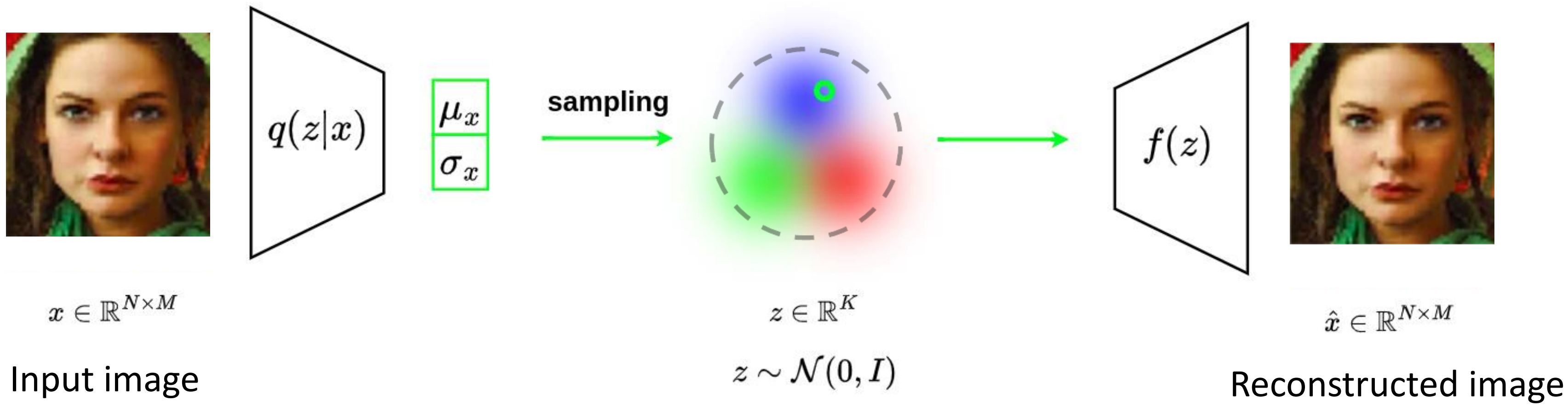
- Interpretation of the loss function

$$\text{loss} = \alpha \|x - f(z)\|^2 + D_{KL}\left(\mathcal{N}\left(g(x), diag\left(h(x)\right)\right), \mathcal{N}\left(0, I\right)\right)$$

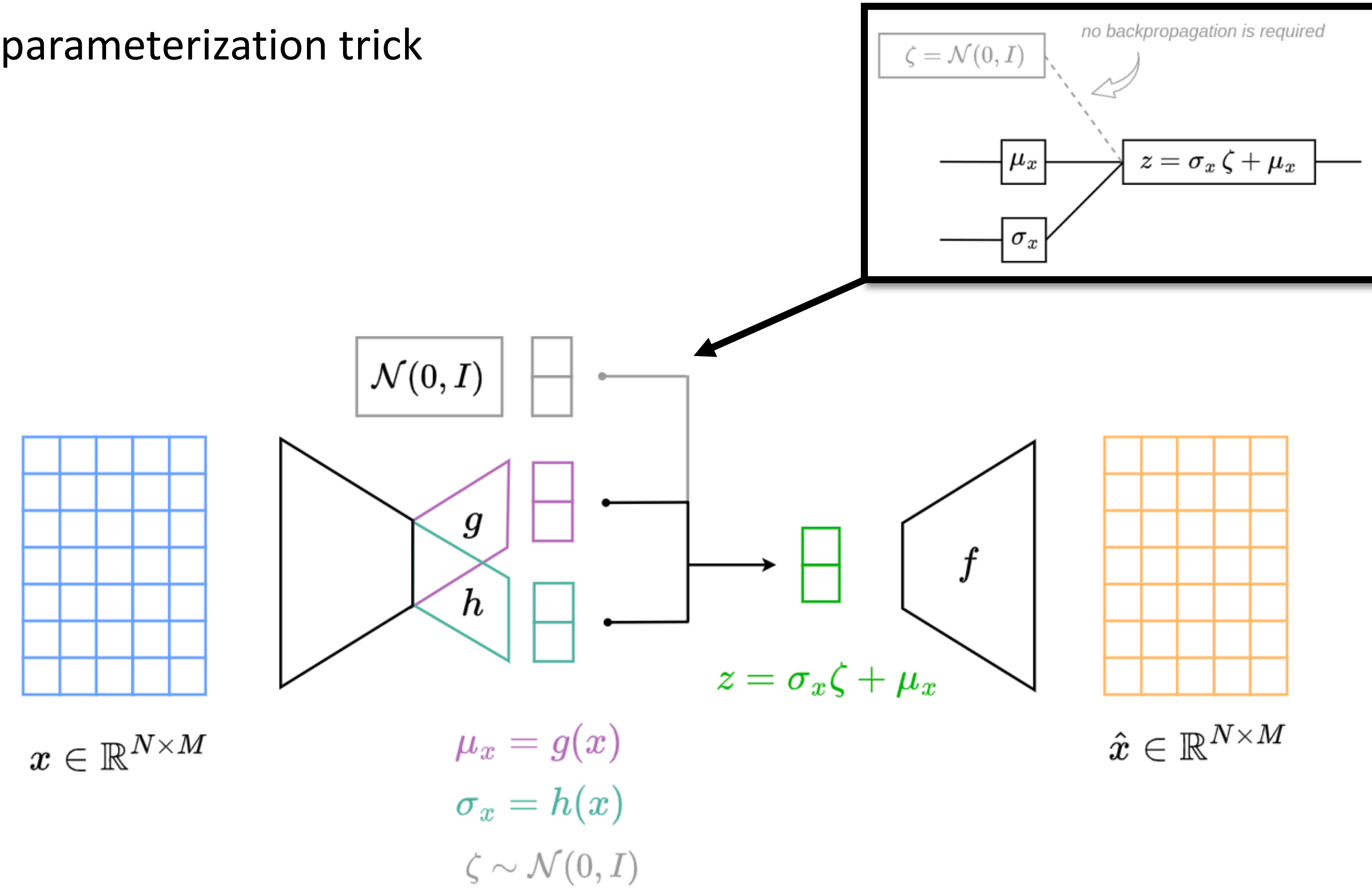
Data attachment term

Completeness constraint

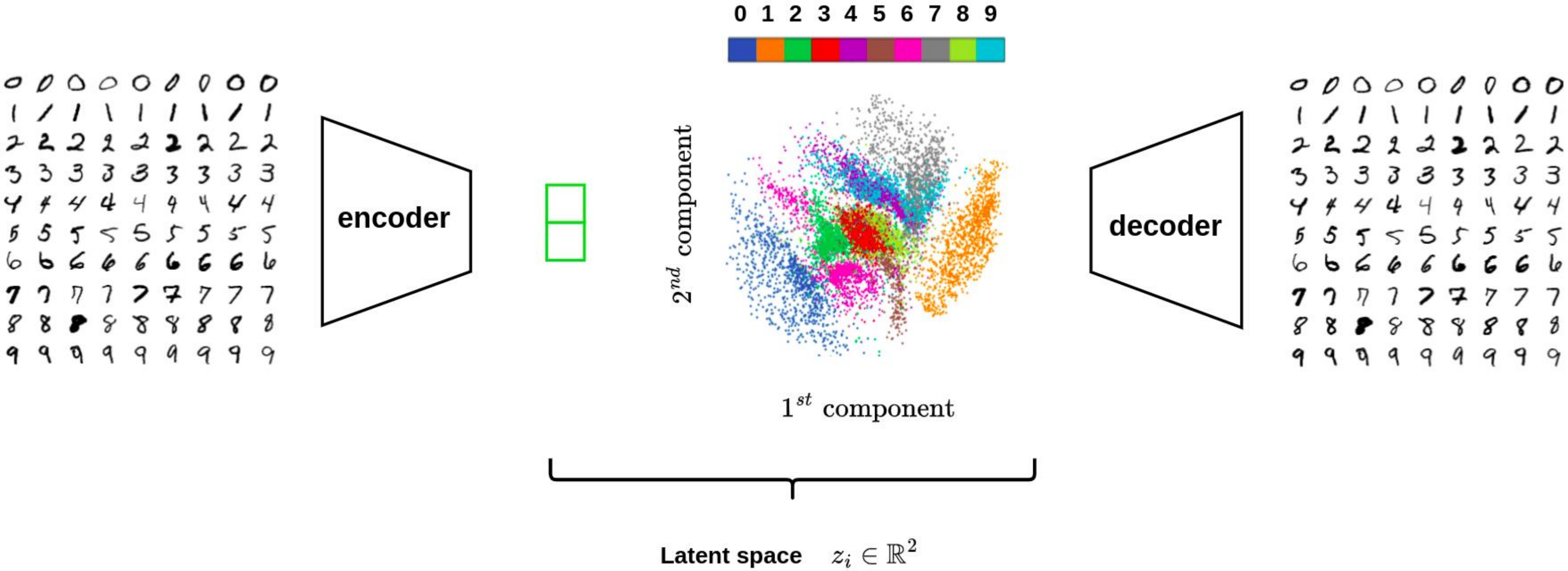
Continuity constraint



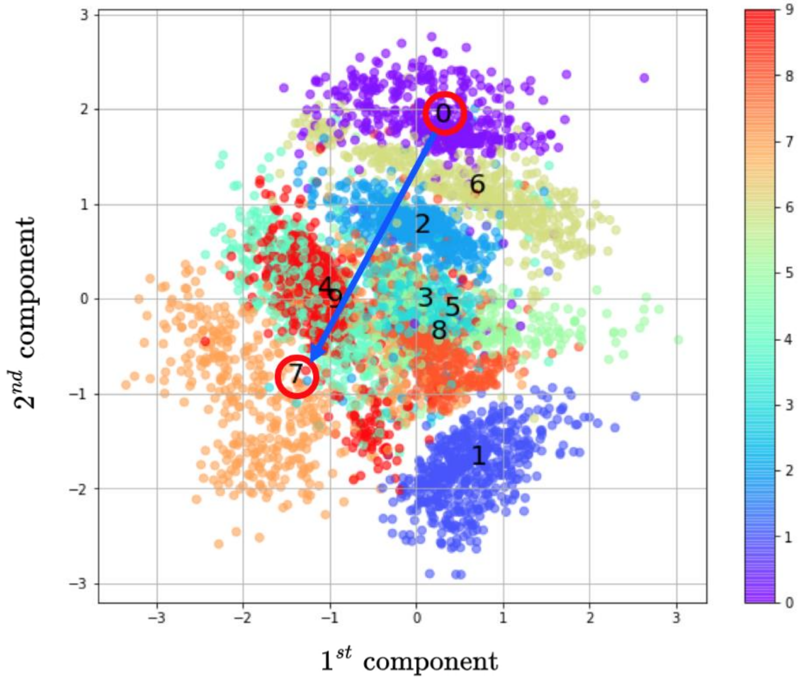
- Reparameterization trick



- Illustration from MNIST dataset
  - (train,valid,test) = (50 000,10 000,10 000)
  - Input image size: 28x28 / latent space K=16 (compression factor around 50)

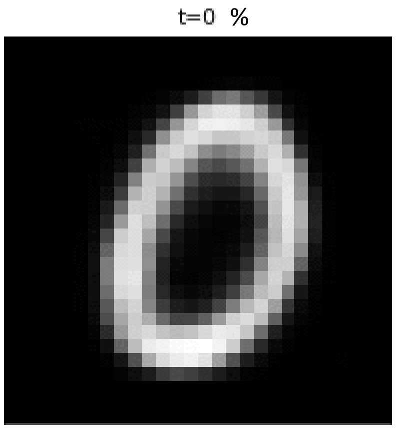


- Generative model with variational framework



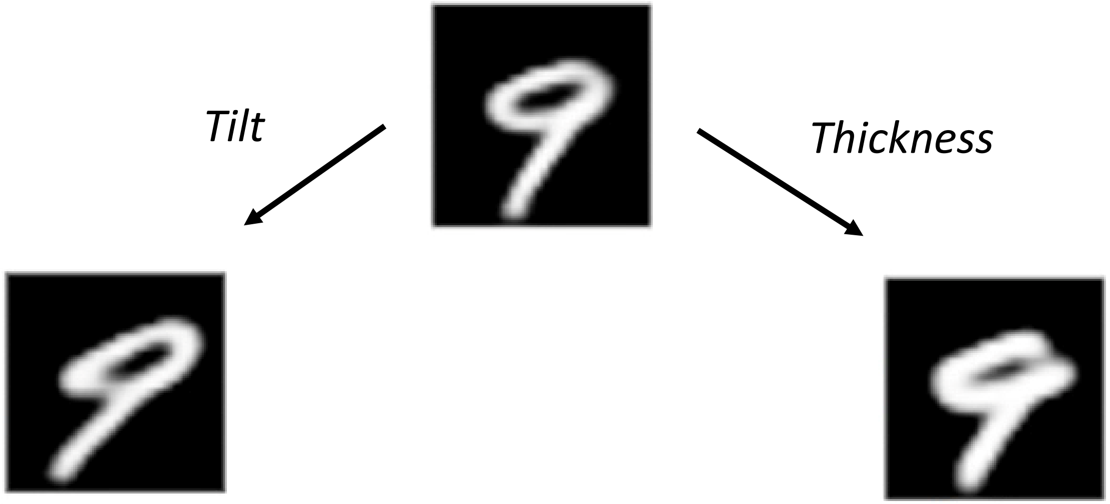
Linear interpolation into the latent space

$$t \cdot z_0 + (1 - t) \cdot z_7, \qquad 0 \leq t \leq 1$$



Reinforcement of the generative process

- Structuration of latent space based on image attributes
  - What is an attribute ?
    - → Measurement performed in image space to characterize a target object
    - → E.g.: handwritten digits (MNIST database)
      - Attributes: line thickness, inclination, length, area, ...
    - → Pre-training image attribute measurements used as input data



- Structuration of latent space based on image attributes
  - Each attribute are coded according to a specific latent dimension

$$Loss = \mathcal{L}_{recons} + \beta\mathcal{L}_{KLD} + \gamma\sum_{l=0}^{L-1}\mathcal{L}_{r_l,a_l}$$

Data attachment term

KL divergence term

Attribute regularization term

Structuring latent space

Attribute regularization term

- During the learning phase

  → Computation for each attribute a of a distance matrix $D_a \in \mathbb{R}^{m \times m}$ from the m images $\{x_i\}_{1 \leq i \leq m}$ present in the current batch

$$D_a(i,j) = a(x_i) - a(x_j) \qquad \text{with} \qquad i,j \in [0,m)$$

  → Computation for each attribute r of a distance matrix $D_r \in \mathbb{R}^{m \times m}$ from the m latent vector $\{z_i\}_{1 \leq i \leq m}$ corresponding to the images in the current batch

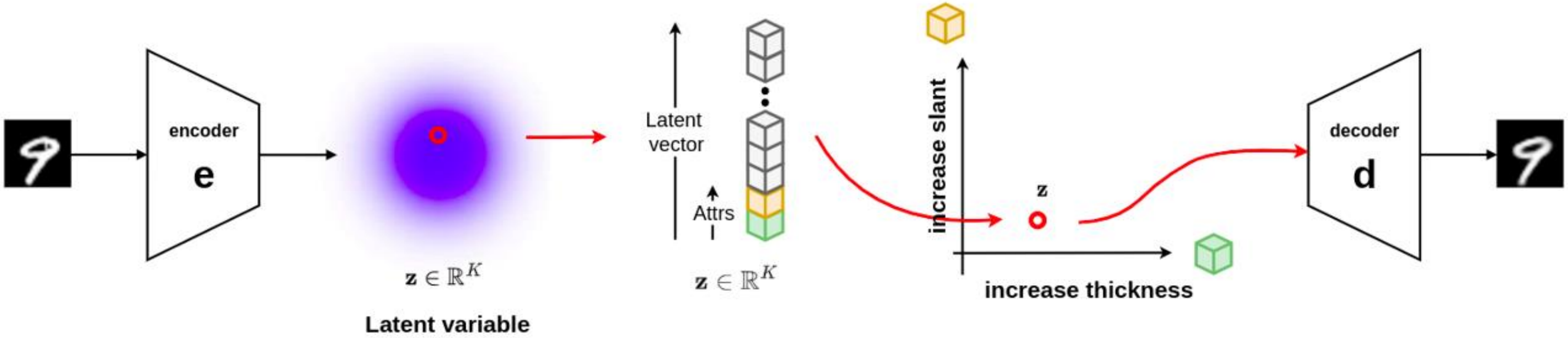
$$D_r(i,j) = z_i^r - z_j^r \qquad \text{with} \qquad i,j \in [0,m)$$

  → Introduction of the following loss term

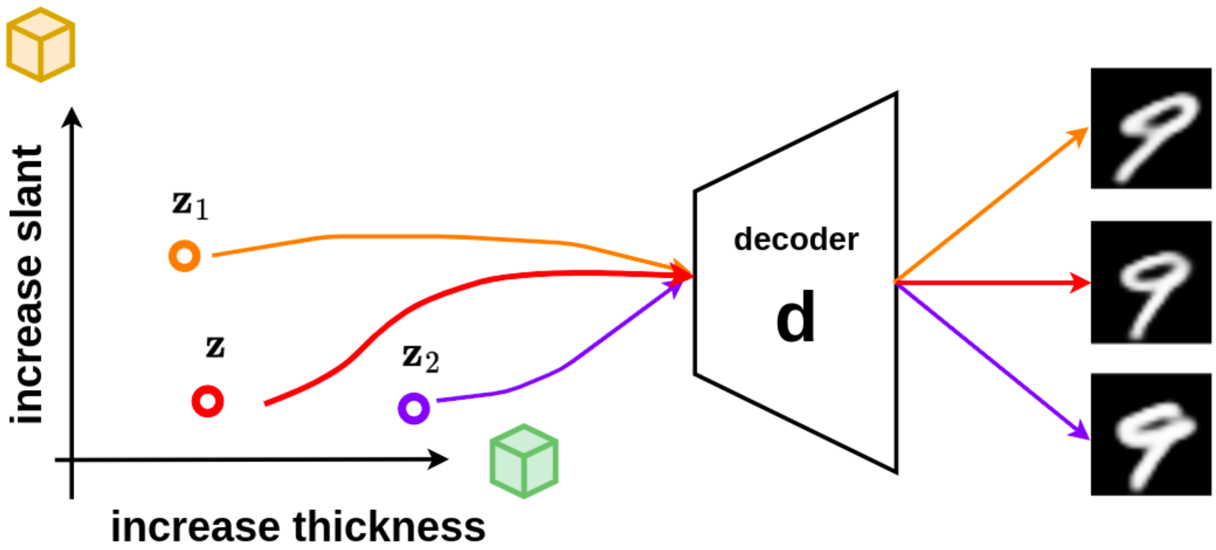
$$\mathcal{L}_{r,a} = MAE\left(\tanh\left(D_r\right) - sign\left(D_a\right)\right)$$

Structuration of the latent space: AR-VAE

- Generate a latent space structured according to attributes

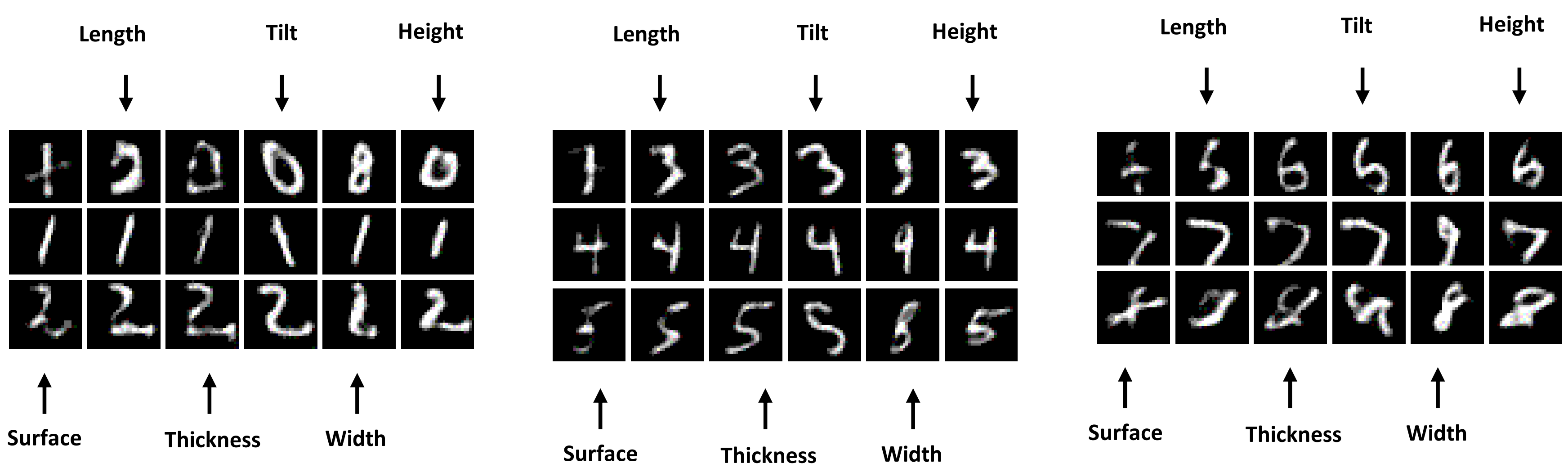


- Generate a latent space structured according to attributes
  - Sampling of the structured latent space



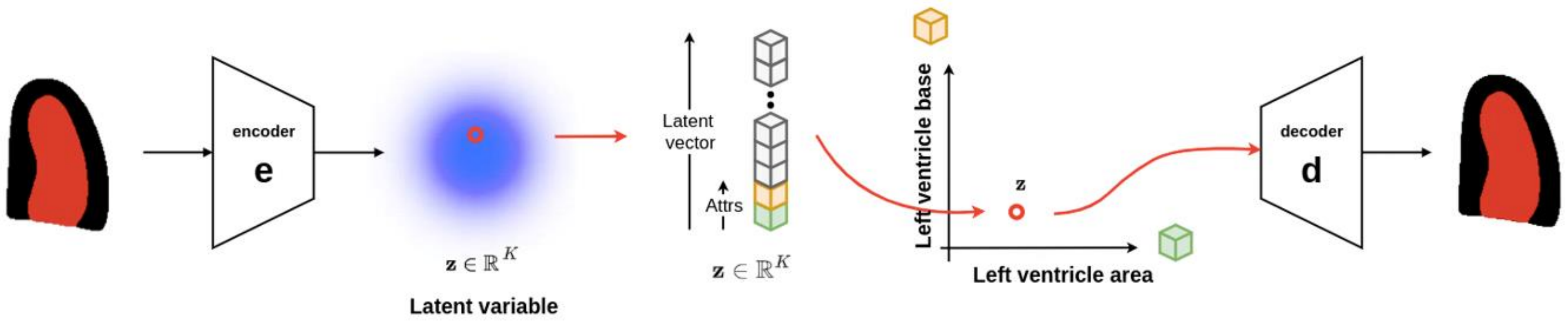
Structuration of the latent space: AR-VAE

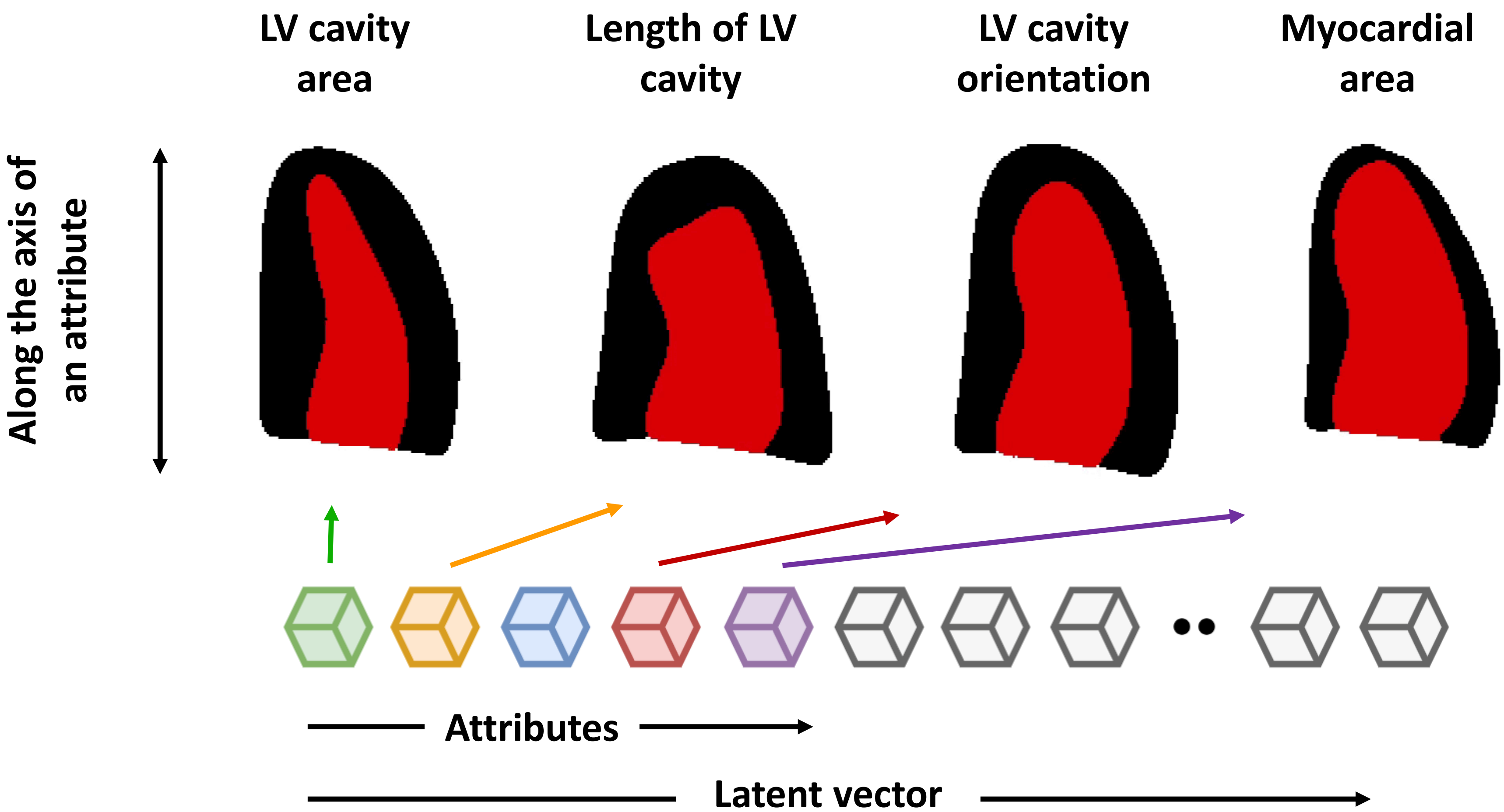
- Generate a latent space structured according to attributes
  - Sampling of the structured latent space
    - ➔ Specific attributes: surface, length, thickness, inclination, width, height
    - ➔ Each column corresponds to a traverse along a regularized dimension



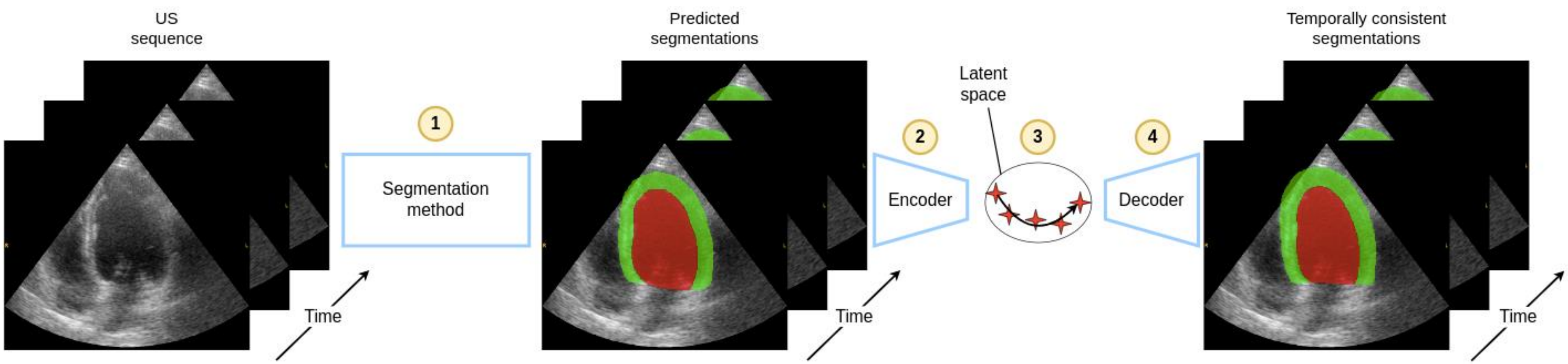
Medical applications

- Application example: representation of cardiac shapes
  - Generation of a latent space structured according to the following attributes
    - ➔ Left ventricular (LV) cavity: surface area, length, basal width, orientation
    - ➔ Myocardial surface
    - ➔ Epicardial wall center



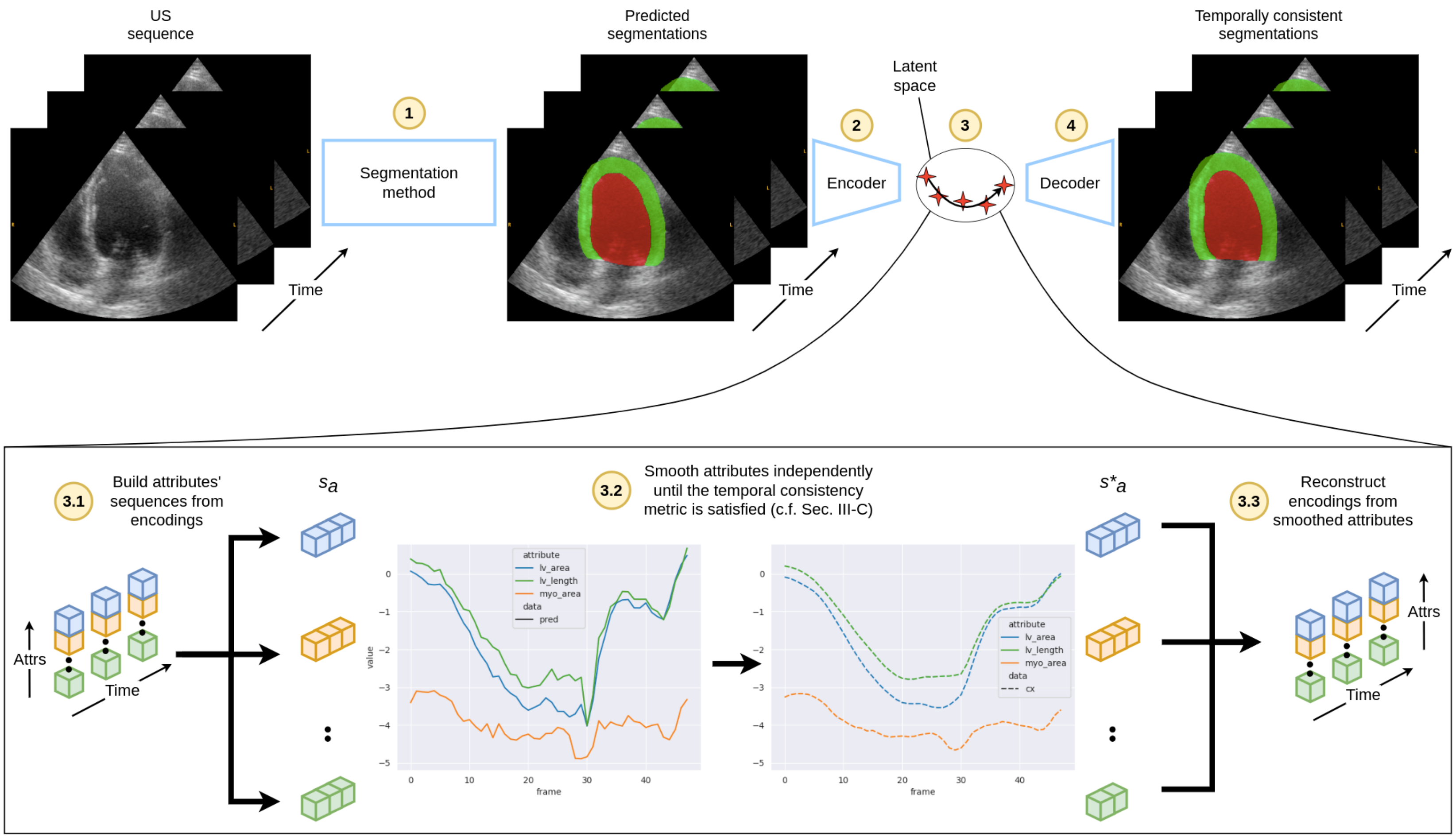

LV cavity area
Length of LV cavity
LV cavity orientation
Myocardial area
Along the axis of an attribute
Attributes
Latent vector

- Post-processing to ensure temporal consistency



[Painchaud, IEEE TMI, 2022]

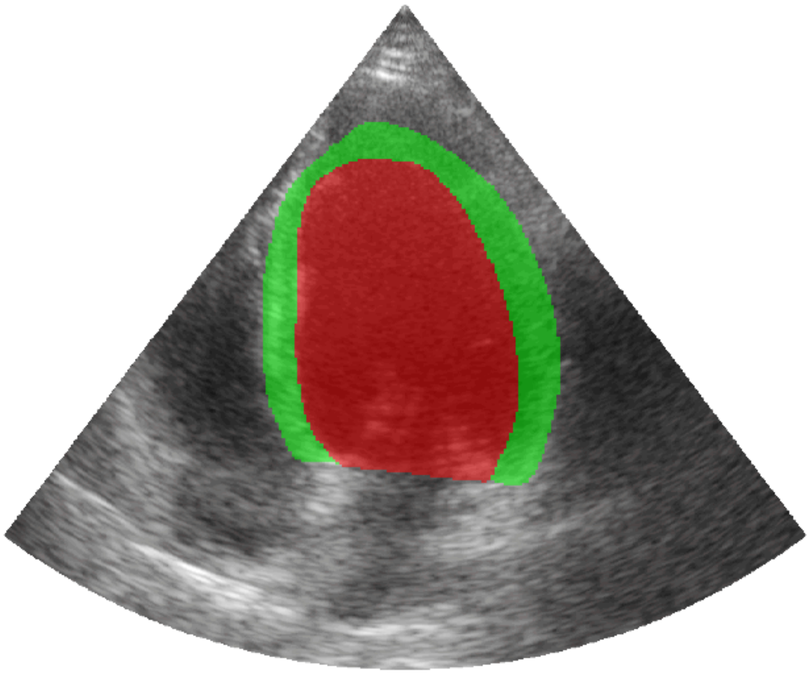
Cardiac segmentation with temporal consistency



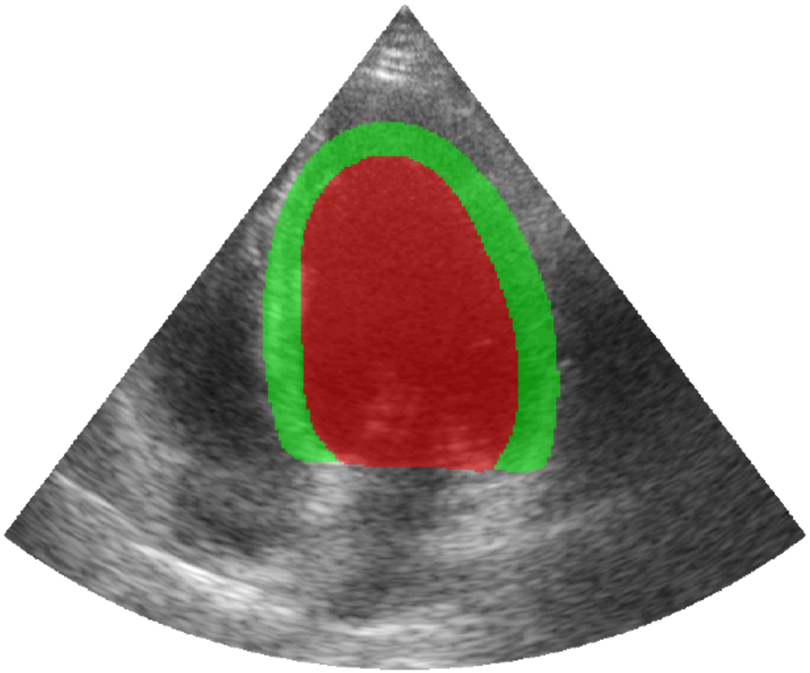
Cardiac segmentation with temporal consistency

- Some post-processing examples

Original segmentation

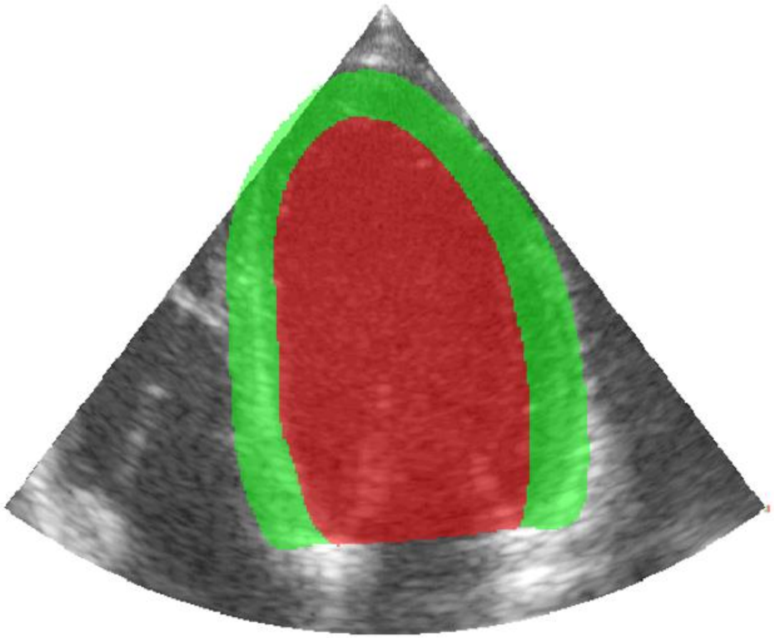


Post-processed segmentation

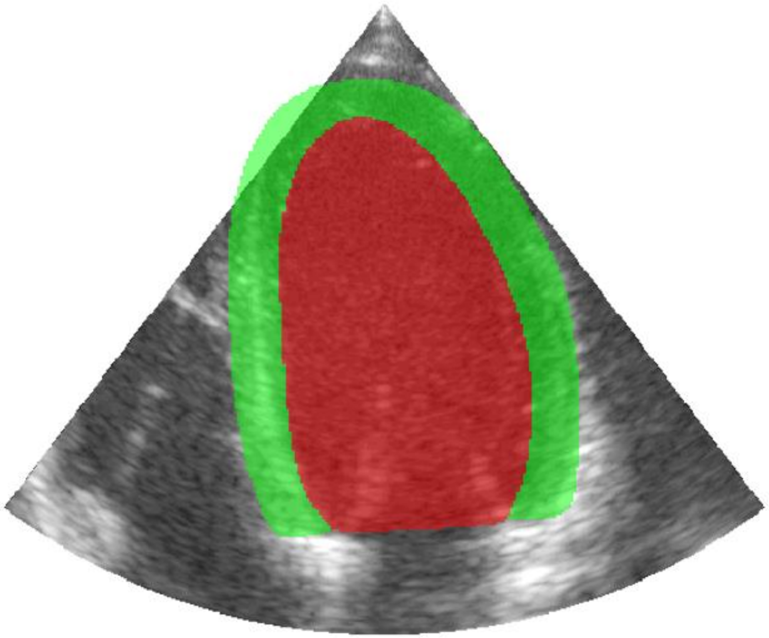


- Some post-processing examples

Original segmentation



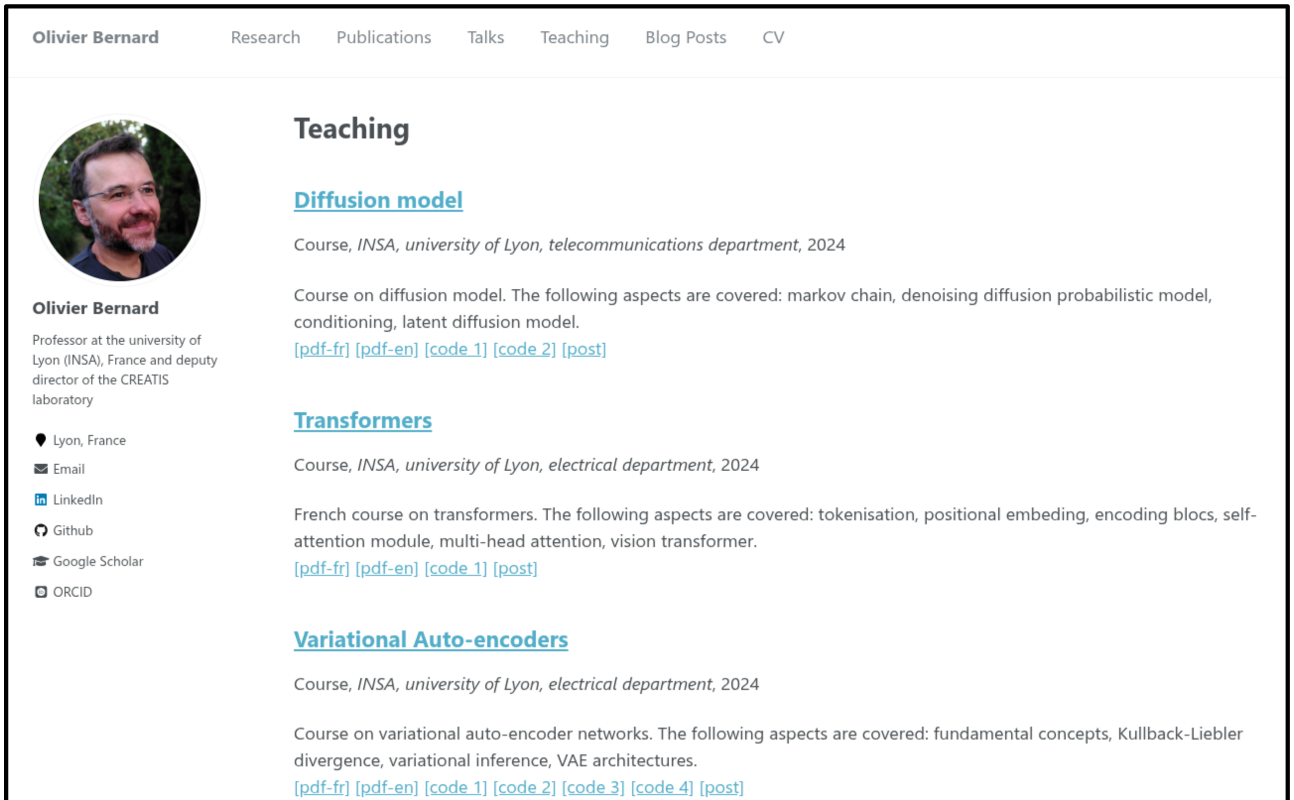
Post-processed segmentation



Hands-on session

Hands-on session

- https://olivier-bernard-creatis.github.io//teaching/



Olivier Bernard Research Publications Talks Teaching Blog Posts CV

Olivier Bernard

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Lyon, France
Email
LinkedIn
Github
Google Scholar
ORCID

Teaching

Diffusion model

Course, *INSA, university of Lyon, telecommunications department*, 2024

Course on diffusion model. The following aspects are covered: markov chain, denoising diffusion probabilistic model, conditioning, latent diffusion model.
[pdf-fr] [pdf-en] [code 1] [code 2] [post]

Transformers

Course, *INSA, university of Lyon, electrical department*, 2024

French course on transformers. The following aspects are covered: tokenisation, positional embeding, encoding blocs, self-attention module, multi-head attention, vision transformer.
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Variational Auto-encoders

Course, *INSA, university of Lyon, electrical department*, 2024

Course on variational auto-encoder networks. The following aspects are covered: fundamental concepts, Kullback-Liebler divergence, variational inference, VAE architectures.
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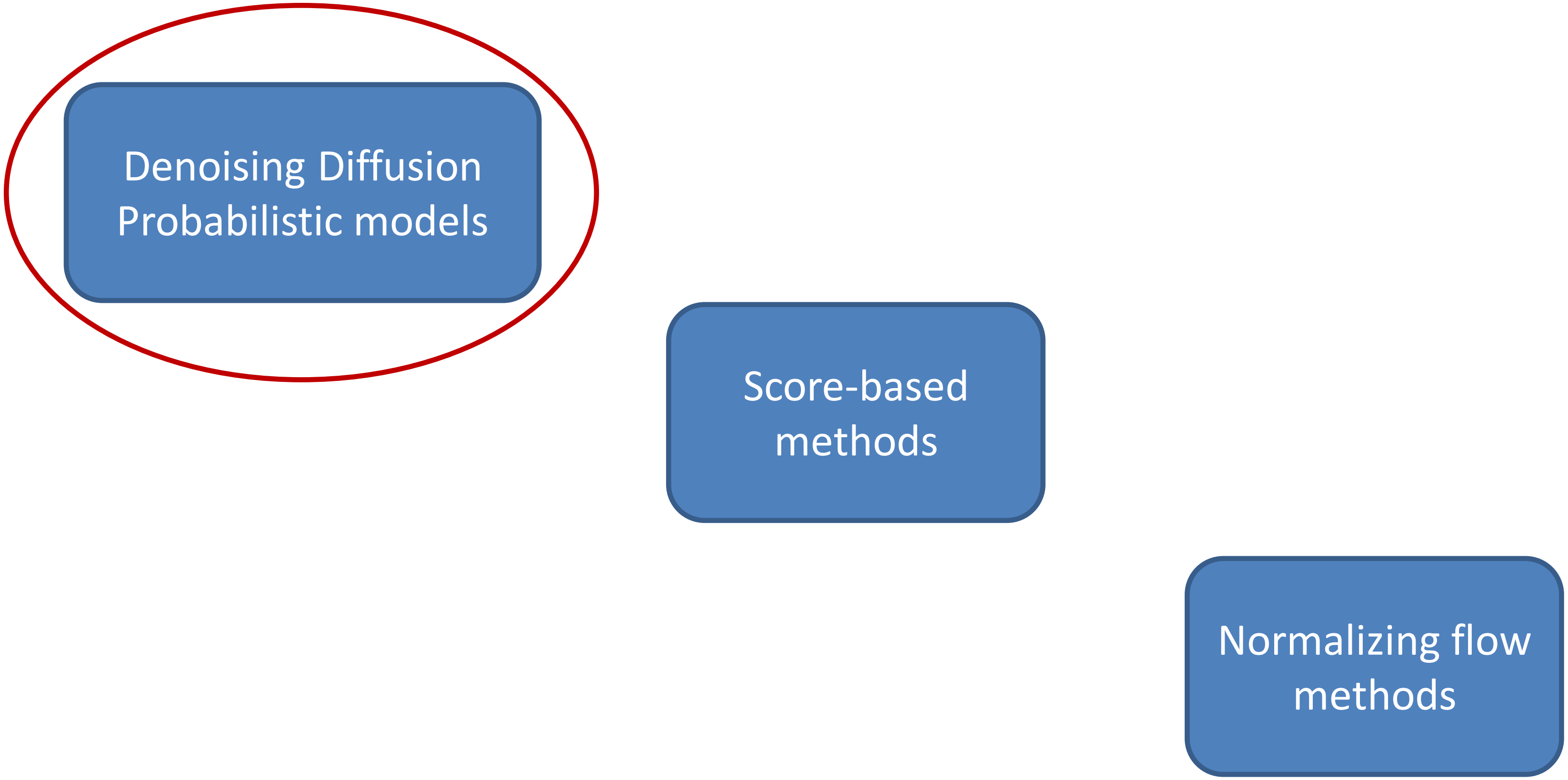
Diffusion models

- Best current methods for synthetic image generation
- Allows generating images in a *conditioned* form
- Many software solutions, such as Midjourney, DALL-E

An Asian girl in ancient coarse linen clothes rides a giant panda and carries a wooden cage. A chubby little girl with two buns walks on the snow. High-precision clothing texture, real tactile skin, foggy white tone, low saturation, retro film texture, tranquil atmosphere, minimalism, long-range view, telephoto lens

What is the purpose of diffusion models?

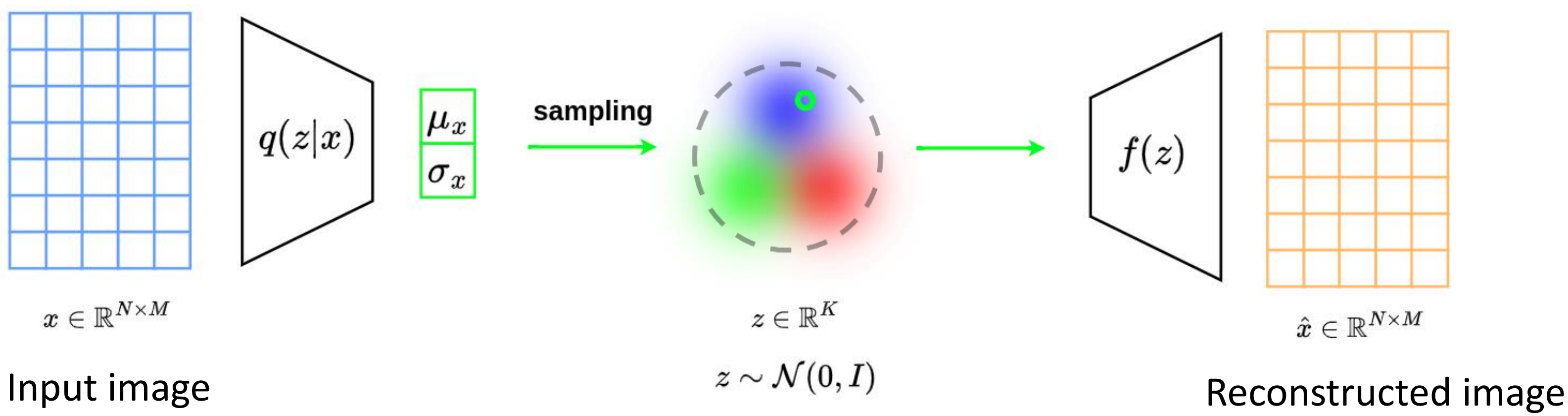
- Family of diffusion networks



Intuition behind diffusion models

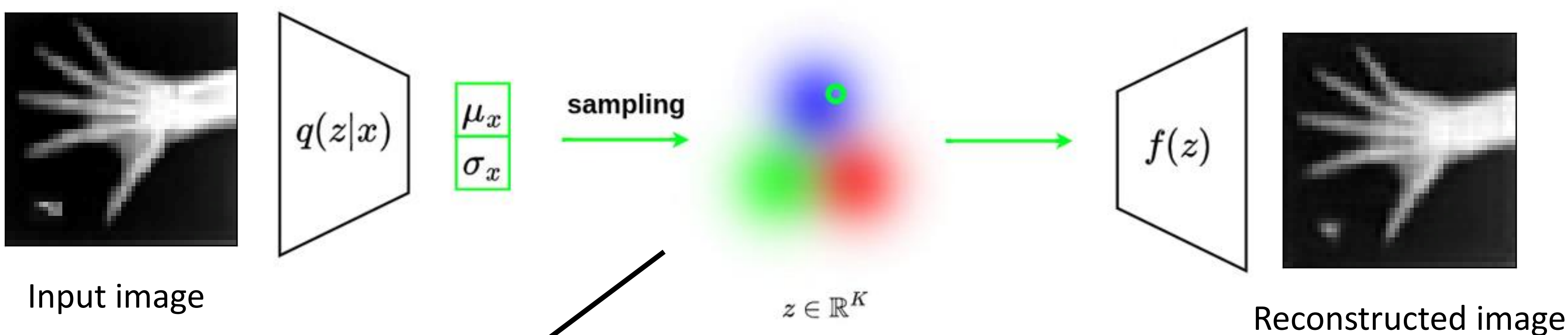
- Completeness is expressed as a ***soft constraint*** !

→ $\mathcal{N}(g(x), diag(h(x)))$ and $\mathcal{N}(0, I)$ should remain close in terms of distributional distance

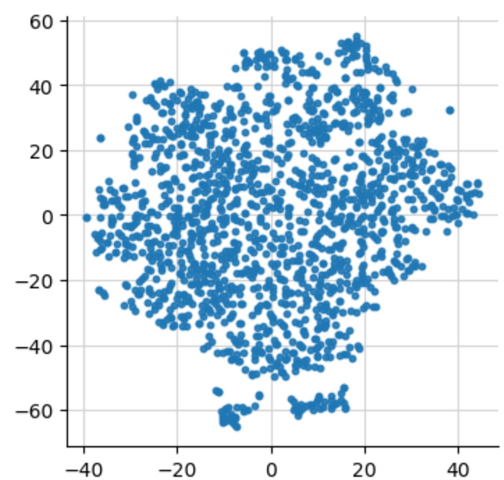


Sampling from the latent space $\mathcal{N}(0, I)$ does not guarantee to obtain a reconstructed image from the target distribution

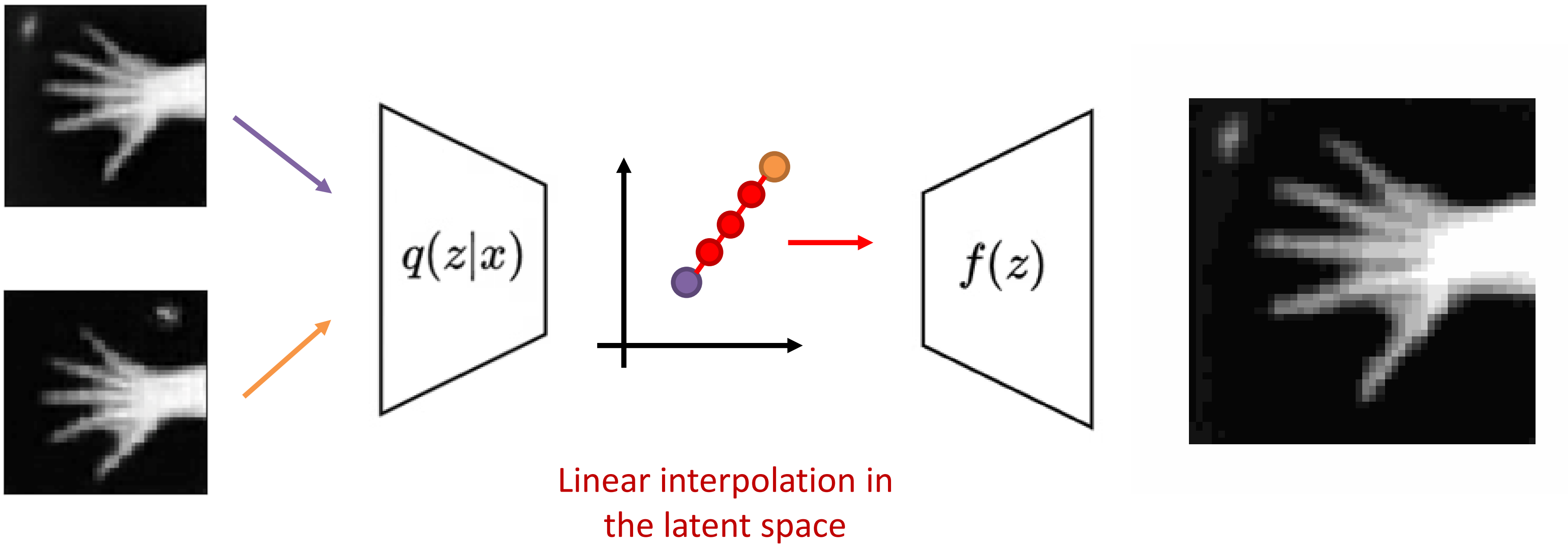
- Illustration from Mednist dataset
  - (train,valid,test) = (1491,373,223)
  - Input image size: 48x48 / latent space K=432 (compression factor around 5)



t-SNE visualization of the latent space using the training data as sample points

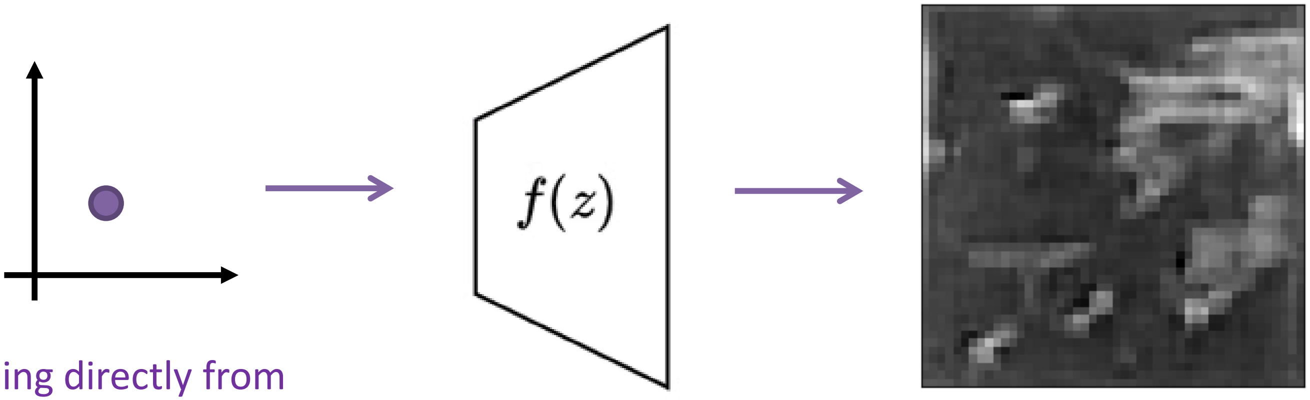


- Linear interpolation between two real images



- Sampling directly from the latent space

$$z \in \mathbb{R}^{(K)} \quad \text{with} \quad z_i \sim \mathcal{N}(0, I)$$



Sampling directly from
the latent space

A soft constraint on the latent space to remain close to $\mathcal{N}(0, I)$ is not sufficient to build generative models that effectively learn a target distribution

The denoising diffusion probabilistic models

DDPM

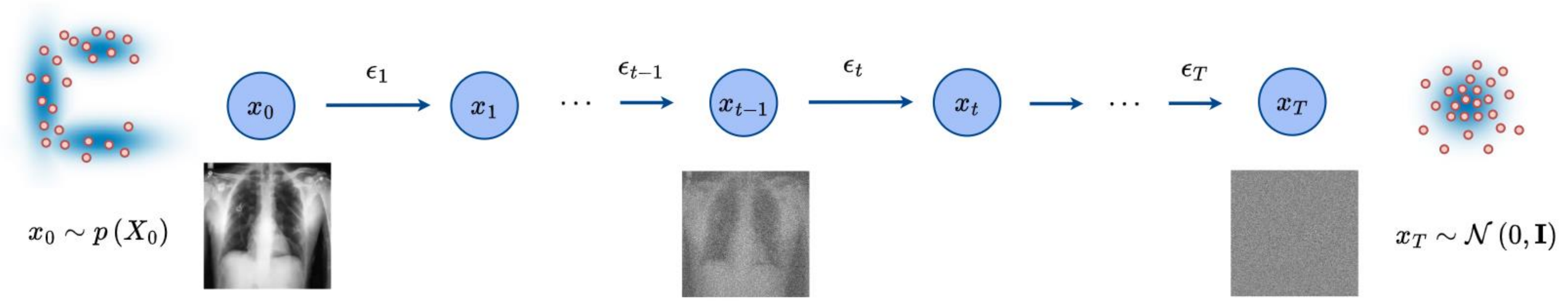
All the mathematics are described in the following blog

https://creatis-myriad.github.io/tutorials/2023-11-30-tutorial-ddpm.html

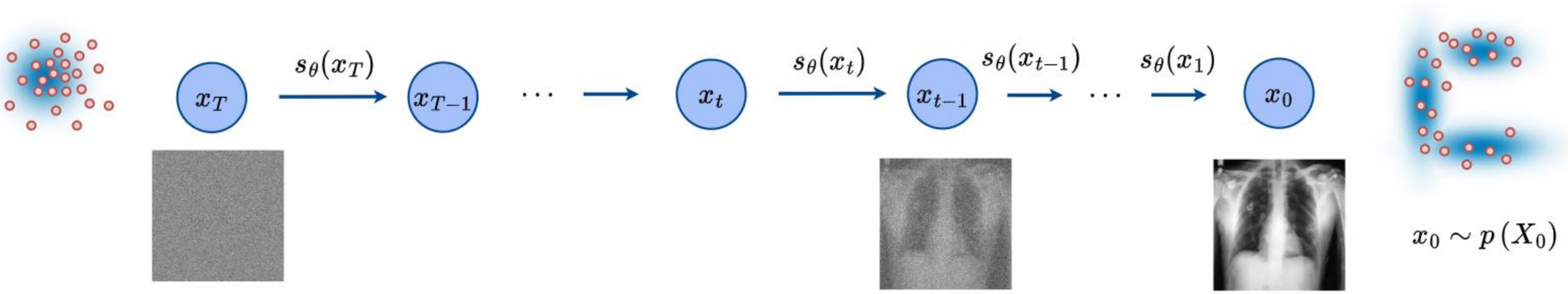
Basic idea of denoising diffusion model

How can a hard constraint be enforced to ensure a direct transformation from the latent space (modeled as a Gaussian) to the target distribution?

- Noising process



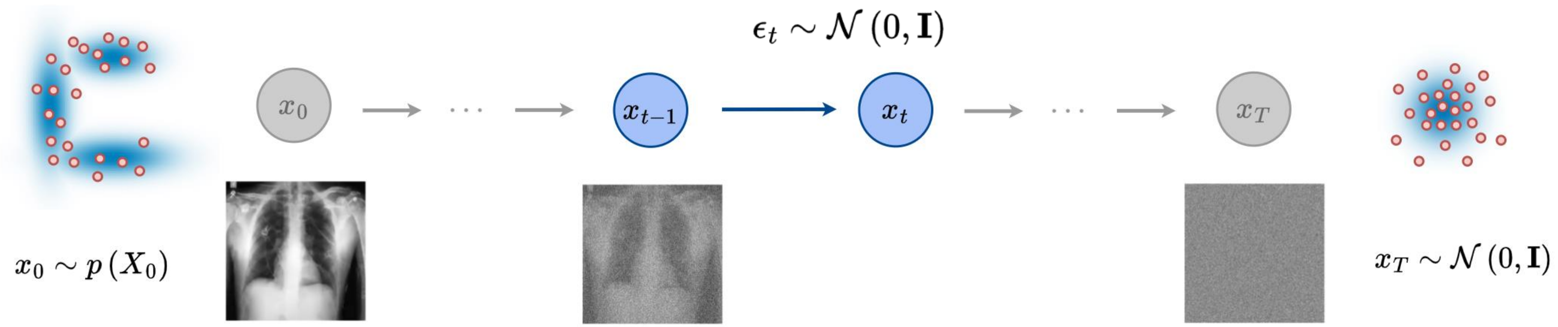
- Learning of the denoising process



Noising process (forward diffusion process)

- Modeled as a sequence of normal distributions (Markov chain process)

$$q\left(x_t \mid x_{t-1}\right) = \mathcal{N}\left(\left(\sqrt{1-\beta_t}\right) x_{t-1}, \beta_t \mathbf{I}\right)$$

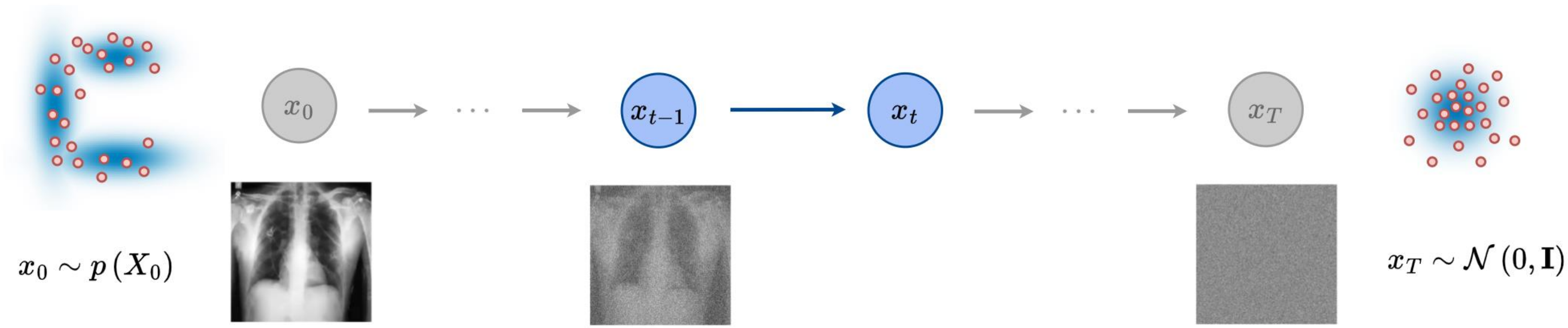


$$q\left(x_t \mid x_{t-1}\right) = \left(\sqrt{1-\beta_t}\right) x_{t-1} + \beta_t \mathbf{I} \,.\, \epsilon_t$$

Noising process (forward diffusion process)

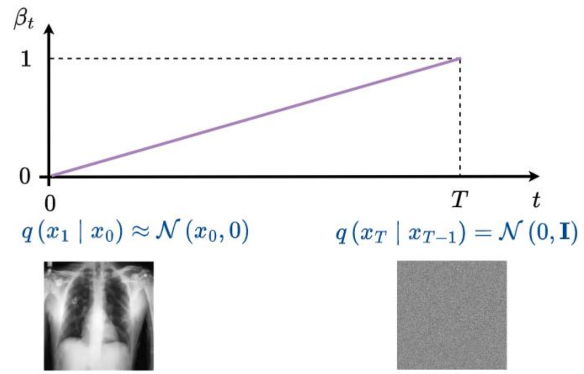
- Modeled as a sequence of normal distributions (Markov chain process)

$$q\left(x_t \mid x_{t-1}\right) = \mathcal{N}\left(\left(\sqrt{1-\beta_t}\right) x_{t-1}, \beta_t \mathbf{I}\right)$$



- β_t : variance varying over the iterative process from 0 to 1

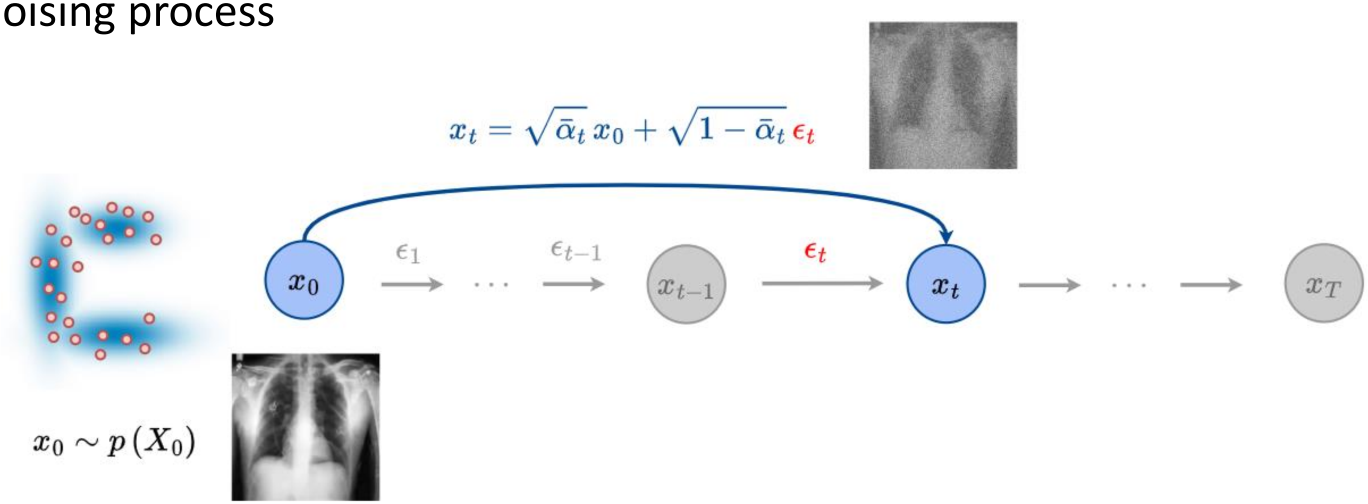
$$\begin{aligned} &\text{if} \quad \beta_t = 0, \quad \text{then} \quad q(x_t \mid x_{t-1}) = x_{t-1} \\ &\text{if} \quad \beta_t = 1, \quad \text{then} \quad q(x_t \mid x_{t-1}) = \mathcal{N}(0, \mathbf{I}) \end{aligned}$$



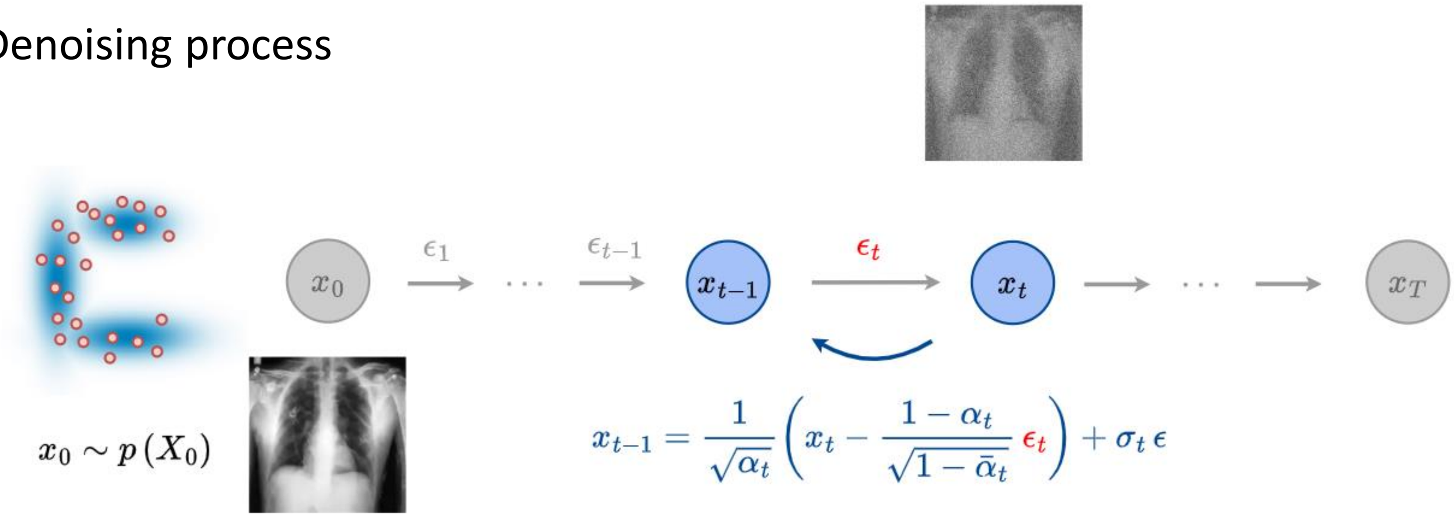
Noising / denoising processes

- Noising process

$$\begin{cases} \alpha_t = 1 - \beta_t \\ \bar{\alpha}_t = \prod_{k=1}^{t} \alpha_k \\ \epsilon_t \sim \mathcal{N}(0, \mathbf{I}) \end{cases}$$

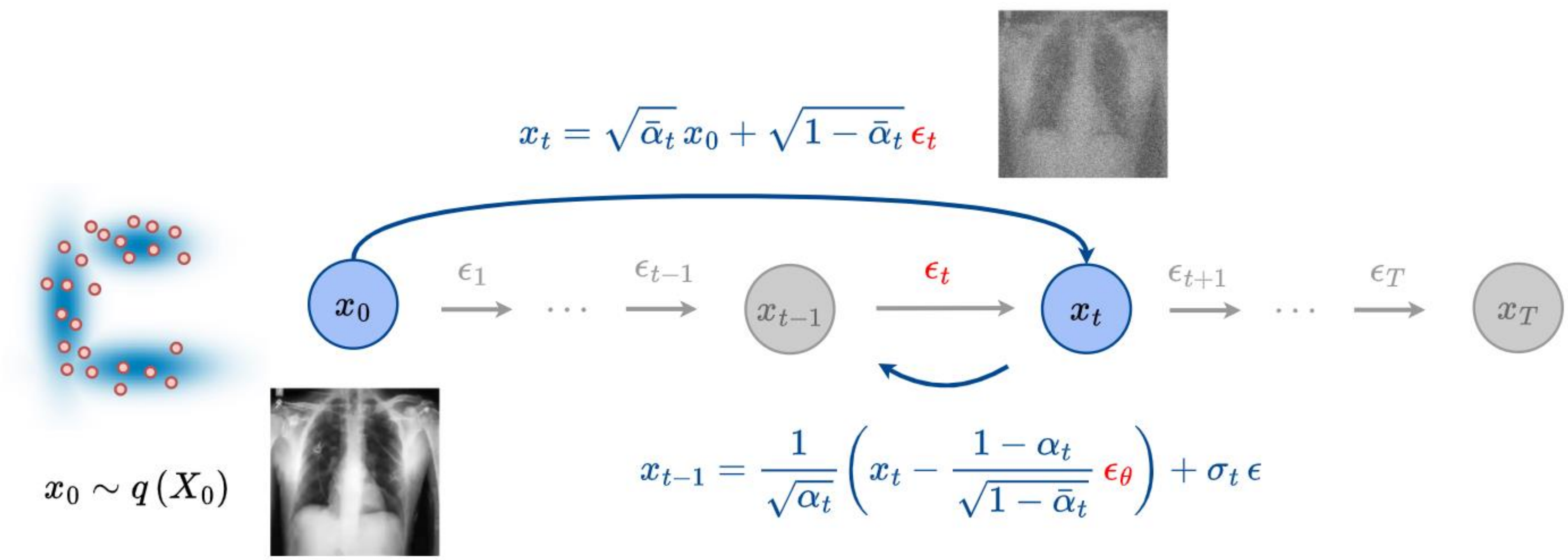


- Denoising process



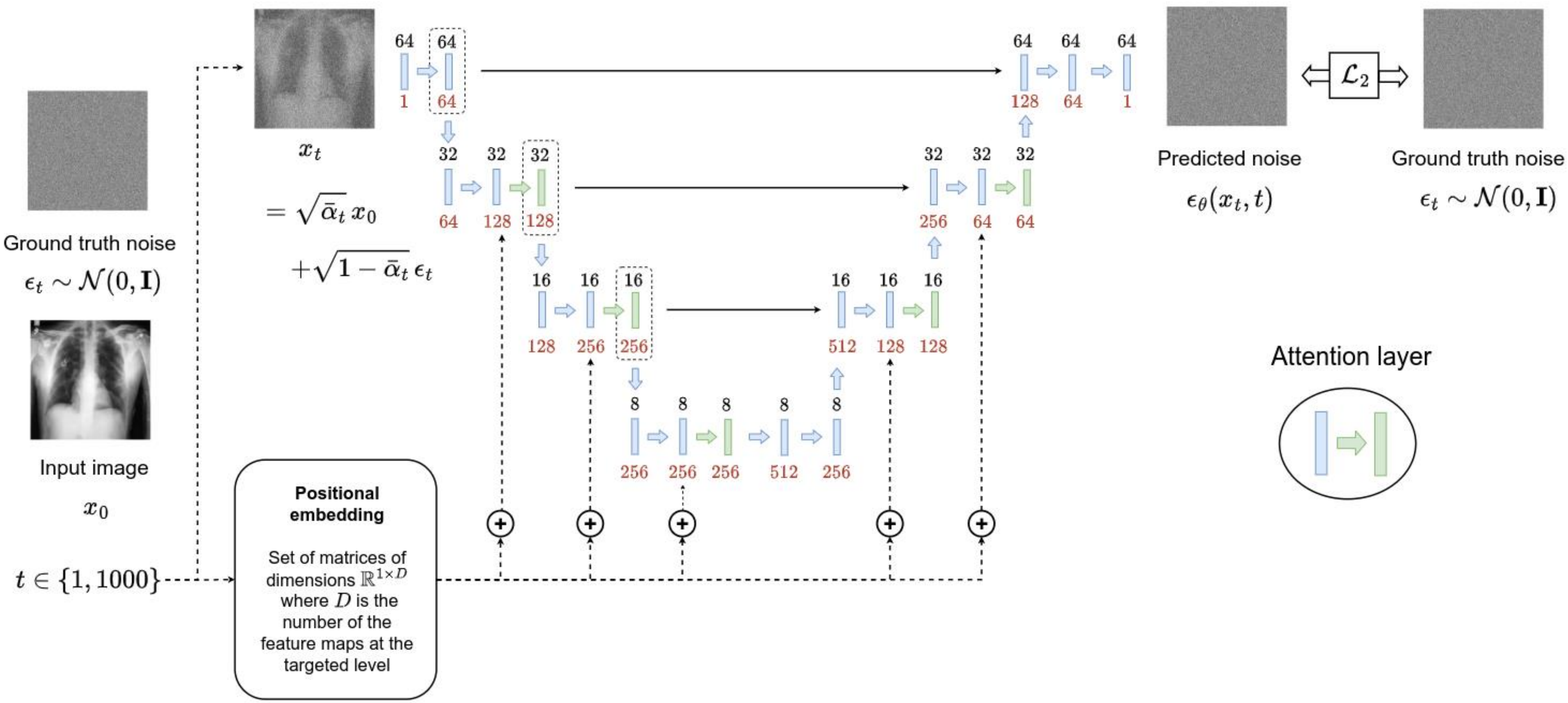
Training procedure

- Choose a random step $t \in \{1, \cdots, T\}$
- Train a U-Net model to predict the noise pattern ε_θ to remove from x_t

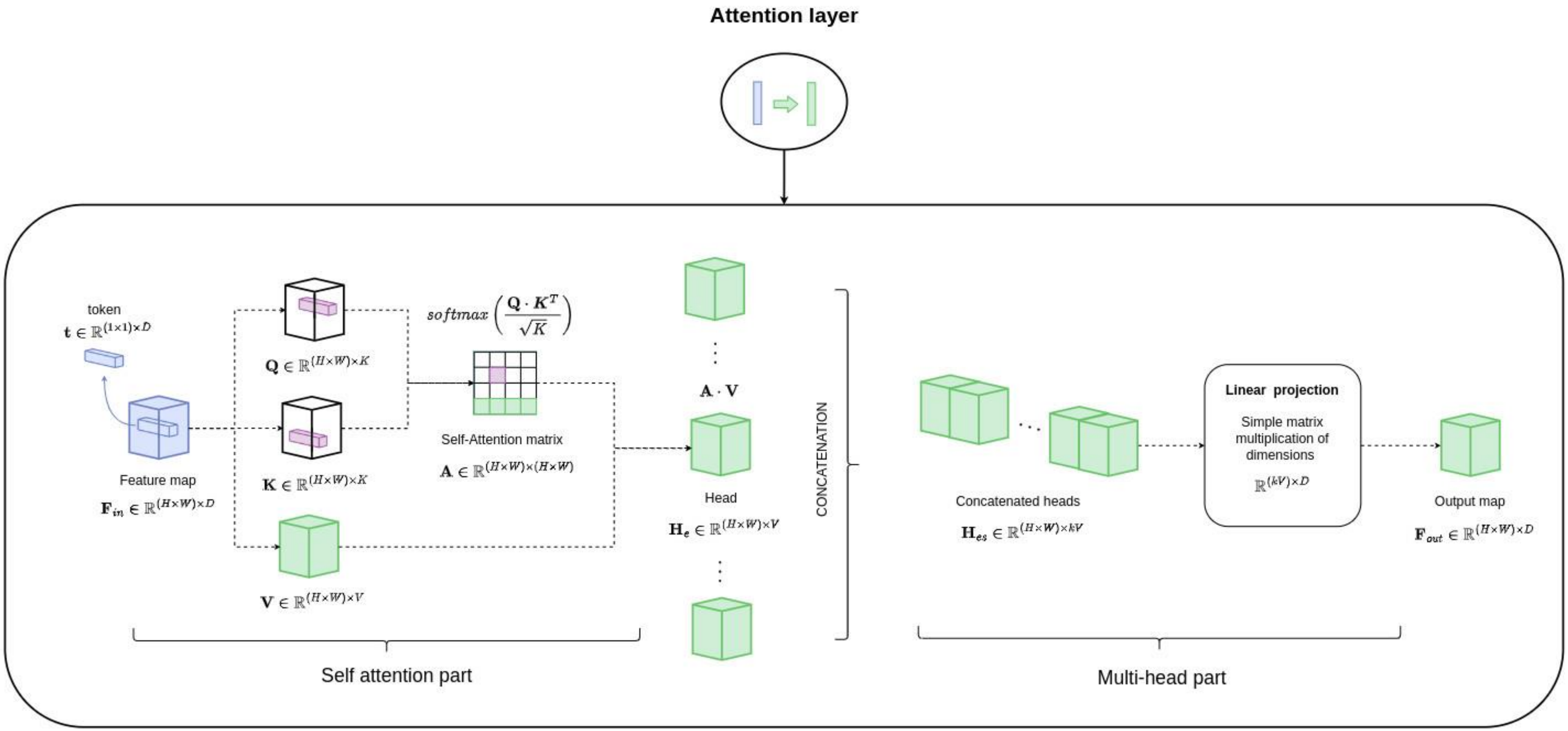


Standard U-Net with attention layers and position encoding to integrate temporal information

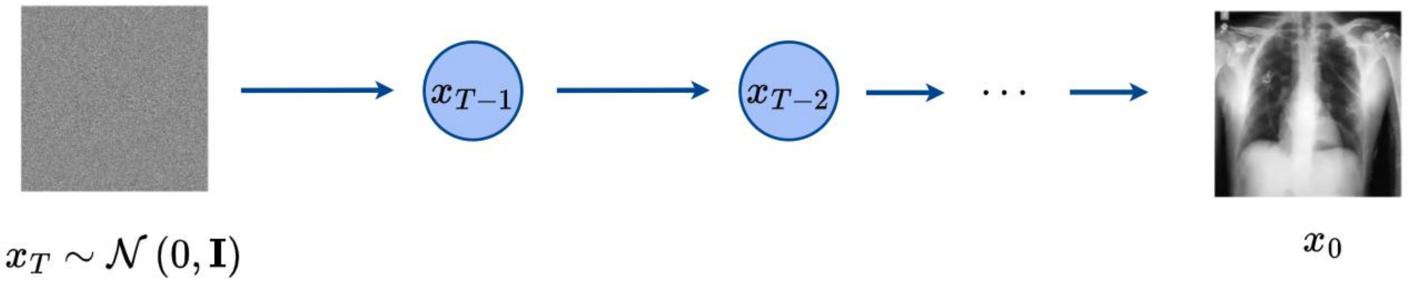
➔ Integration of t is necessary because the added noise varies over time



➔ Attention layer



Inference: generation of synthetic data



- Generate a random image $x_T \sim \mathcal{N}(0, I) \in \mathbb{R}^{N \times M}$
- At each step from T to 0, use the U-Net model to compute

$$x_{t-1} = \frac{1}{\sqrt{\alpha_t}} \left(x_t - \frac{1 - \alpha_t}{\sqrt{1 - \bar{\alpha}_t}} \epsilon_\theta(x_t, t) \right) + \sigma_t \epsilon$$

U-Net

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

Mathematical formalism

Mathematical formulation

- Useful notations

$$q(x_1, \cdots, x_T \mid x_0) = q(x_1 \mid x_0)\, q(x_2 \mid x_1, x_0) \cdots q(x_T \mid x_{T-1}, \cdots, x_0)$$

← Complete forward process

$$q(x_1, \cdots, x_T \mid x_0) = q(x_1 \mid x_0)\, q(x_2 \mid x_1) \cdots q(x_T \mid x_{T-1})$$

← Markov chain

$$q(x_{1:T} \mid x_0) = q(x_1 \mid x_0)\, q(x_2 \mid x_1) \cdots q(x_T \mid x_{T-1})$$

$$q(x_{1:T} \mid x_0) = \prod_{t=1}^{T} q(x_t \mid x_{t-1})$$

Compact reformulation

$$q(x_{1:T} \mid x_0) = \prod_{t=1}^{T} q(x_t \mid x_{t-1})$$

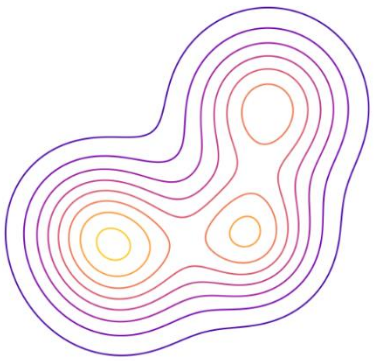
Complete forward process

$$p_\theta(x_{0:T}) = p(x_T) \prod_{t=1}^{T} p(x_{t-1} \mid x_t)$$

Complete reverse process

Mathematical formulation

- Optimization process
  - → Maximization of $\log(p_\theta(x))$ / Minimization of $-\log(p_\theta(x))$



$$-\log\left(p_\theta(x)\right)$$

$$-\log\left(p_\theta(x)\right) = -\log\left(\int p_\theta(x_{0:T})\, dx_{1:T}\right)$$

← Marginal distribution

$$-\log\left(p_\theta(x)\right) = -\log\left(\int \frac{q(x_{1:T} \mid x_0)}{q(x_{1:T} \mid x_0)} p_\theta(x_{0:T})\, dx_{1:T}\right)$$

Expectation reformulation

$$-\log\left(p_\theta(x)\right) = -\log\left(\mathbb{E}_{q(x_{1:T}|x_0)}\left[\frac{p_\theta(x_{0:T})}{q(x_{1:T} \mid x_0)}\right]\right)$$

Jensen's inequality

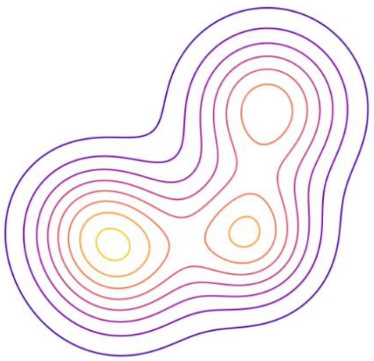
$$-\log\left(p_\theta(x)\right) \leq -\mathbb{E}_{q(x_{1:T}|x_0)}\left[\log\left(\frac{p_\theta(x_{0:T})}{q(x_{1:T} \mid x_0)}\right)\right]$$

Mathematical formulation

- Evidence lower bound (ELBO)

$$-\log\left(p_\theta(x)\right) \leq -\mathbb{E}_{q(x_{1:T}|x_0)}\left[\log\left(\frac{p_\theta(x_{0:T})}{q(x_{1:T} \mid x_0)}\right)\right]$$

ELBO



→ Minimization of the ELBO

$$-\mathbb{E}_{q(x_{1:T}|x_0)}\left[\log\left(\frac{p_\theta(x_{0:T})}{q(x_{1:T} \mid x_0)}\right)\right]$$

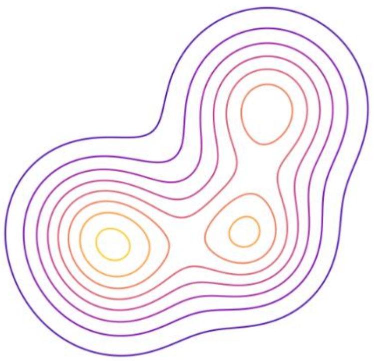
$$\vdots$$

$$-\mathbb{E}_q\left[D_{KL}\left(q(x_T \mid x_0) \,\|\, p_\theta(x_T)\right) + \sum_{t>1} D_{KL}\left(q(x_{t-1} \mid x_t, x_0) \,\|\, p_\theta(x_{t-1} \mid x_t)\right) - \log\left(p_\theta(x_0 \mid x_1)\right)\right]$$

No parameter to be learned

Very small

- ELBO minimization



$$\mathcal{L} = -\mathbb{E}_q \left[\sum_{t>1} D_{KL} \left(q(x_{t-1} \mid x_t, x_0) \,\|\, p_\theta(x_{t-1} \mid x_t) \right) \right]$$

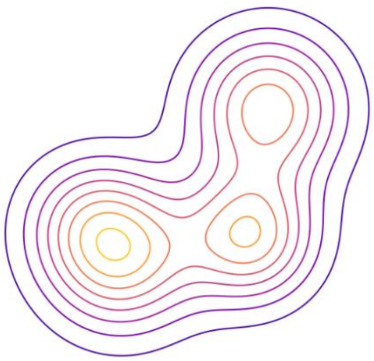
→ Exploitation of the Gaussian properties of the forward process and modeling of the reverse process using Gaussian distribution

$$q(x_{t-1} \mid x_t, x_0) = \mathcal{N}\left(\tilde{\mu}_t, \tilde{\beta}_t\right) \qquad p_\theta(x_{t-1} \mid x_t) = \mathcal{N}\left(\mu_\theta, \sigma_\theta\right)$$

→ Reformulation

$$D_{KL} \left(q(x_{t-1} \mid x_t, x_0) \,\|\, p_\theta(x_{t-1} \mid x_t) \right) = -\frac{1}{2\sigma_t^2} \left\| \tilde{\mu}_t - \mu_\theta \right\|^2$$

$$\mathcal{L} = \mathbb{E}_q \left[\sum_{t>1} \frac{1}{2\sigma_t^2} \left\| \tilde{\mu}_t - \mu_\theta(x_t, t) \right\|^2 \right]$$



- ELBO minimization

$$\mathcal{L} = \mathbb{E}_q \left[\sum_{t>1} \frac{1}{2\sigma_t^2} \left\| \tilde{\mu}_t - \mu_\theta(x_t, t) \right\|^2 \right]$$

→ Expressions of means

$$\tilde{\mu}_t = \frac{1}{\sqrt{\alpha_t}} \left(x_t - \frac{\beta_t}{\sqrt{1-\bar{\alpha}_t}} \epsilon_t \right) \qquad \mu_\theta(x_t, t) = \frac{1}{\sqrt{\alpha_t}} \left(x_t - \frac{\beta_t}{\sqrt{1-\bar{\alpha}_t}} \epsilon_\theta(x_t, t) \right)$$

$$\mathcal{L} = \mathbb{E}_q \left[\sum_{t>1} \frac{\beta_t^2}{2\sigma_t^2 \alpha_t (1-\bar{\alpha}_t)} \left\| \epsilon_t - \epsilon_\theta(x_t, t) \right\|^2 \right]$$

→ Simplifications

$$\mathcal{L} = \mathbb{E}_{q,t} \left[\left\| \epsilon_t - \epsilon_\theta(x_t, t) \right\|^2 \right]$$

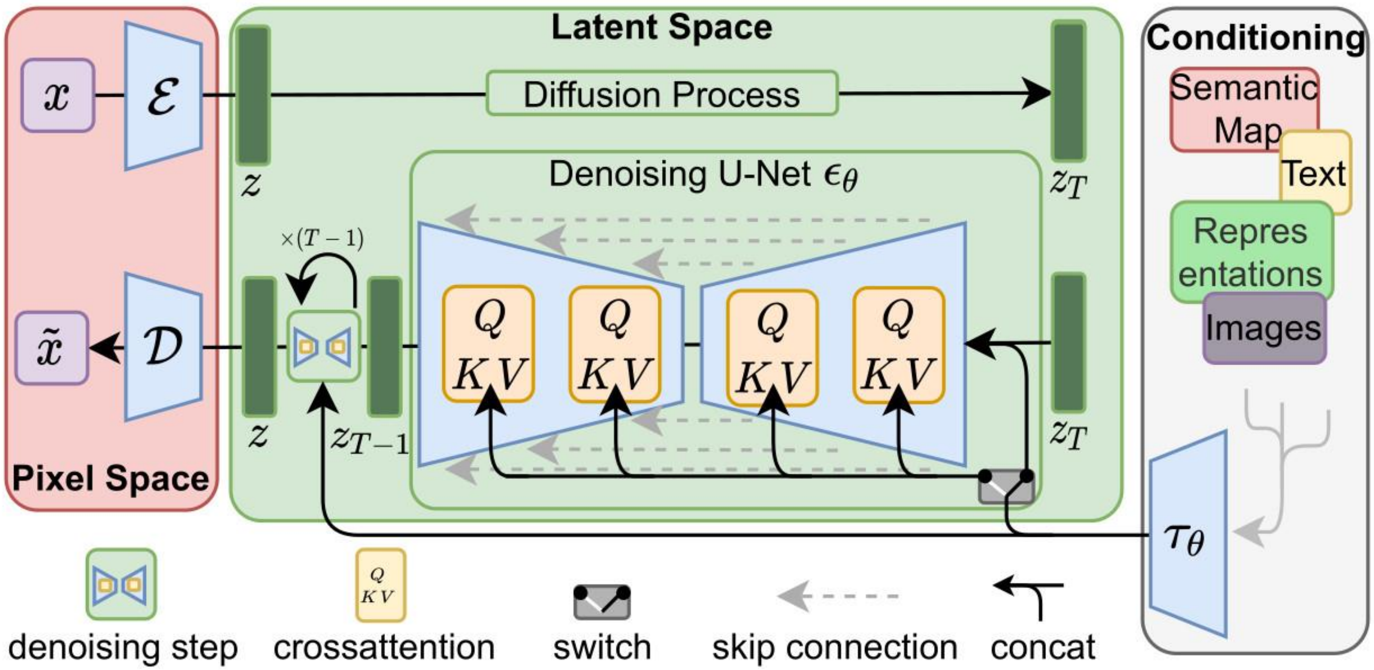
Practical application

Latent diffusion models

Latent diffusion model (LDM)

- VAE is learned independently of DDPM and its architecture is fixed
  - Efficiently reduce the dimensionality of the input space
  - Efficiently initiate the Gaussian diffusion process

- LDM architecture



- Properties

Parameters	LDM – 256×256
z dimensions	$64 \times 64 \times 3$
Diffusion steps	1000
Noise scheduler (β_t)	linear
Number of parameters	274 Million
Channels	224
Channel multiplier	$1, 2, 3, 4$
Levels for attention	$2, 3, 4$
Number of head	1
Batch size	48
Iterations	410 k
Learning rate	$9.6\, e^{-5}$

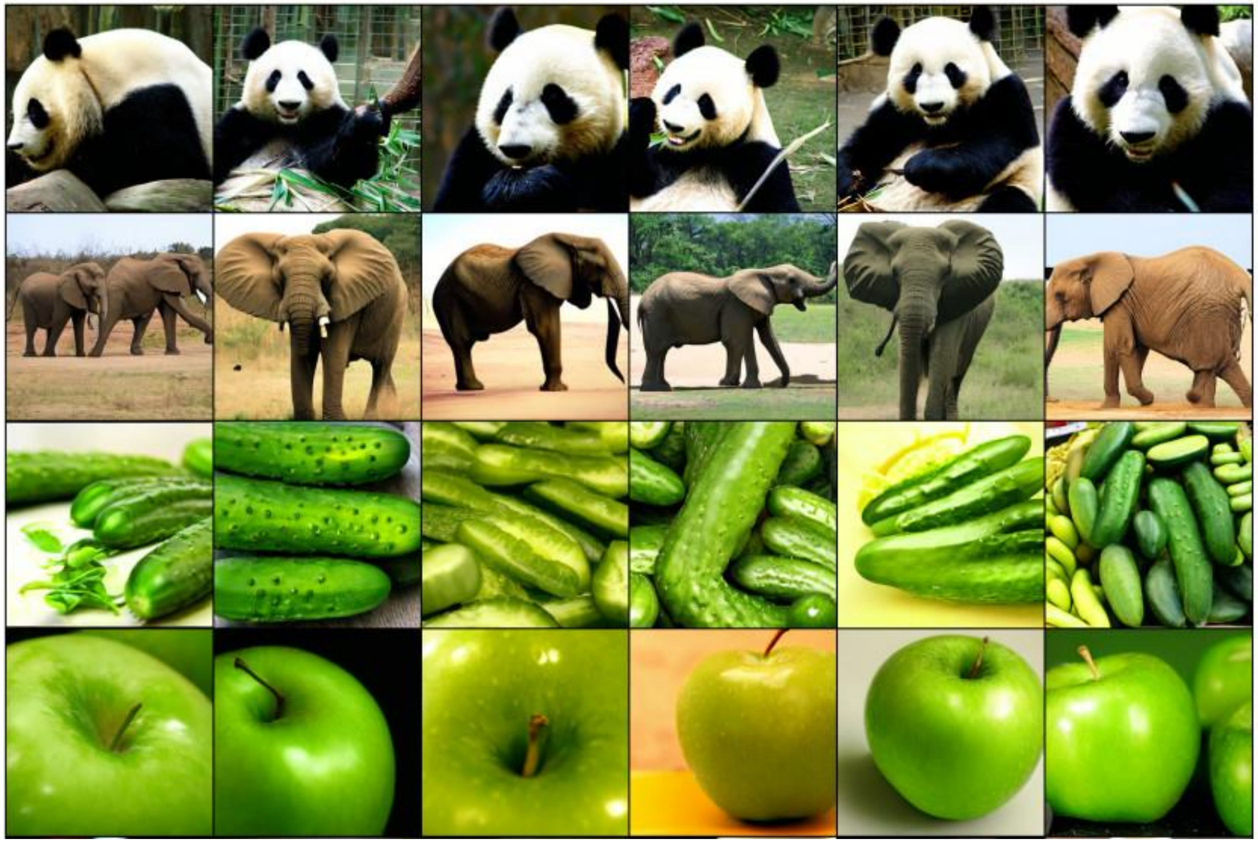
- Random generation of synthetic images *without conditioning* learned from the CelebA-HQ database

Random samples on the CelebA-HQ dataset

Latent diffusion model (LDM)

- Random generation of synthetic images *with conditioning on the class* learned from the ImageNet database

Random class conditional samples on the ImageNet dataset



Latent diffusion model (LDM)

- Random generation of synthetic images *with conditioning on masks* learned from the Flickr-landscapes database

- Random generation of synthetic images *with conditioning on text* learned from LAION-400M database

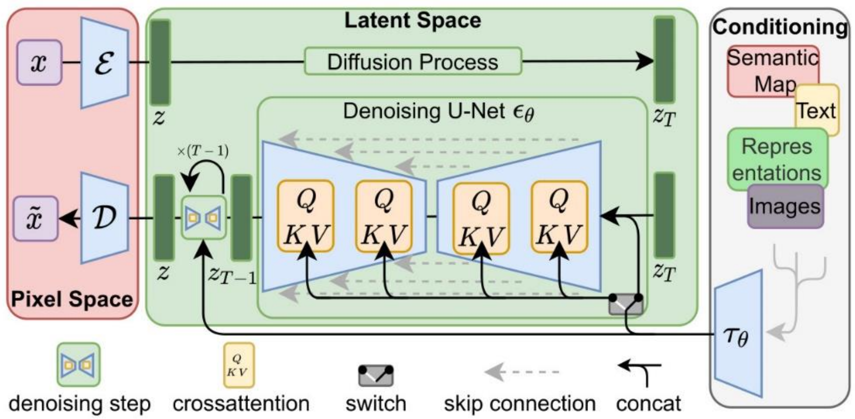
  - → Using the BERT tokenizer
  - → This model has over 1.45 billion parameters!

'A painting of the last supper by Picasso.'

Medical applications

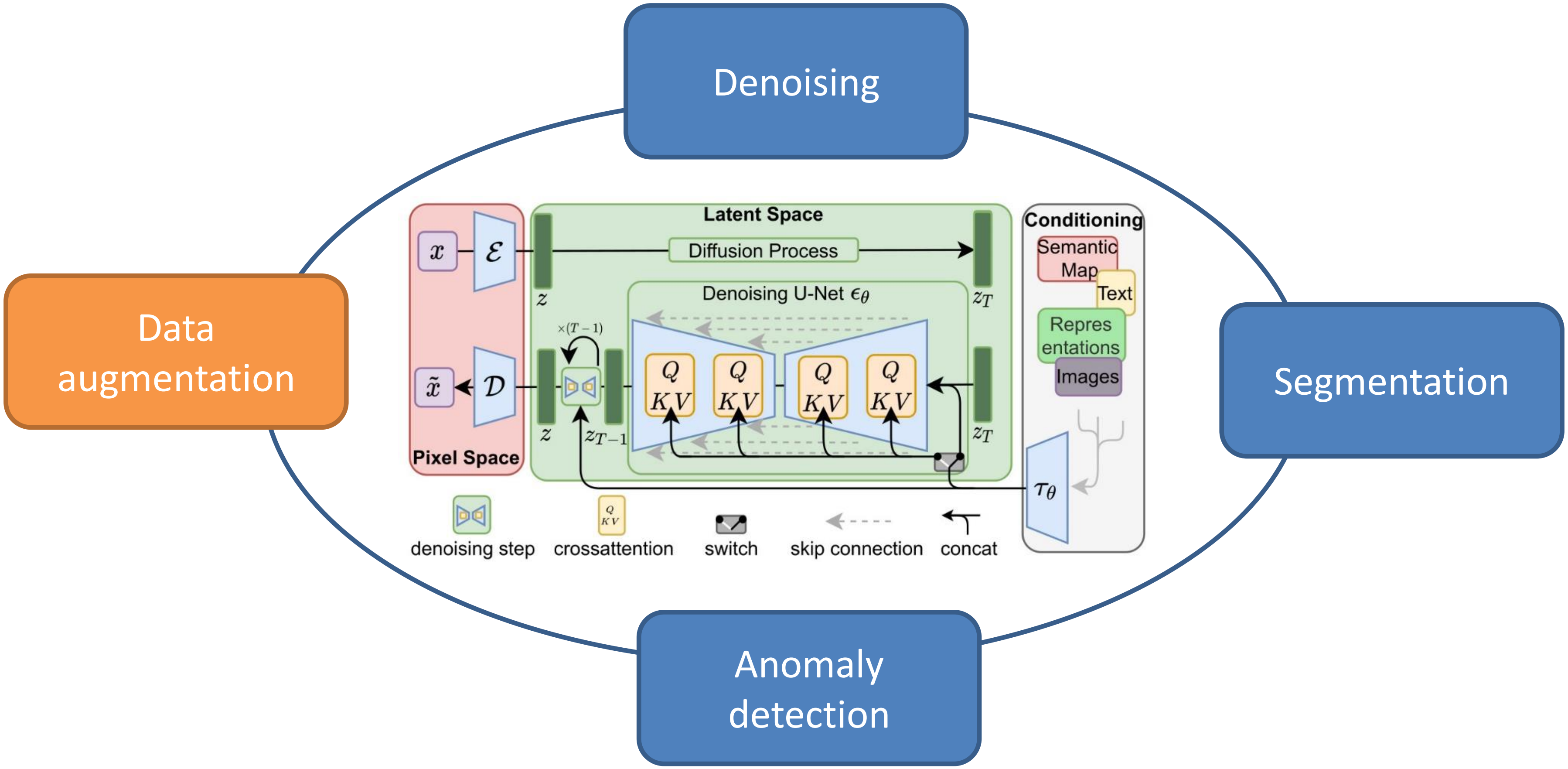
Denoising

Data augmentation



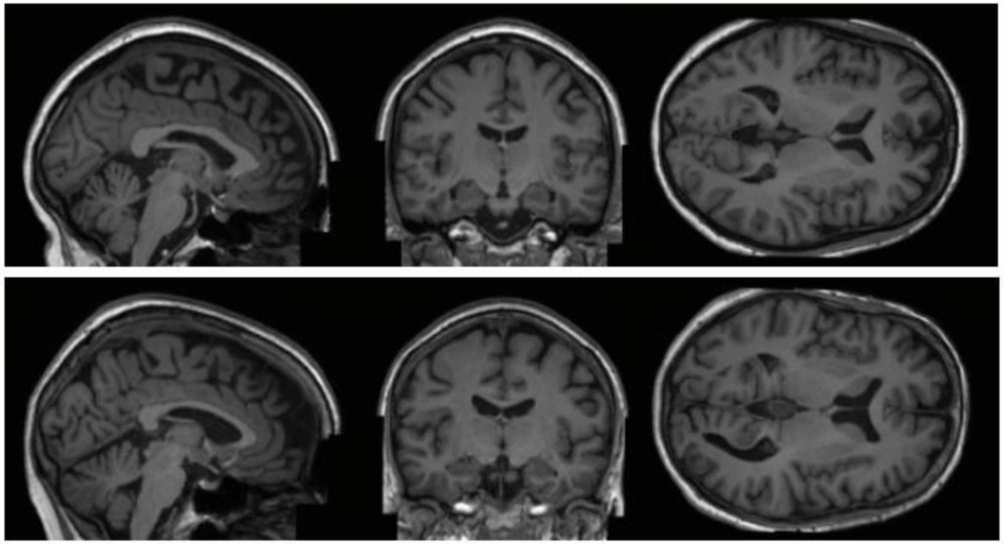
Segmentation

Anomaly detection


Denoising
Data augmentation
Segmentation
Anomaly detection
Latent Space
Diffusion Process
Denoising U-Net ϵ_θ
Pixel Space
Conditioning
Semantic Map
Text
Representations
Images
denoising step
crossattention
switch
skip connection
concat

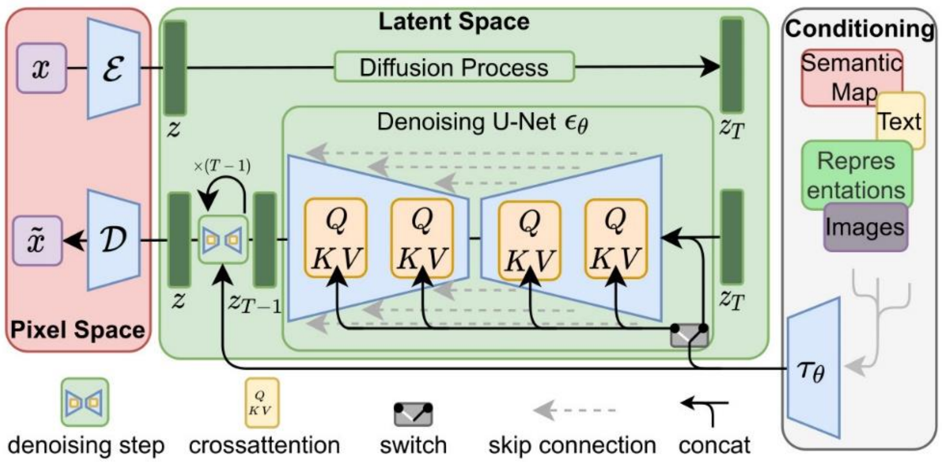
Diffusion models for data augmentation

- Synthetic dataset generation for brain MR volumes [Walter et al., MICCAI workshop 2022]
- UK Biobank dataset
  - 3D MR volumes (T1w)
  - Training: 31,740 patients
  - with covariables: age (44 to 82 years), gender (53% women), brain structure volumes
  - Quality of synthetic data measured using FID: Fréchet Inception Distribution



Diffusion models for data augmentation

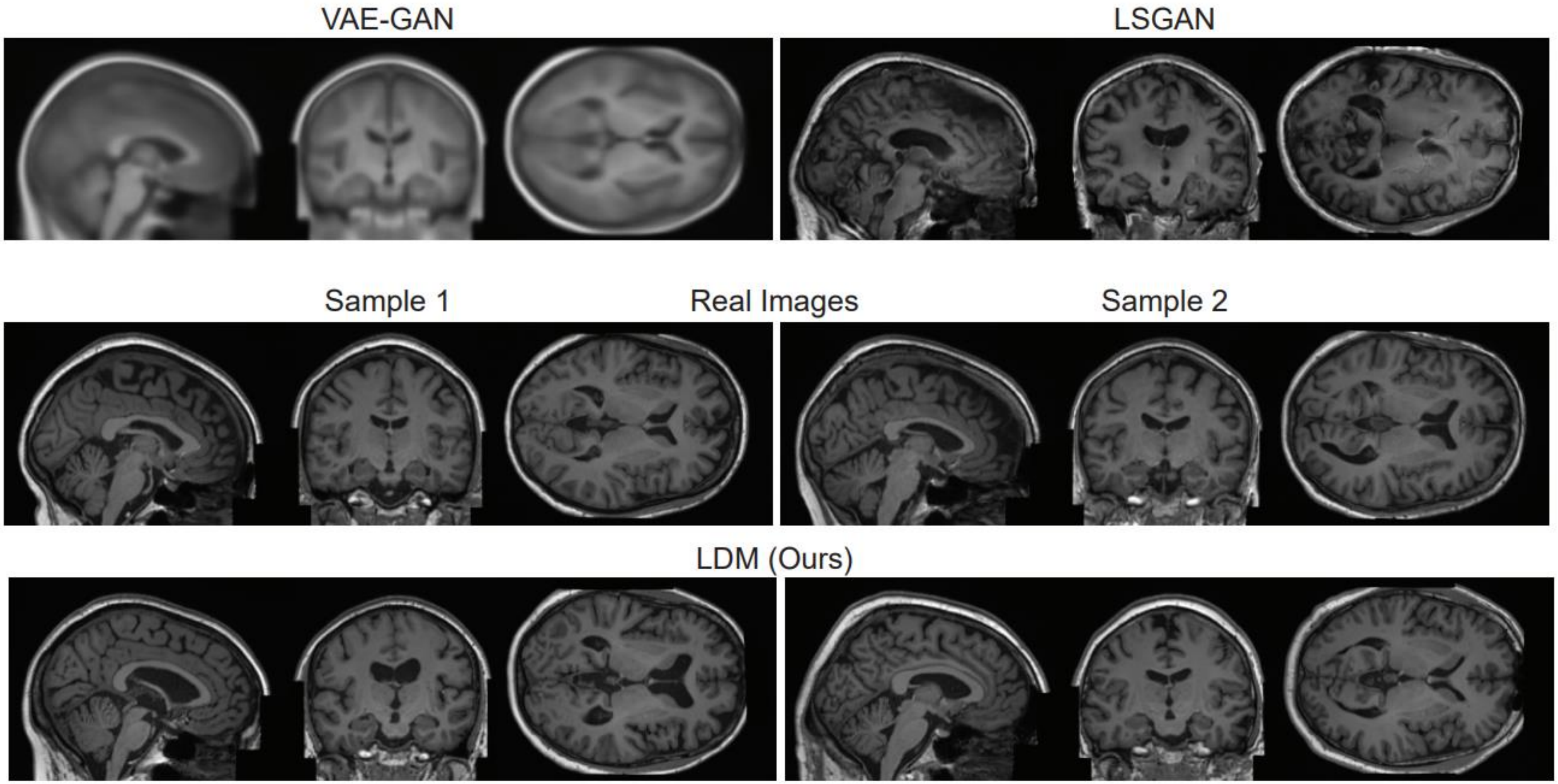
- VAE
  - 3D convolutions
  - Latent space dimension: 20 x 28 x 20
- DDPM
  - 3D convolutions
  - T=1000 time steps
  - Conditioning: vector encoding each covariable



Diffusion models for data augmentation

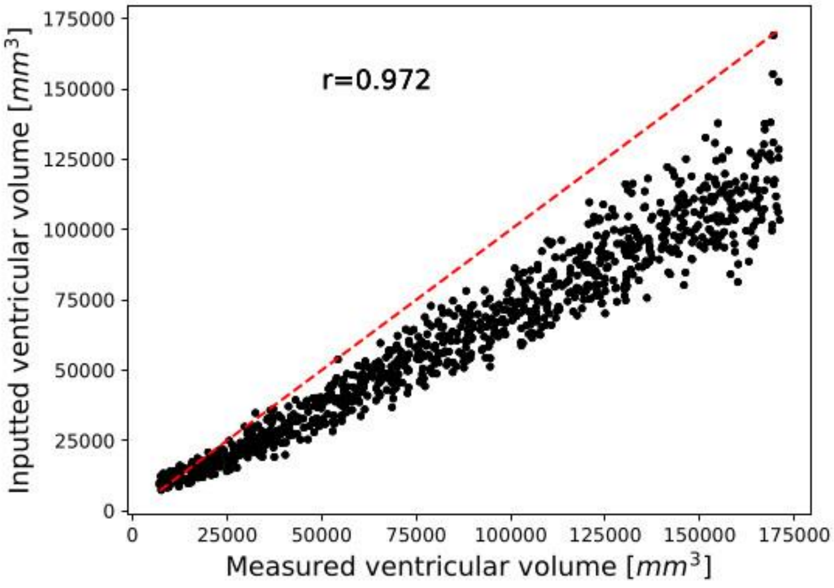
- Results
  - FID: generated from 1,000 samples drawn from each of the two distributions to be compared

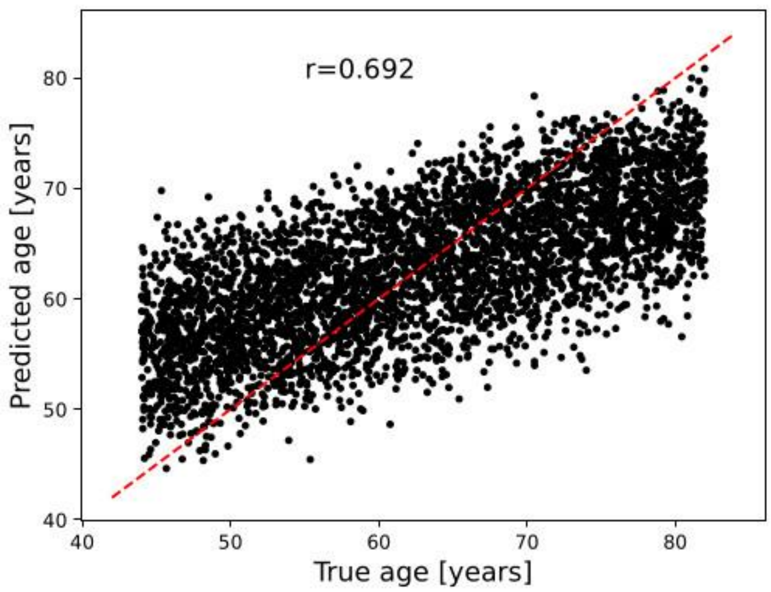
	FID ↓
LSGAN	0.0231
VAE-GAN	0.1576
LDM	**0.0076**
Real images	0.0005



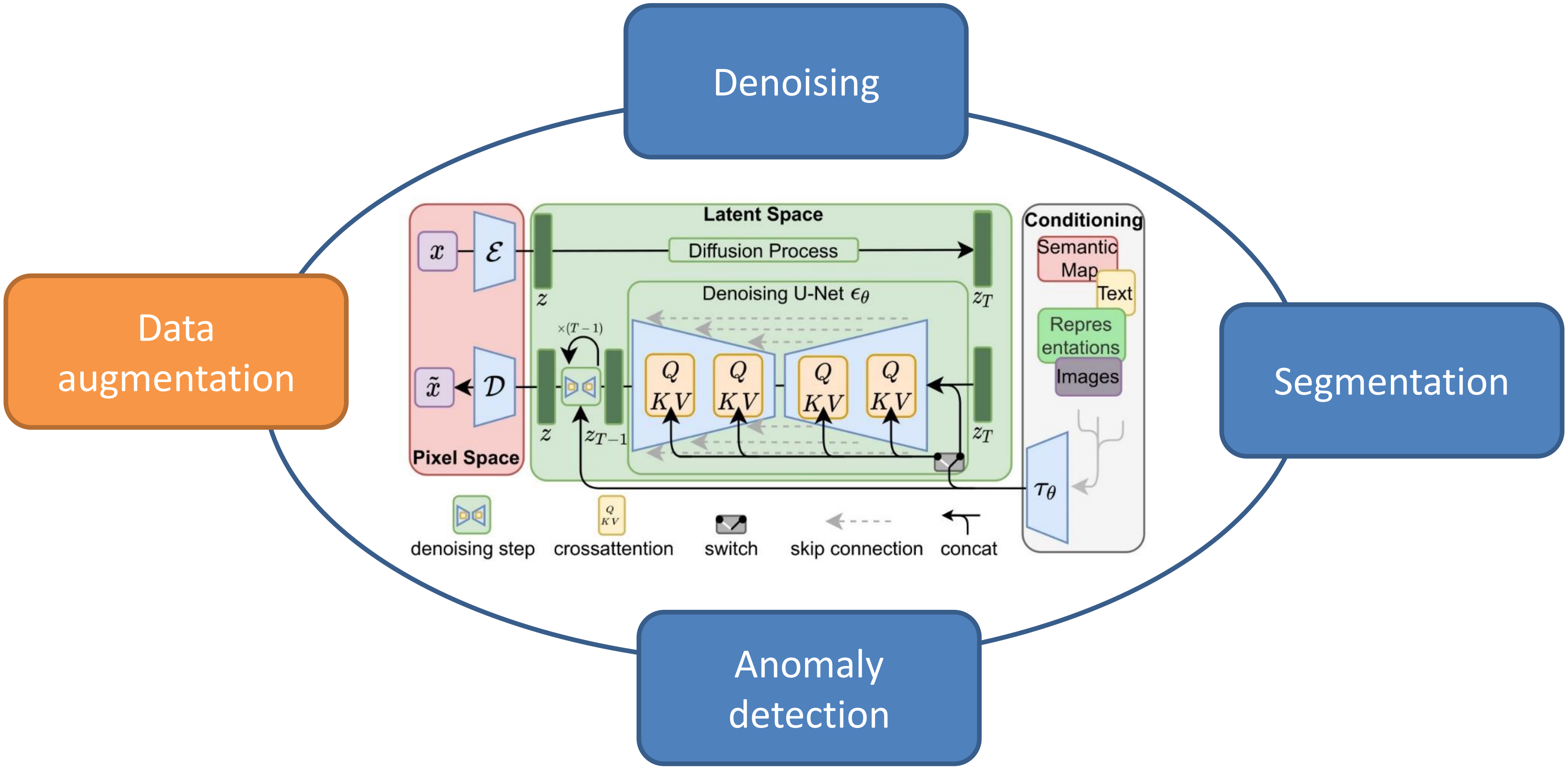
Diffusion models for data augmentation

- Results
  - SynthSeg model was used to automatically measure brain volumes from synthetic data
  - A 3D CNN trained from the UK biobank was used to automatically predict the age from the synthetic data





- Synthetic dataset of 100,000 human brain was generated and made publicly available with the conditioning information
- Promote data sharing with privacy guarantees


Denoising
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switch
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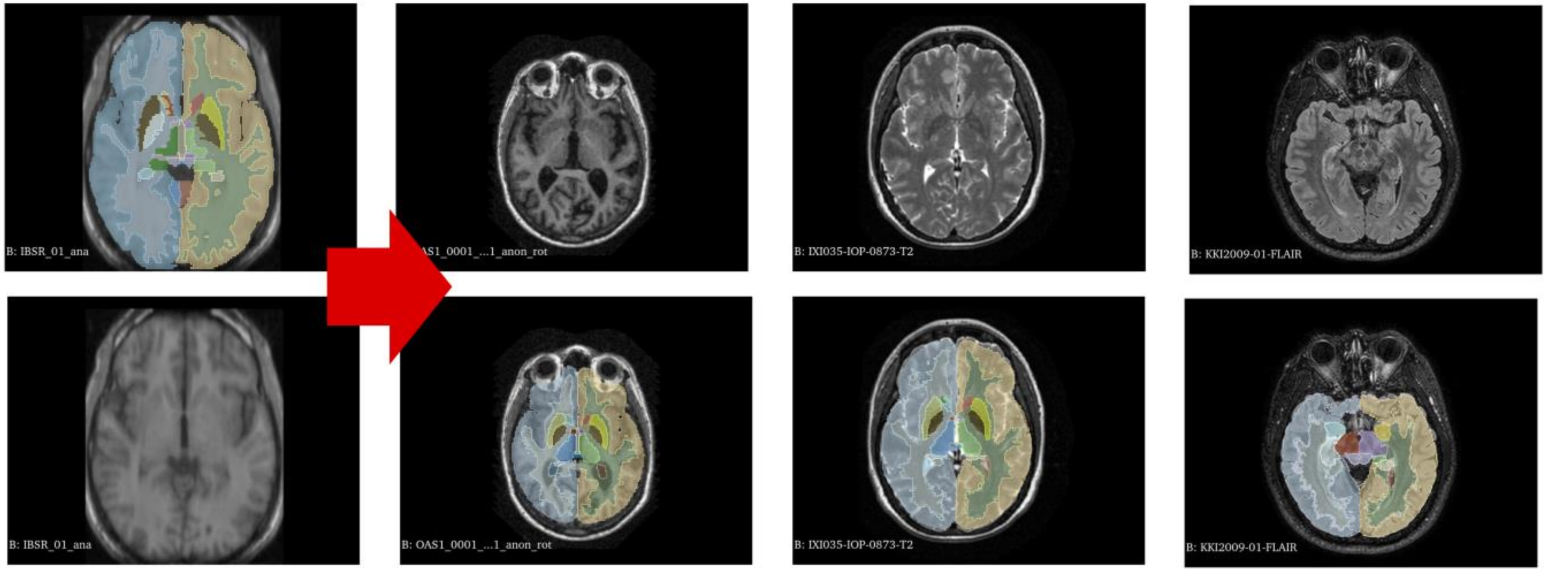
concat

Diffusion models for data augmentation

- Synthetic dataset generation for brain MR volumes [El-Allaly et al., Eusipco 2025]

- Set of public datasets (IBSR, OASIS, IXI, Kirby)
  - 3D MR volumes (T1w, T2w, FLAIR)
  - Training: 40,000 axial MRI slices
  - with textual description generated from atlas registration + [...]

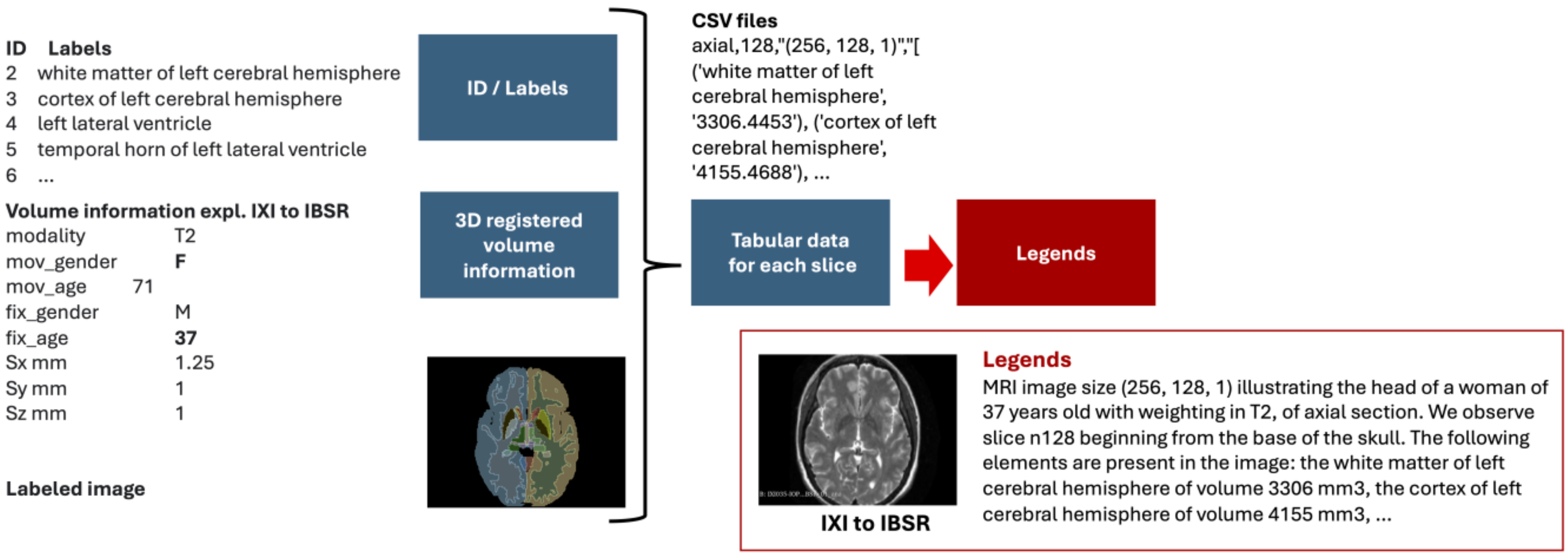


18 IBSR Atlas T1-weighted MRI | 77 new OASIS Atlas T1-weighted MRI | 64 new IXI Atlas T2-weighted MRI | 42 new Kirby Atlas FLAIR MRI

Diffusion models for data augmentation

- Synthetic dataset generation for brain MR volumes [El-Allaly et al., Eusipco 2025]

- Set of public datasets (IBSR, OASIS, IXI, Kirby)
  - 3D MR volumes (T1w, T2w, FLAIR)
  - Training: 40,000 axial MRI slices
  - with textual description generated from atlas registration + metadata + natural language description using template-based text synthesis



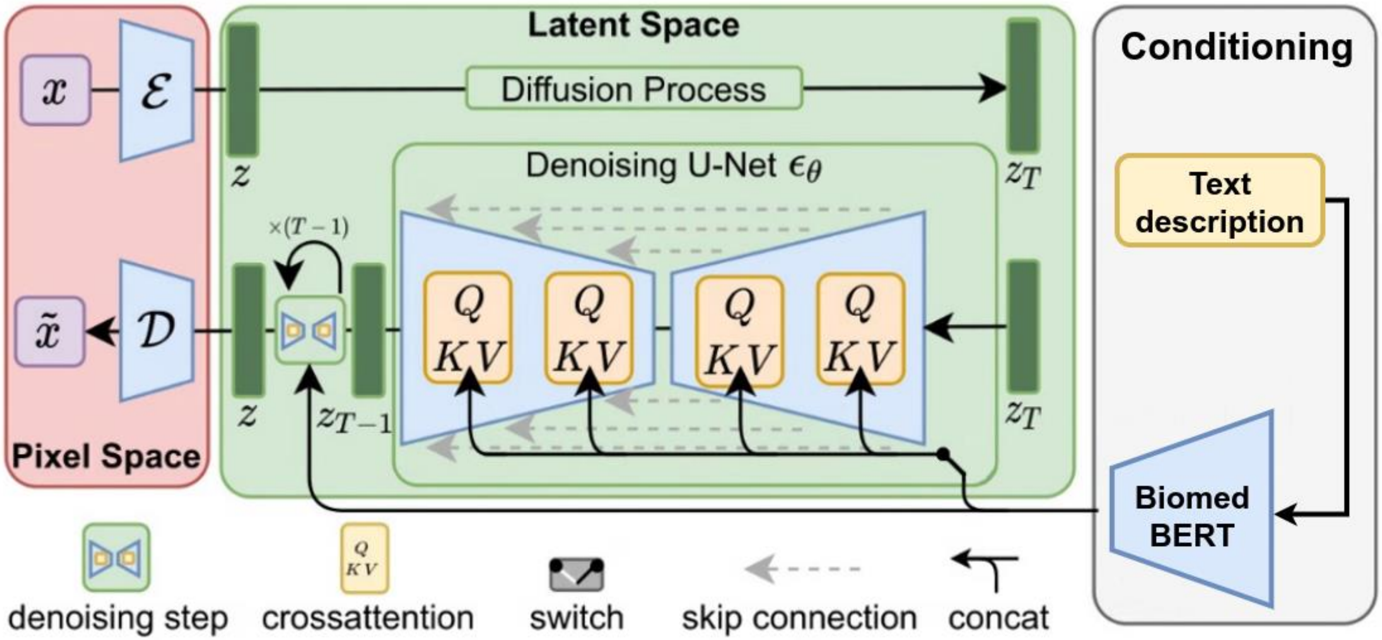
Diffusion models for data augmentation

- Text encoder
  - WordPiece tokenizer
  - BiomedBERT pre-trained model
  - Number of tokens processed : 512
  - Token size (text embedding dimension): 768

- VAE
  - Pre-trained from 40,000 axial MRI slices
  - 2D convolutions
  - Input image dimension: 256 x 256 x 1
  - Latent space dimension: 64 x 64 x 1
  - Training time (GPU 32 GB): 40 hours

Diffusion models for data augmentation

- DDPM
  - 2D convolutions
  - T=1000 time steps
  - Conditioning: set of token encoding the text description of size 512 x 768
  - Input size: 256 x 256 x 1 / Latent space 64 x 64 x 1 / training time (32 GB): 14 days



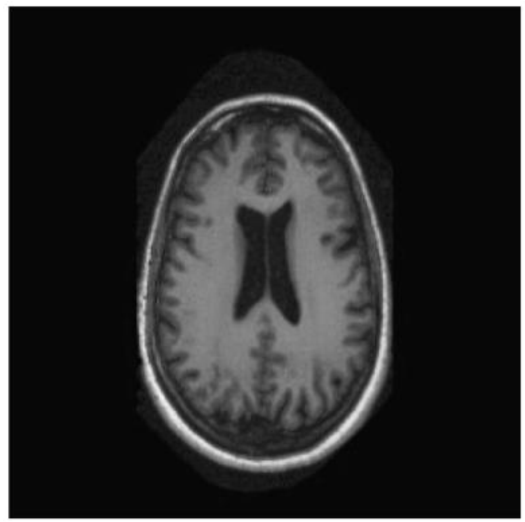
Diffusion models for data augmentation

- Results
  - FID: generated from 1,000 samples drawn from each of the two distributions to be compared

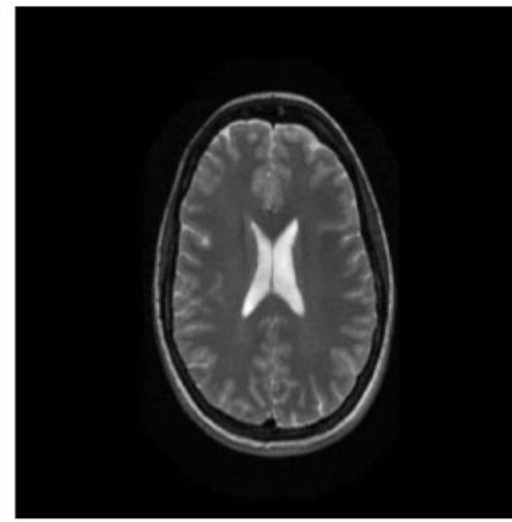
	FID ↓
Train/val	16.9
Test	17.9

"MRI image of the head of a woman of 21 years old in **T1-weighting**, with axial section. We observe slice n°140 beginning from the base of the skull. The observed details include the white matter of left cerebral hemisphere of volume 2728.75 mm3, the cortex of left cerebral hemisphere of volume 4366.25 mm3, the left lateral ventricle of volume 267.50 mm3, the left thalamus of volume 202.50 mm3, the left caudate nucleus of volume 162.50 mm3, the left putamen of volume 180.00 mm³, the cerebrospinal fluid of volume 7.50 mm3, the white matter of right cerebral hemisphere of volume 3017.50 mm3, the cortex of right cerebral hemisphere of volume 4041.25 mm3, the right lateral ventricle of volume 250.00 mm3, the right thalamus proper of volume 217.50 mm3, the right caudate nucleus of volume 165.00mm3, the right putamen of volume 135.00 mm3 and the right thin cerebral white matter of volume 685.00 mm3."

Input prompt



Synthetic image with key word T1-weighted



Synthetic image with key word T2-weighted

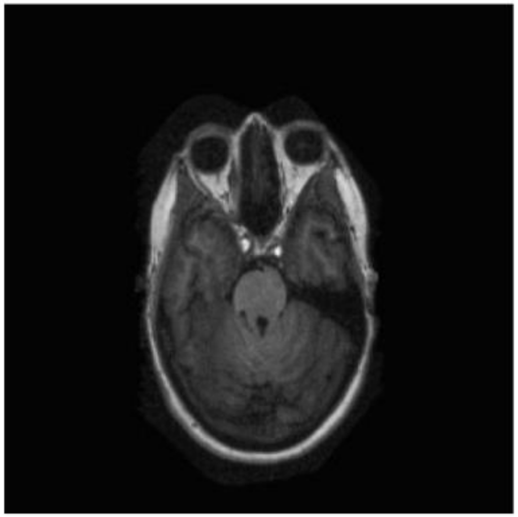
Diffusion models for data augmentation

- Results
  - FID: generated from 1,000 samples drawn from each of the two distributions to be compared

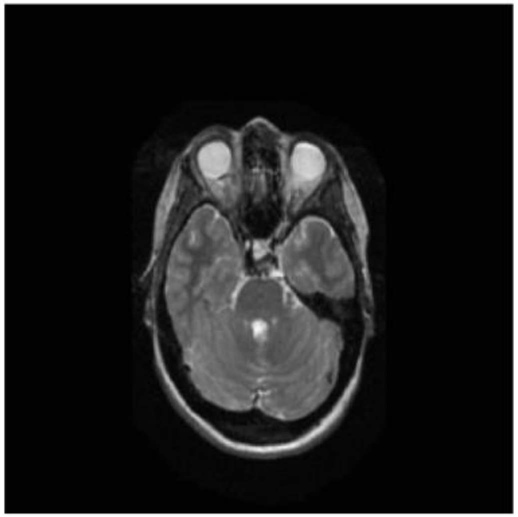
	FID ↓
Train/val	16.9
Test	17.9

"MRI snapshot with **T1-weighting** describing the skull of a woman of age of 52 years old, of axial section n°110 from the base of the skull. We distinguish clearly: the white matter of left cerebral hemisphere of volume 171.25mm^3, the cortex of left cerebral hemisphere of volume 1291.25mm^3, the white matter of left hemisphere of cerebellum of volume 550.00 mm^3, the left cerebellar cortex of volume 1483.75 mm^3, the fourth ventricle of volume 97.50 mm^3, the brainstem of volume 582.50 mm^3, the white matter of right cerebral hemisphere of volume 222.50 mm^3, the cortex of right cerebral hemisphere of volume 1181.25 mm^3, the white matter of right hemisphere of cerebellum of volume 593.75 mm^3, the right cerebellar cortex of volume 1413.75 mm^3 and the right thin cerebral white matter of volume 302.50 mm^3."

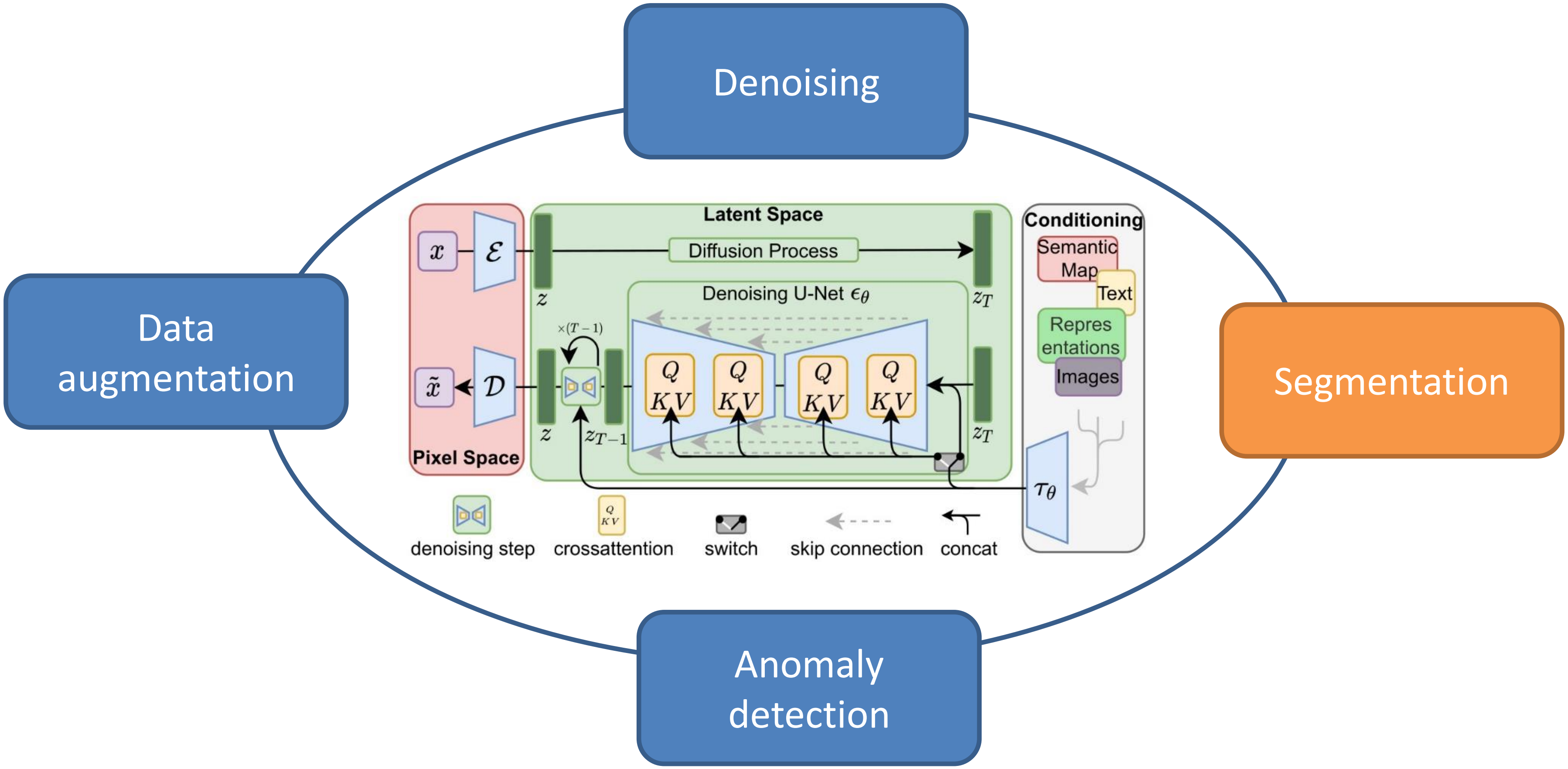
Input prompt



Synthetic image with key word T1-weighted



Synthetic image with key word T2-weighted


Denoising
Data augmentation
Segmentation
Anomaly detection
Latent Space
Diffusion Process
Denoising U-Net ϵ_θ
Pixel Space
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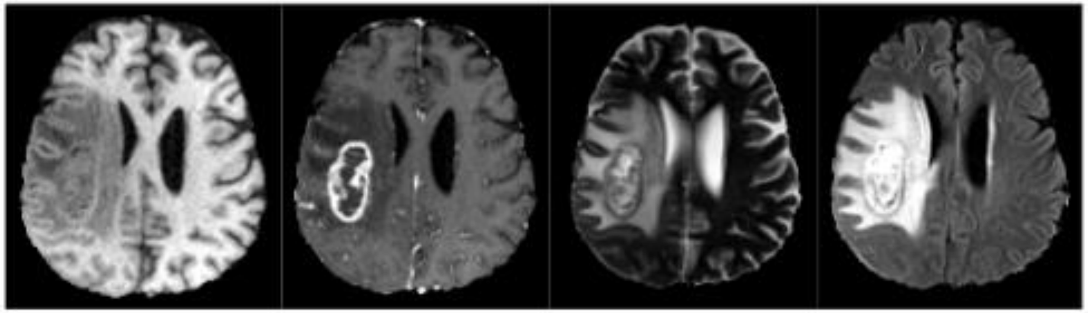
denoising step
crossattention
switch
skip connection
concat

- Segmentation of tumors from MR images [Wolleb et al., MIDL 2022]
- BRATS2020 dataset
  - 4 different MR sequences per patient (T1, T2, T1ce, FLAIR)
  - Training: 332 patients with 3D volumes sequences => 16,998 2D images
  - Testing: 37 patients with 3D volumes sequences => 1,082 2D images

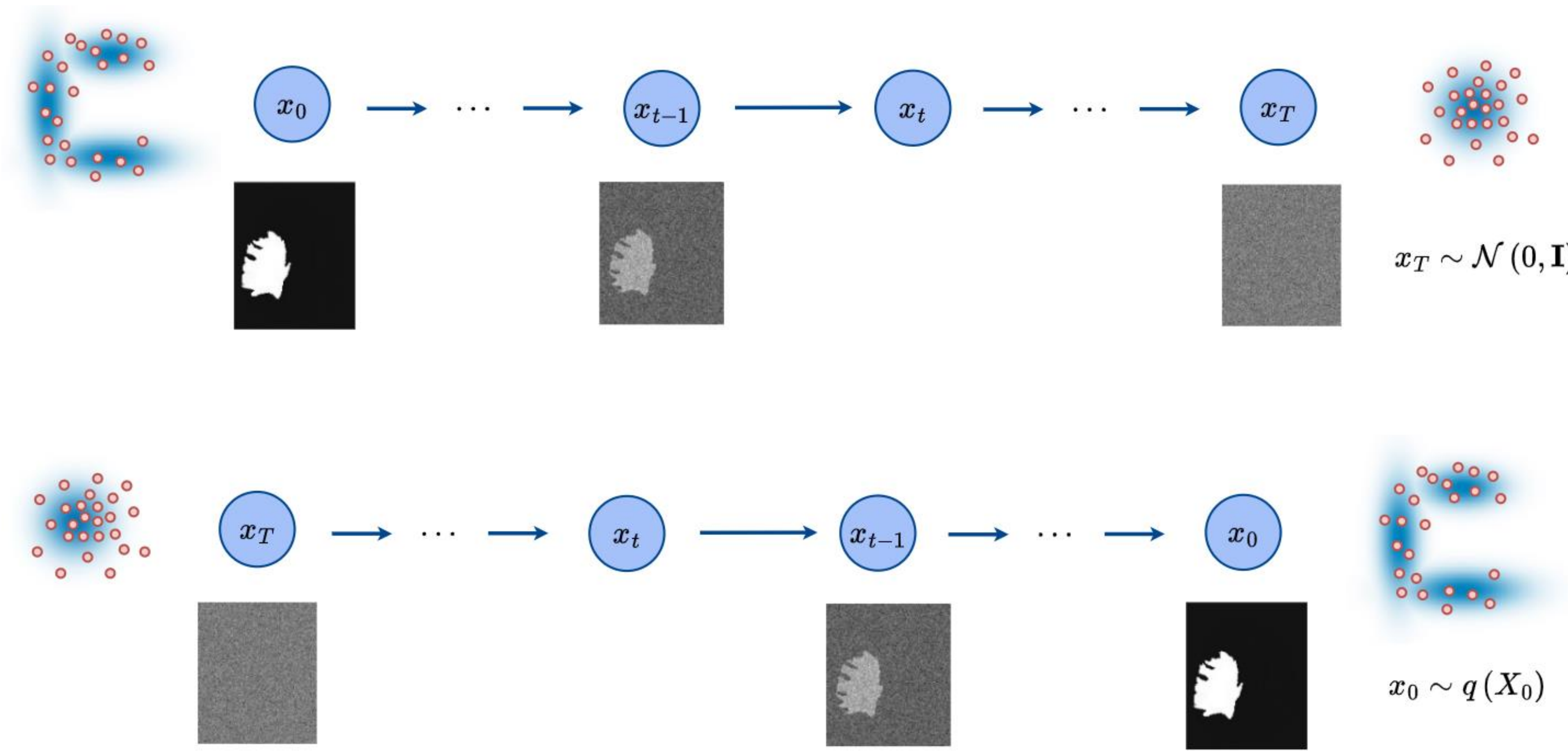


4 MR inputs per patient (T1, T2, T1ec, FLAIR)

Mask output

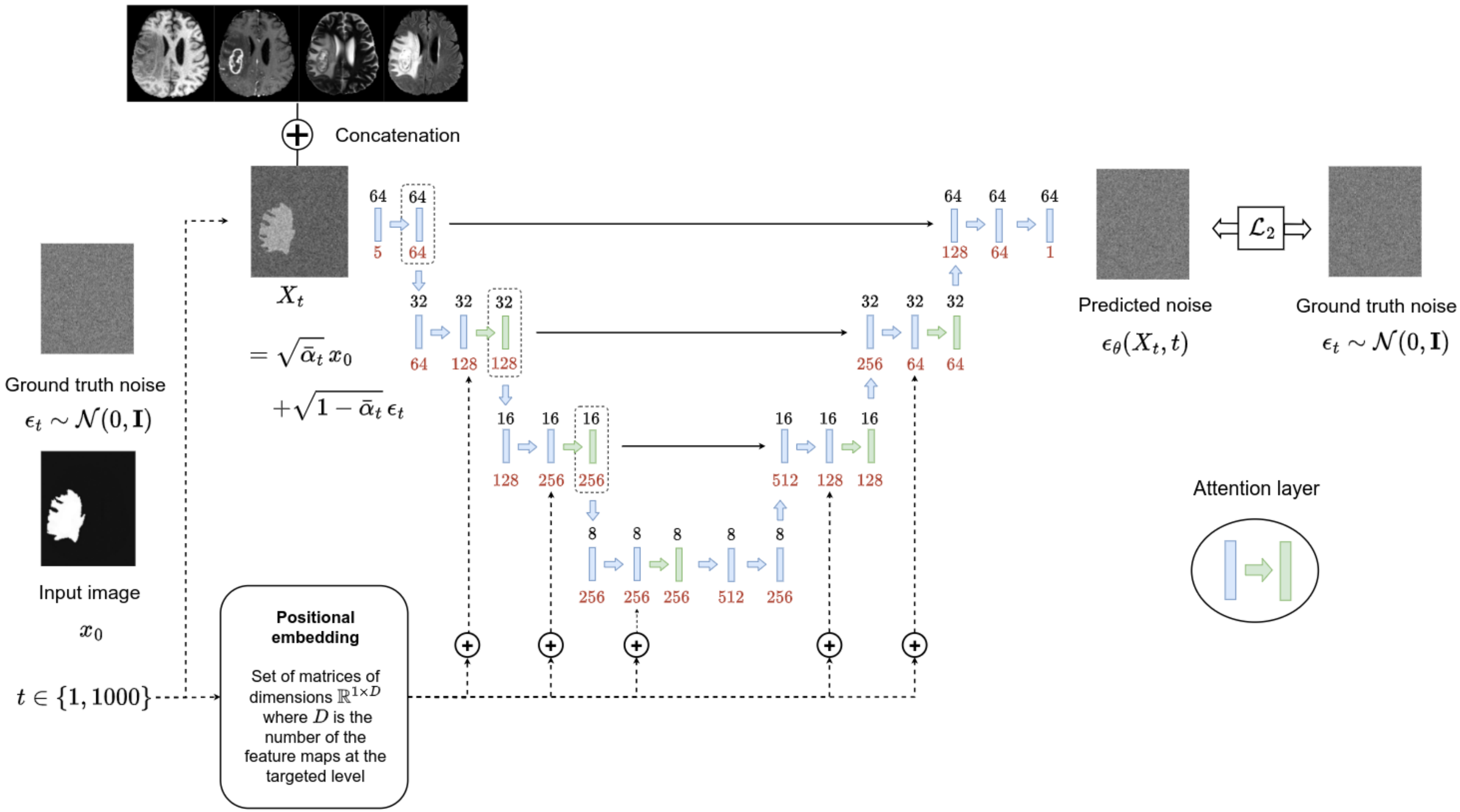
Diffusion models for image segmentation

- Learn the underlying distribution of tumor segmentation masks



Diffusion models for image segmentation

- Conditioning with the 4 MR images using concatenation scheme



- At inference time: modelling of the segmentation uncertainty

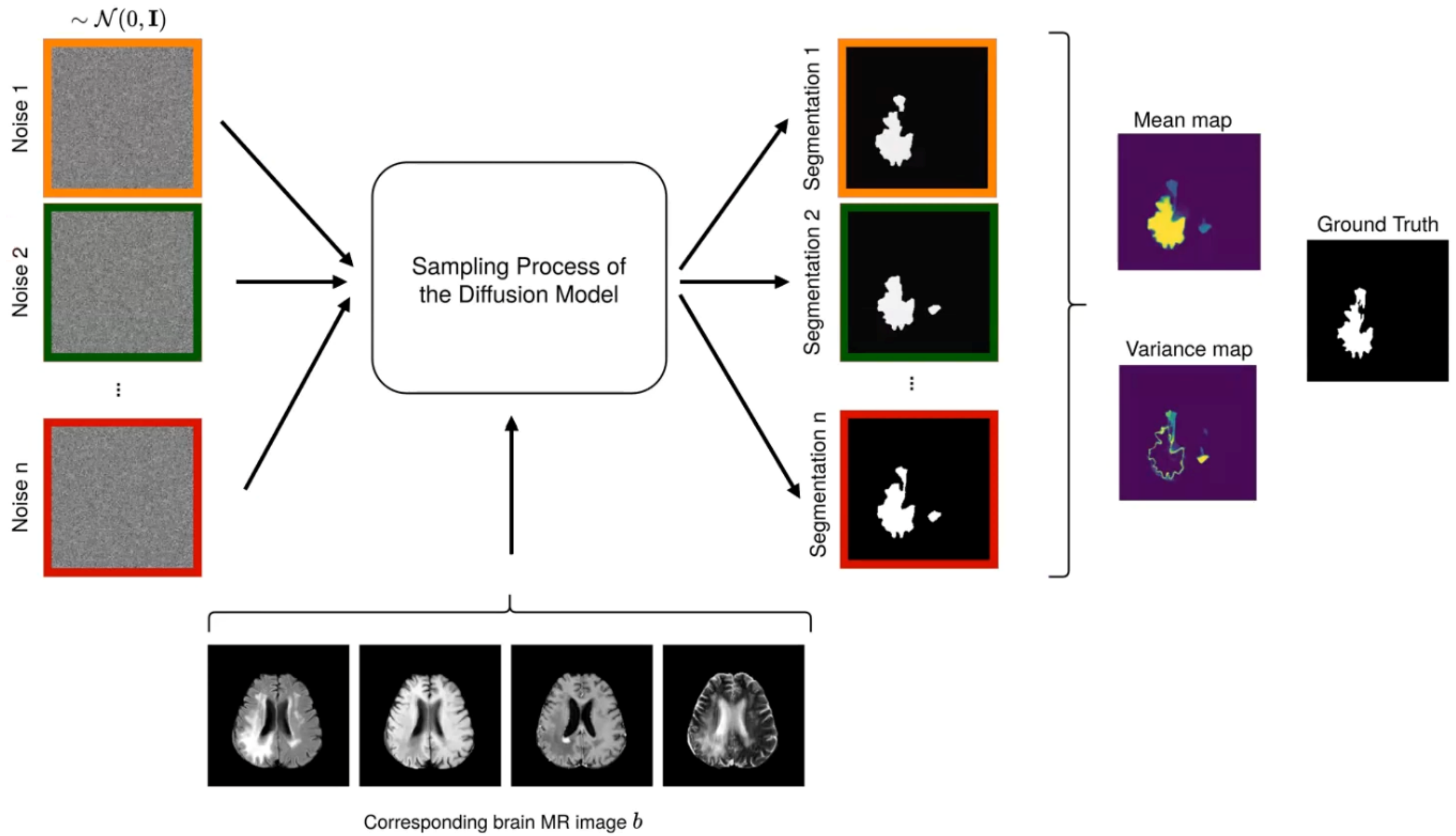


Illustration taken from https://www.youtube.com/watch?v=US9CzPrT2H8

Diffusion models for image segmentation

- Results

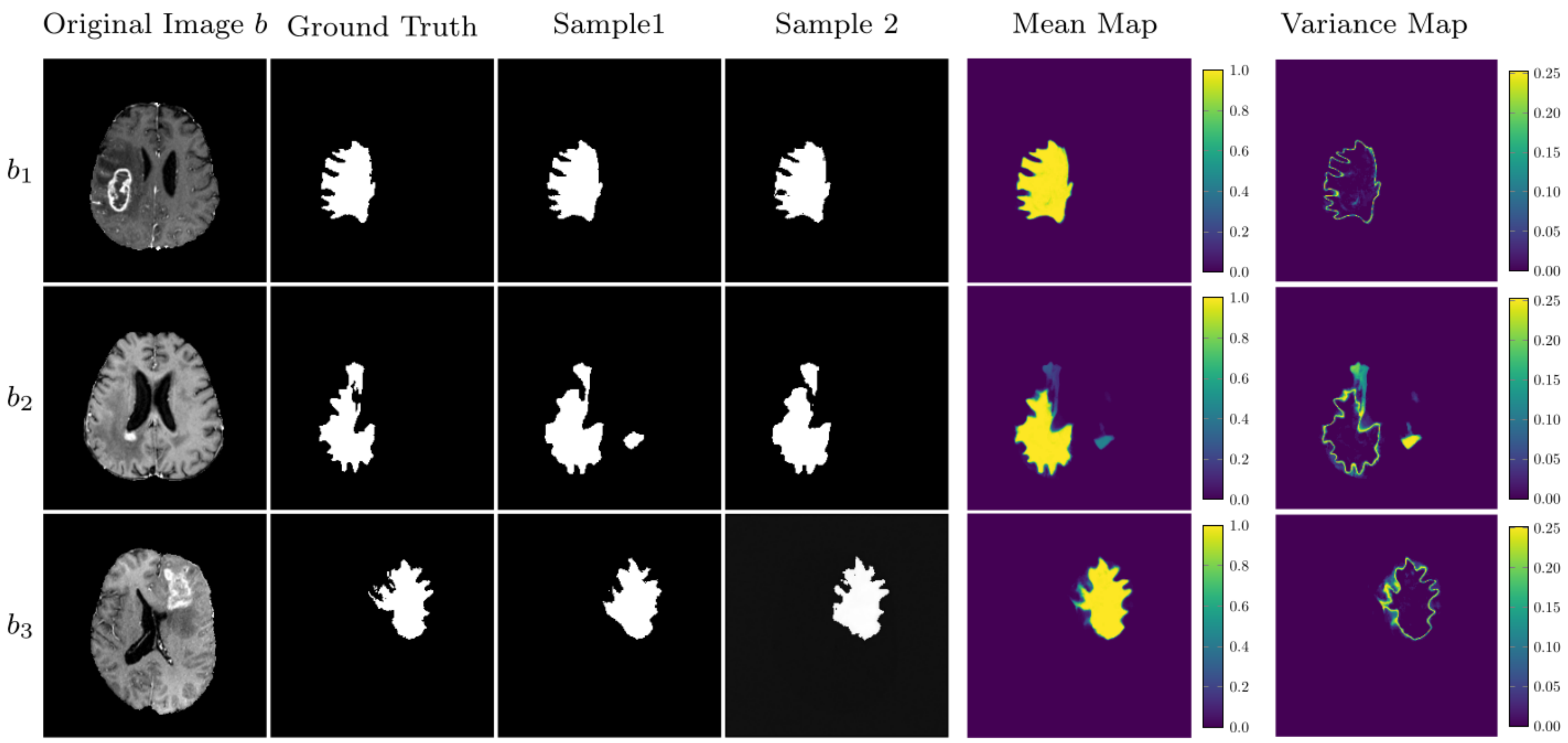
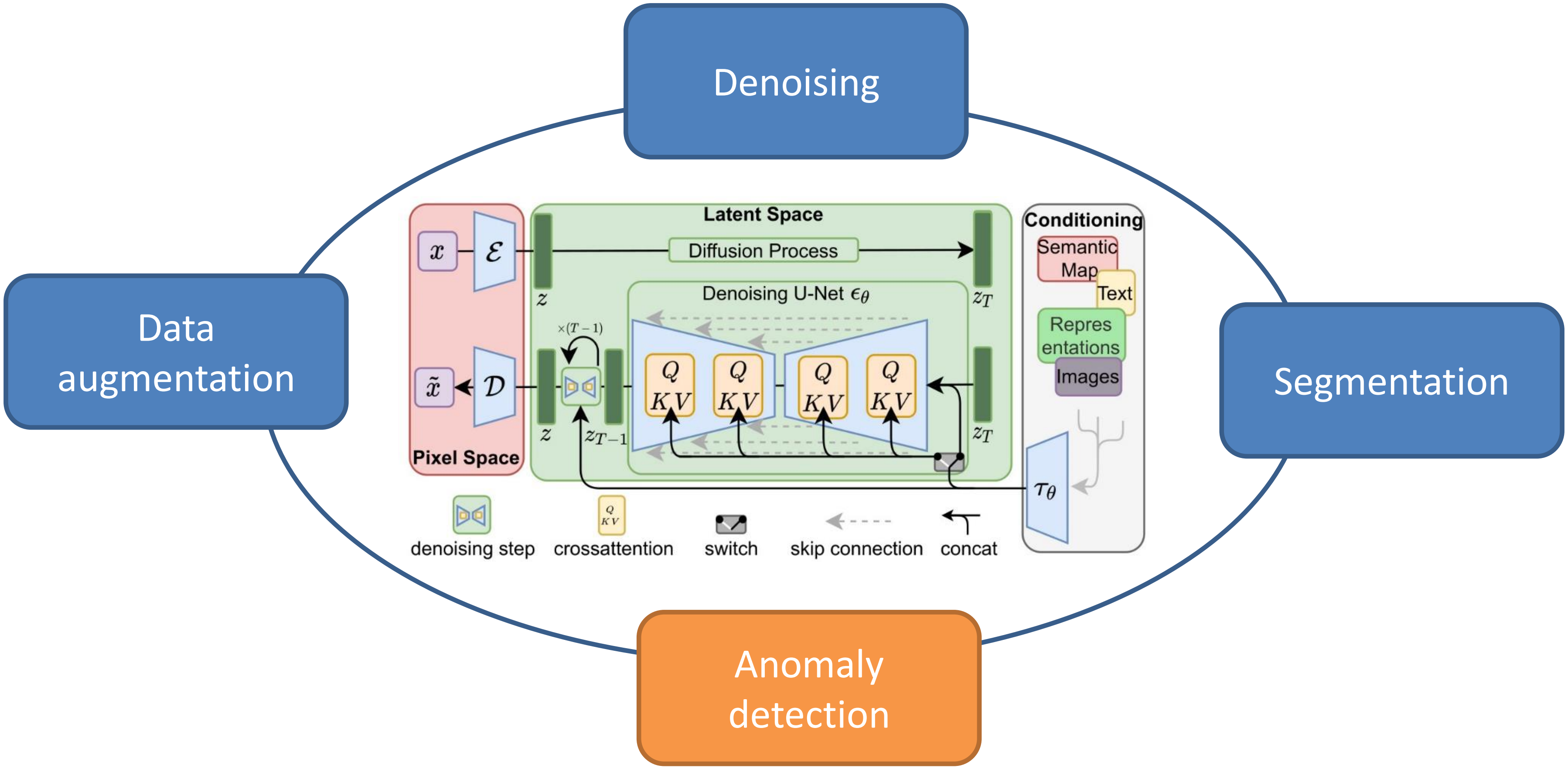


Illustration taken from https://arxiv.org/pdf/2112.03145


Denoising
Data augmentation
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Text
Representations
Images
τ_θ
denoising step
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switch
skip connection
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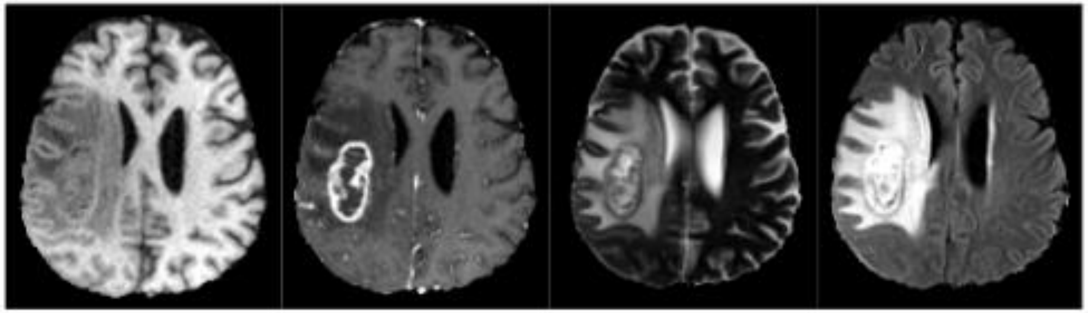
- Anomaly detection from MR images [Wolleb et al., MICCAI 2024]

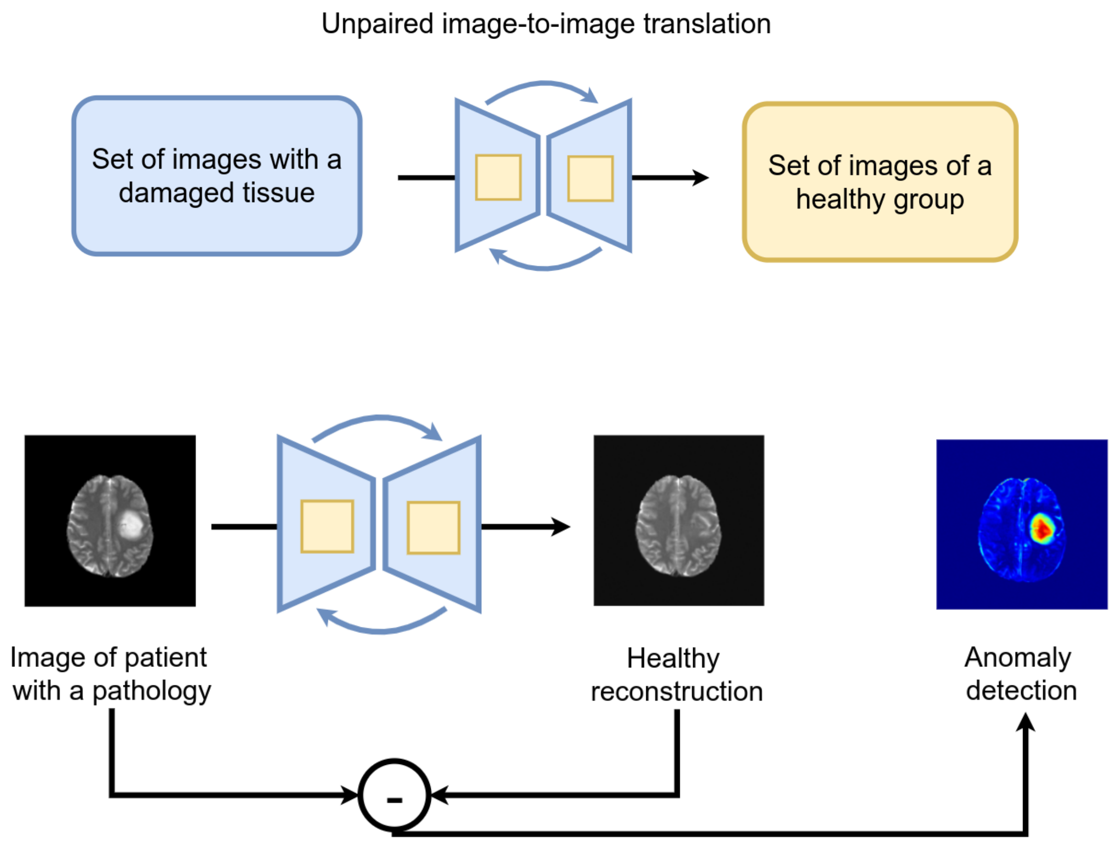
- BRATS2020 dataset
  - 4 different MR sequences per patient (T1, T2, T1ce, FLAIR)
  - Training: 332 patients with 3D volumes sequences => 16,998 2D images
  - 5,598 healthy 2D slices (without tumor) / 10,607 disease 2D slices



4 MR inputs per patient (T1, T2, T1ec, FLAIR)

Mask output

- General idea

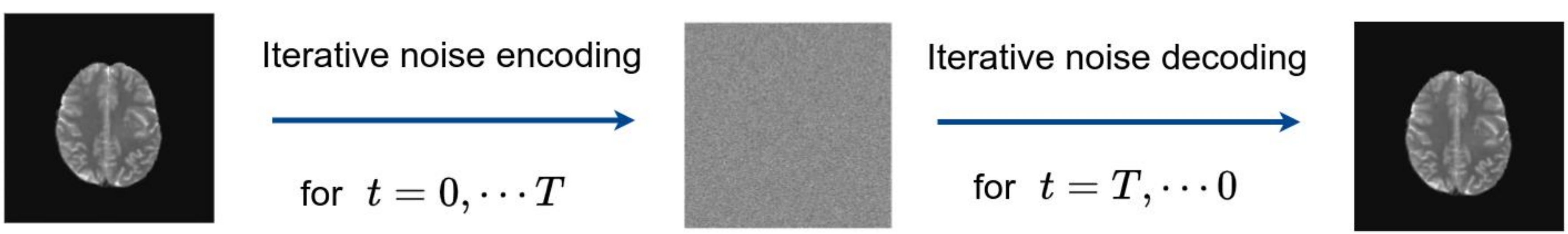


How to preserve spatial anatomical information using a diffusion process?

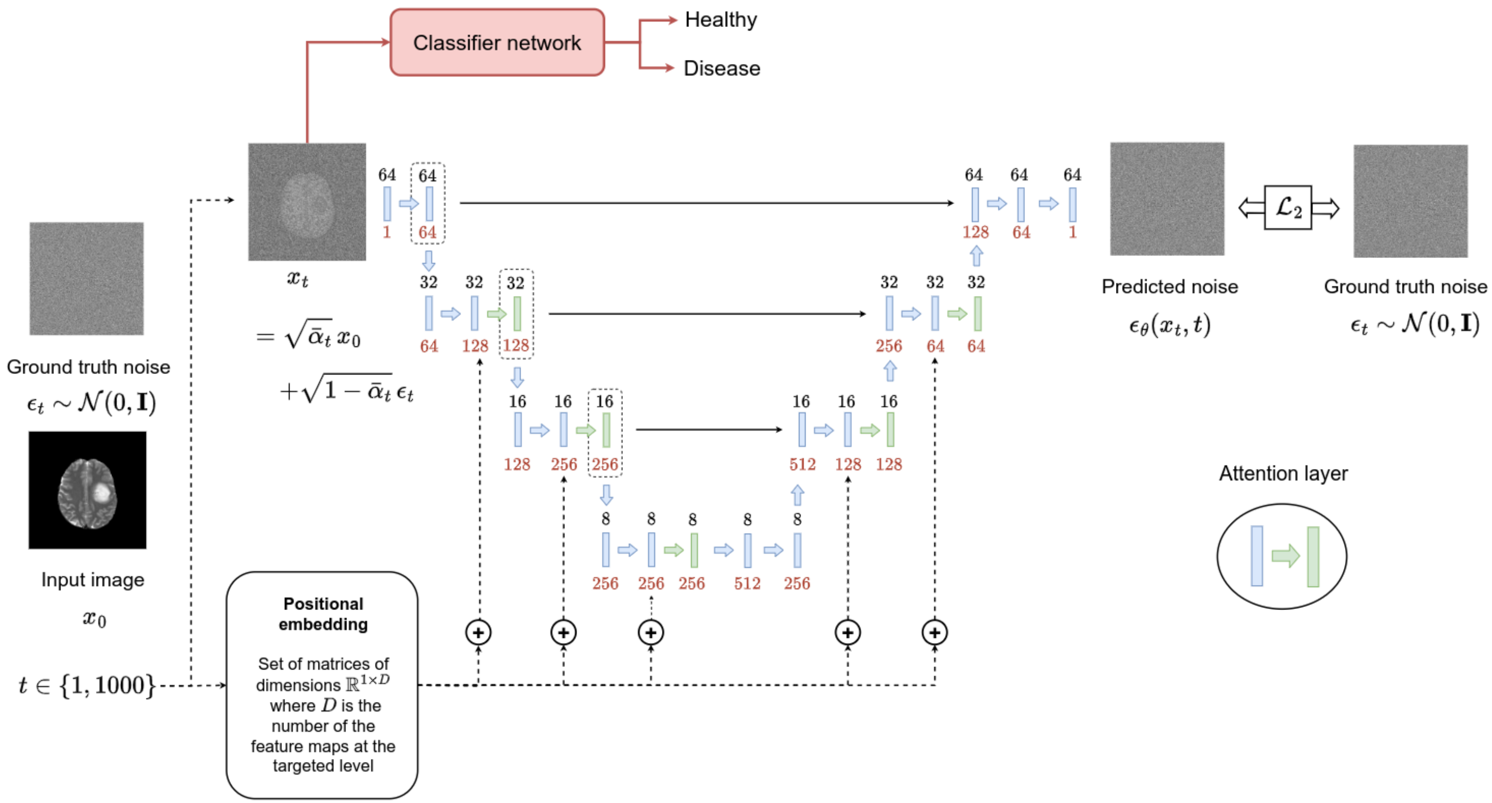
Diffusion models for anomaly detection

▶ Denoising Diffusion Implicit Models (DDIM)

- Reformulation of the diffusion process
- Remove the random component $\sigma_t \epsilon$
- Make the diffusion process deterministic



- Main algorithm – part 1
  - Train a classical DDPM on the dataset containing healthy and disease images
  - Train a classifier network C to predict the class label (healthy vs disease) from any noisy images x_t



- Main algorithm – part 2
  - Use DDIM process
  - Compute the gradient of the classifier to guide the removing of anomaly regions

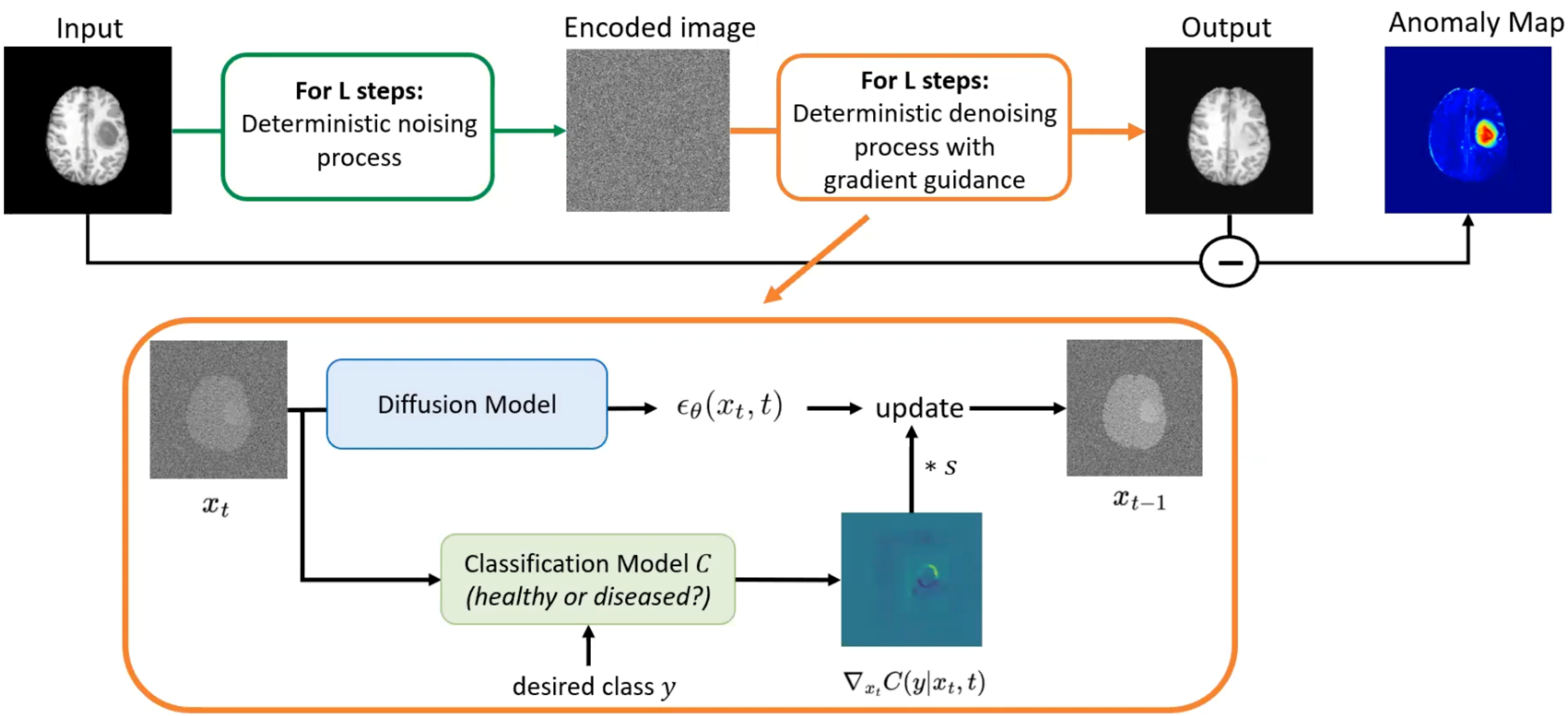
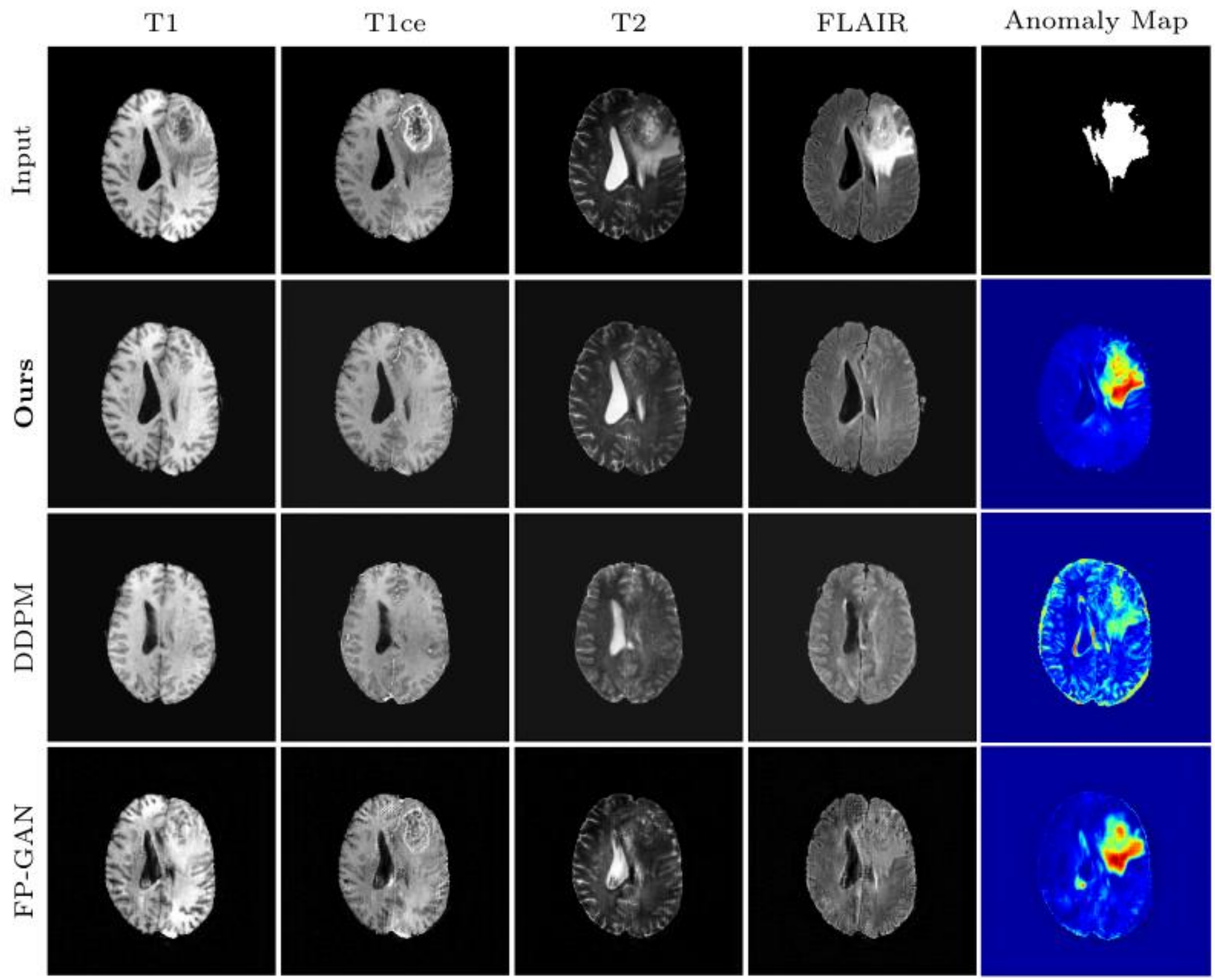


Illustration taken from https://arxiv.org/pdf/2203.04306

Diffusion models for anomaly detection

- Result on an image with a tumor



Diffusion models for anomaly detection

- Result on an image without any tumor

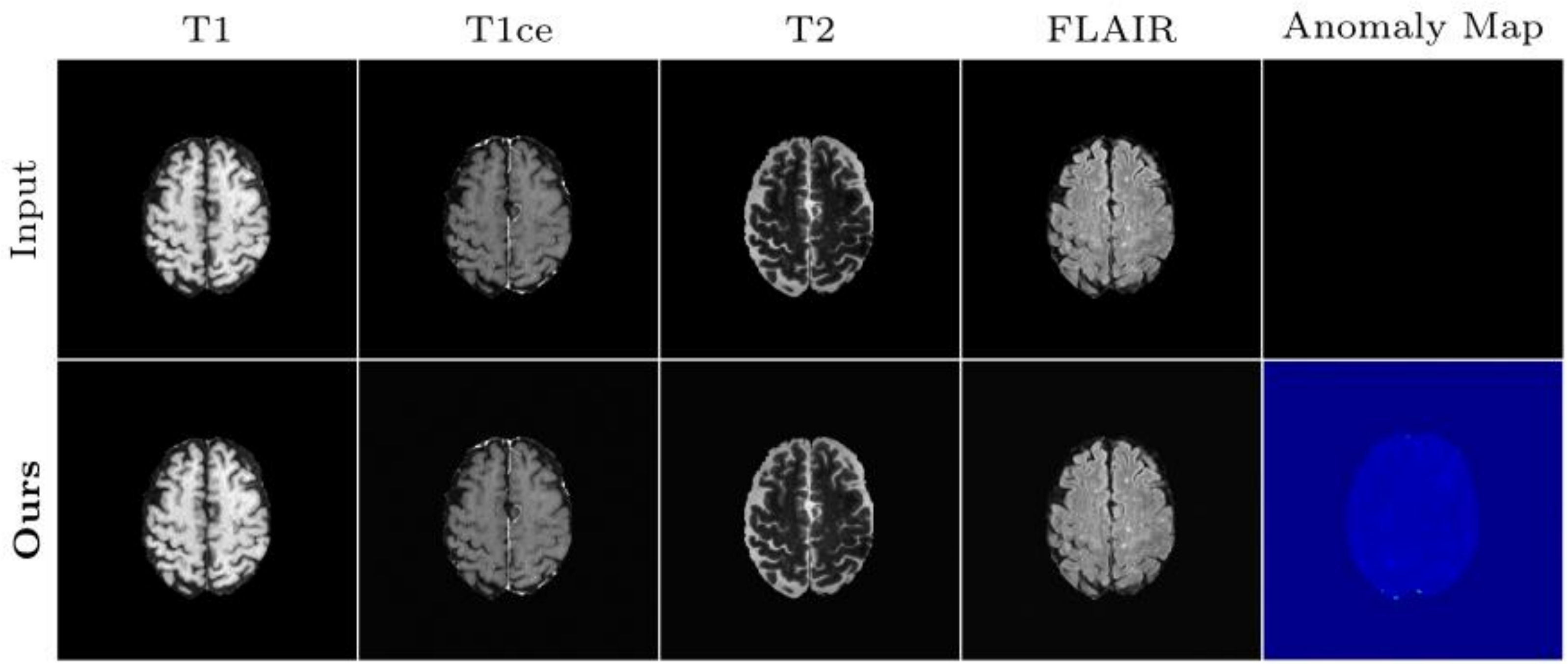


Illustration taken from https://arxiv.org/pdf/2203.04306

That's all folks

Variation Auto Encoder framework

- Key idea
  - Generating sample z according to $p(z|x)$, implies that z has been generated by images from the original data distribution $p(x)$
  - If can reconstruct vectors back into images, we will effectively generate new samples from our original data distribution
  - We need to know the latent distribution, which is assume to be a normal distribution
  - This allows to compute the likelihood p(x/z)
  - The only unknown remains the true posterior p(z/x)
  - Thanks to variational inference, we approximate it using a Gaussian distribution q(z/x)
  - This Gaussian will have parameters mu and sigma that we need to learn, which is an optimization process known as variational Bayes
  - We will train an encoder to estimate these parameters mu and sigma from the images
  - Then we used a decoder to reconstruct images from the latent variables that are sampled from the approximate posterior