UNIVERSITY OF TECHNOLOGY
IN THE EUROPEAN CAPITAL OF CULTURE
CHEMNITZ

Neurocomputing

Diffusion Probabilistic Models

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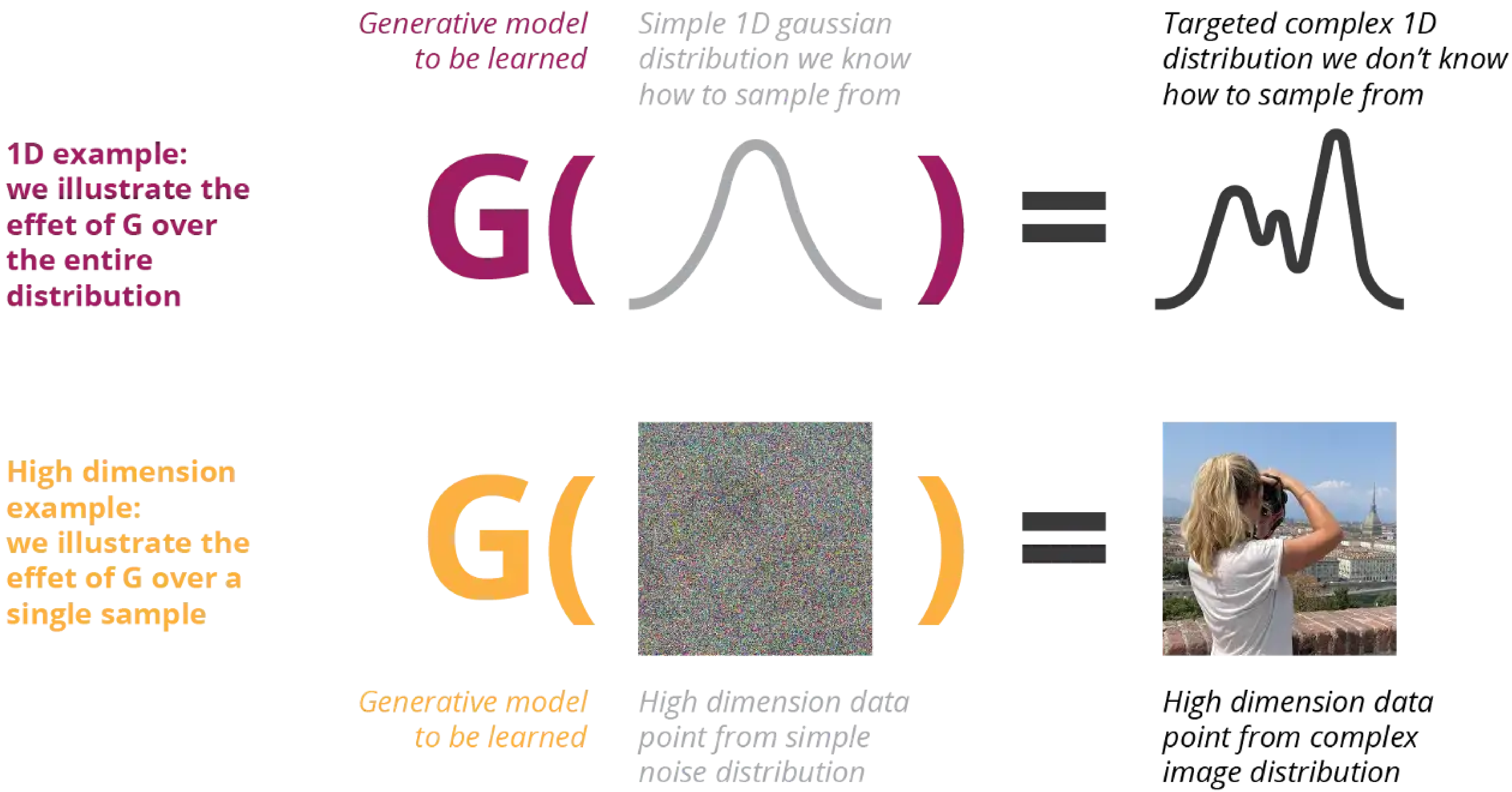
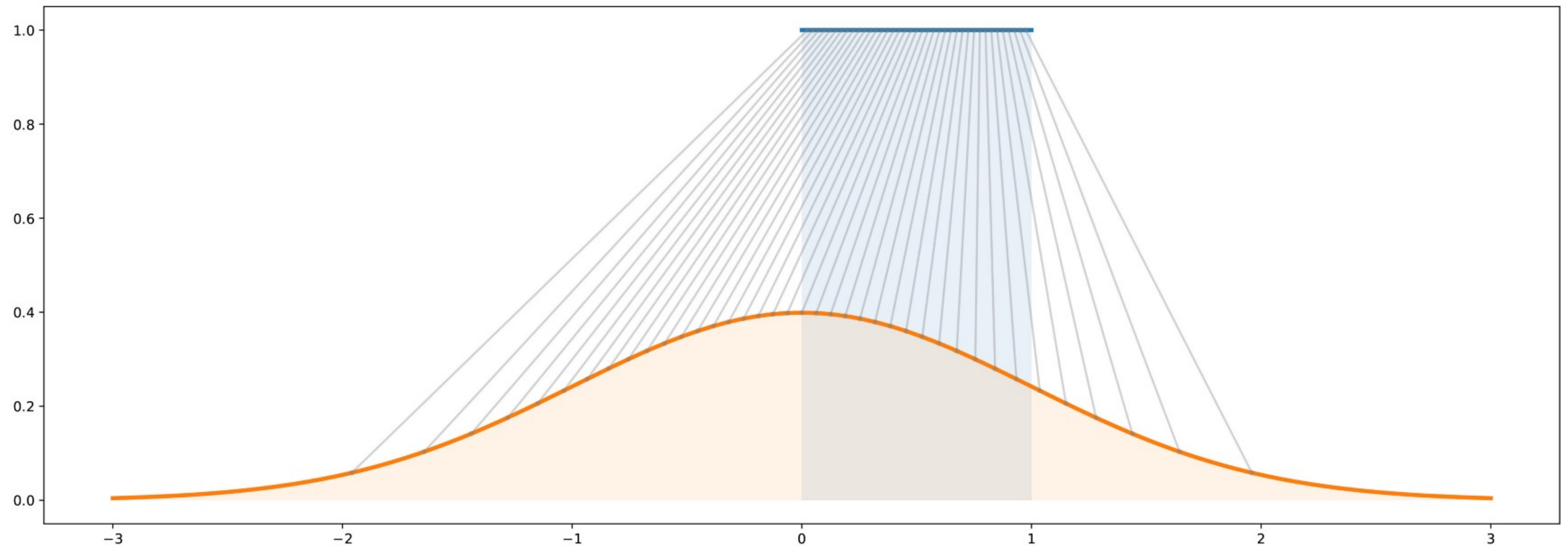
1 - Diffusion probabilistic models

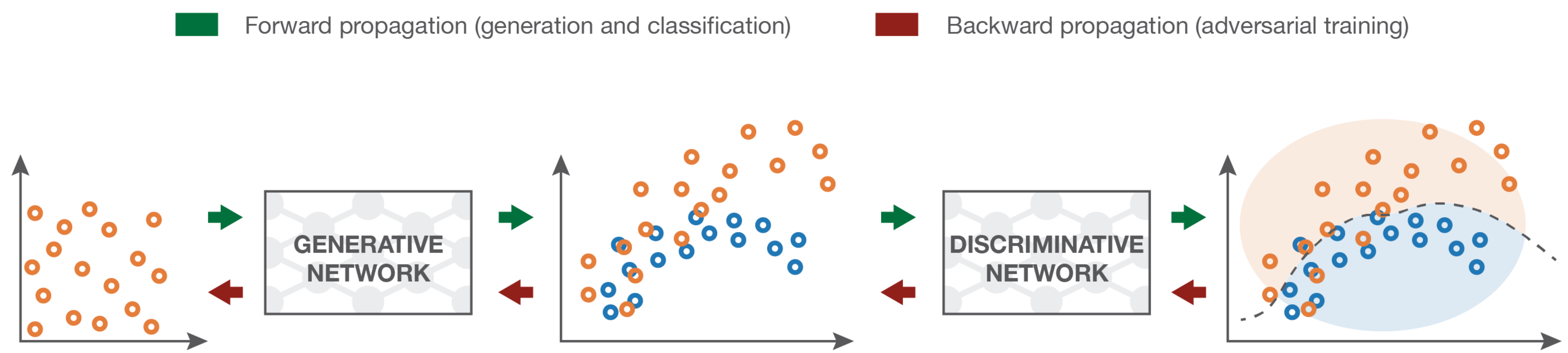
Generative modeling



Source: https://towardsdatascience.com/understanding-diffusion-probabilistic-models-dpms-1940329d6048

VAE and GAN generators transform simple noise to complex distributions





Input random variables.

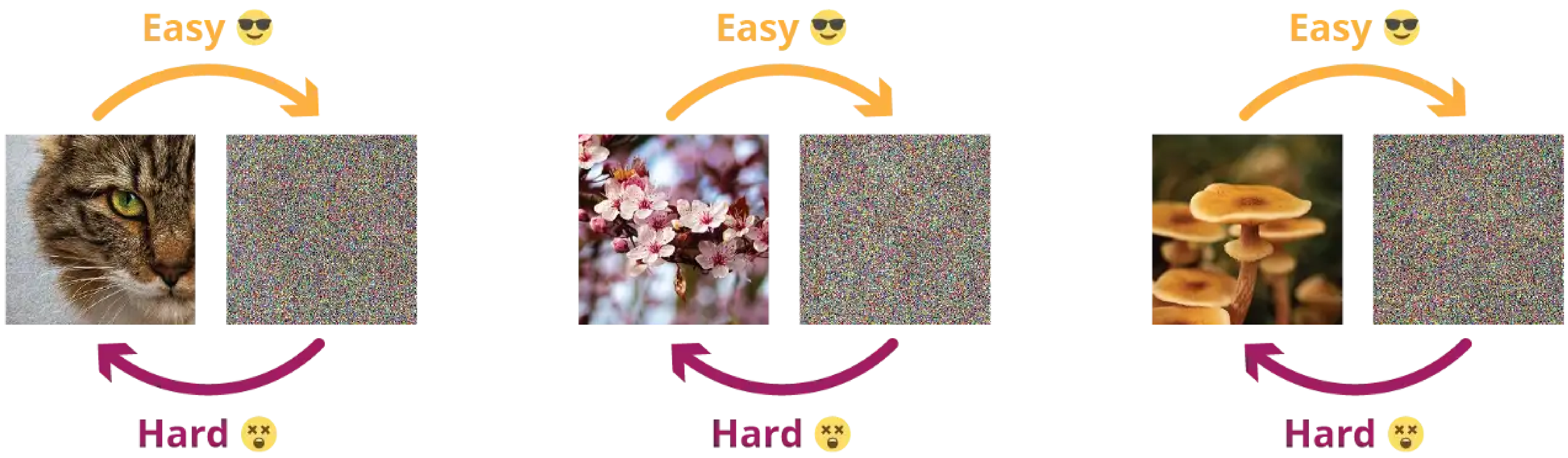
The generative network is trained to **maximise** the final classification error.

The generated distribution and the true distribution are not compared directly.

The discriminative network is trained to **minimise** the final classification error.

The classification error is the basis metric for the training of both networks.

Destroying information is easier than creating it



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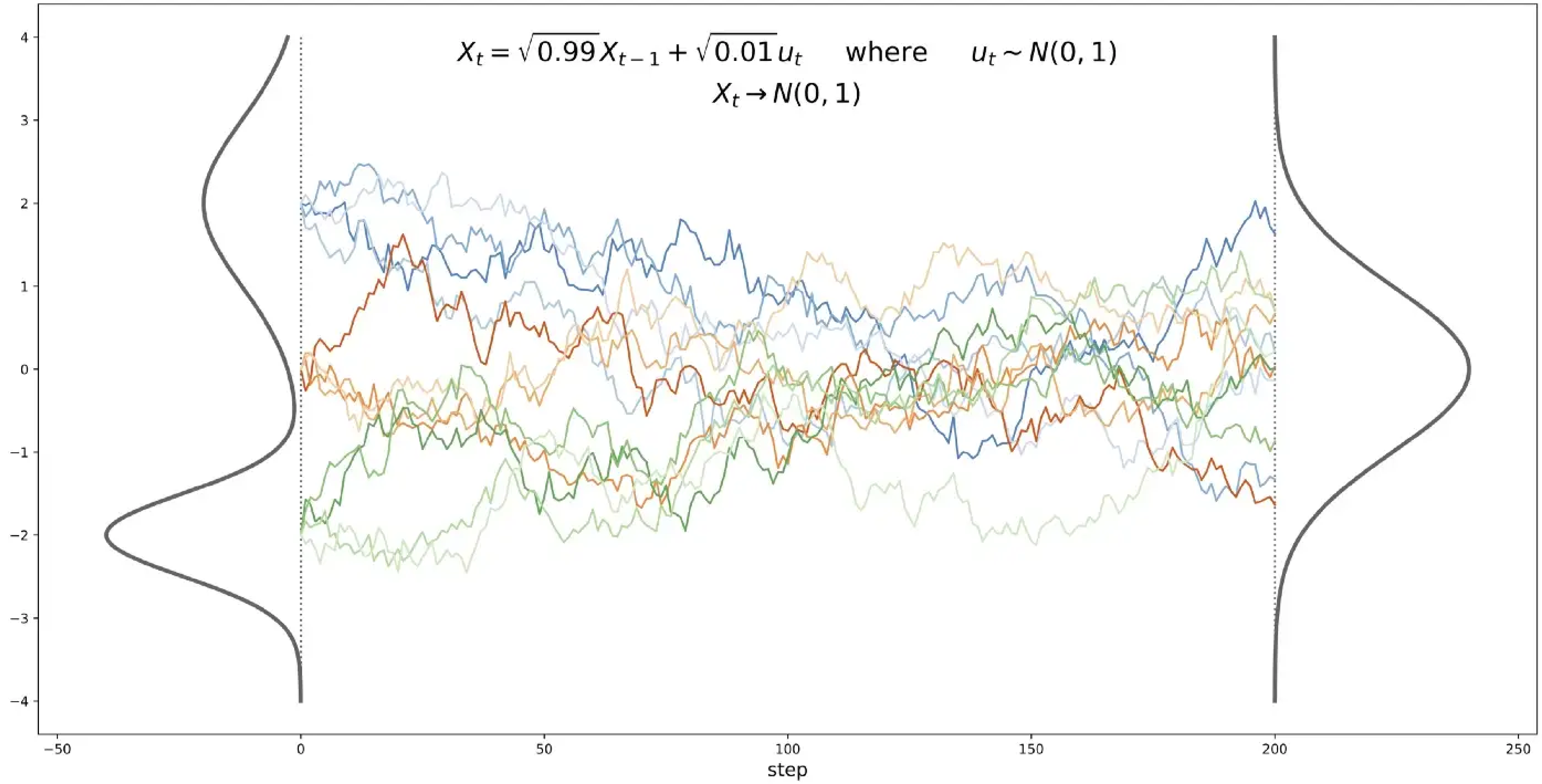
Stochastic processes can destroy information

- Iteratively adding normal noise to a signal creates a **stochastic differential equation** (SDE).

$$X_t = \sqrt{1-p}\, X_{t-1} + \sqrt{p}\, \sigma \qquad \text{where} \qquad \sigma \sim \mathcal{N}(0,1)$$

- Under some conditions, any probability distribution converges to a normal distribution.



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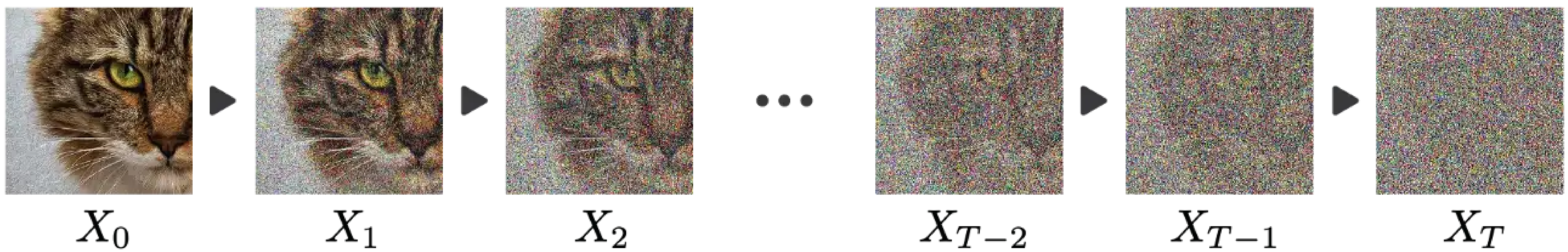
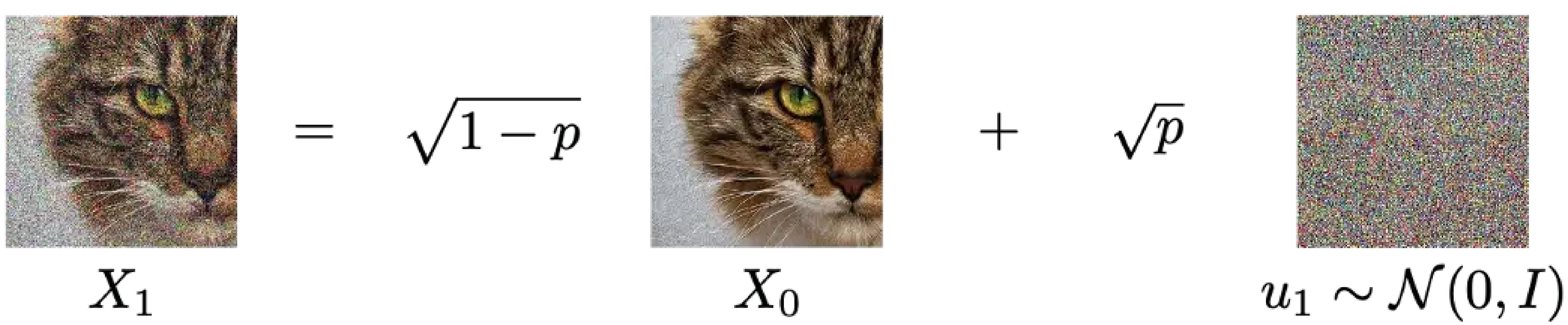
Diffusion process

- A **diffusion process** can iteratively destruct all information in an image through a Markov chain.





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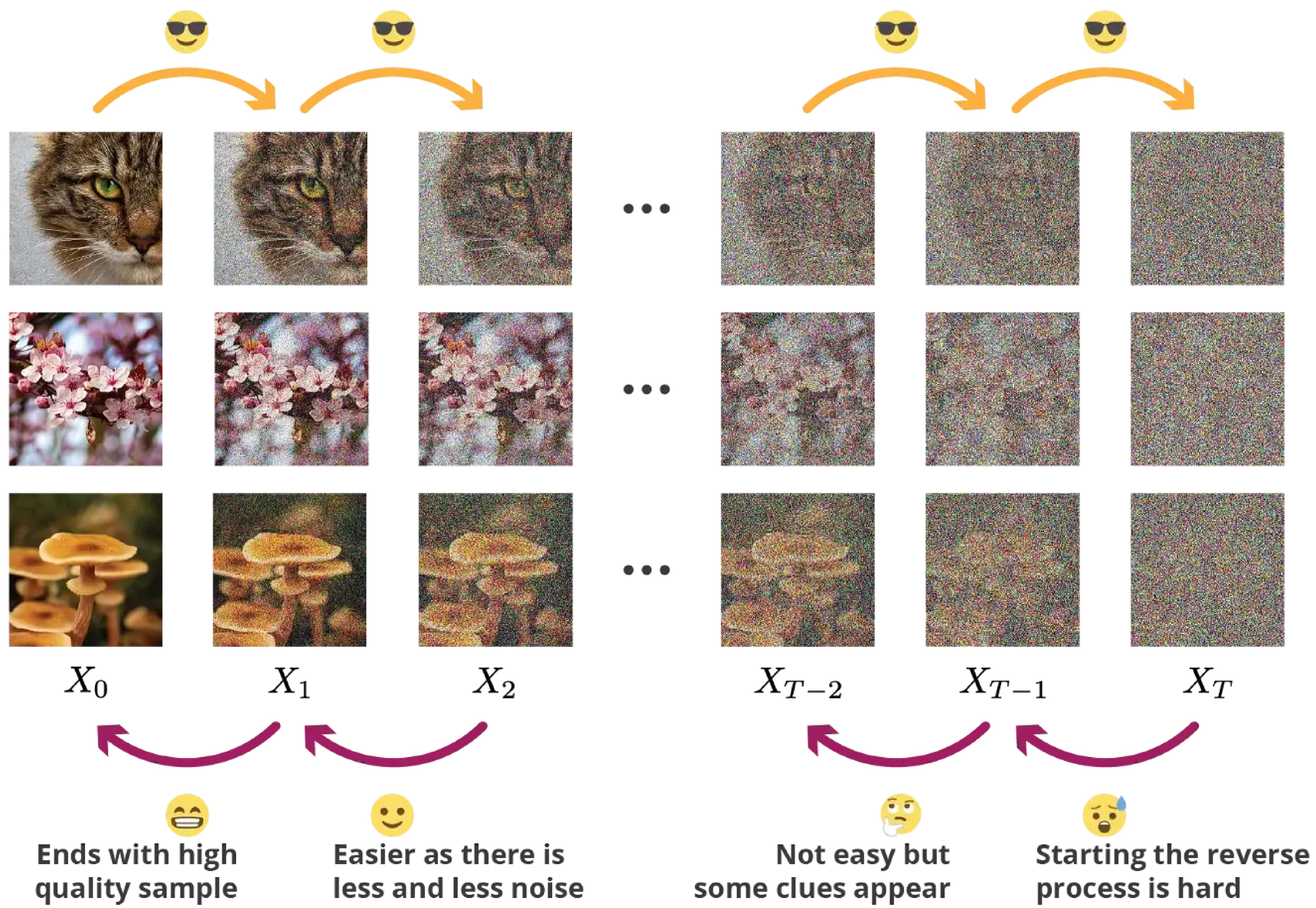
Reverse Diffusion process

- It should be possible to **reverse** each diffusion step by removing the noise using a form of denoising autoencoder.



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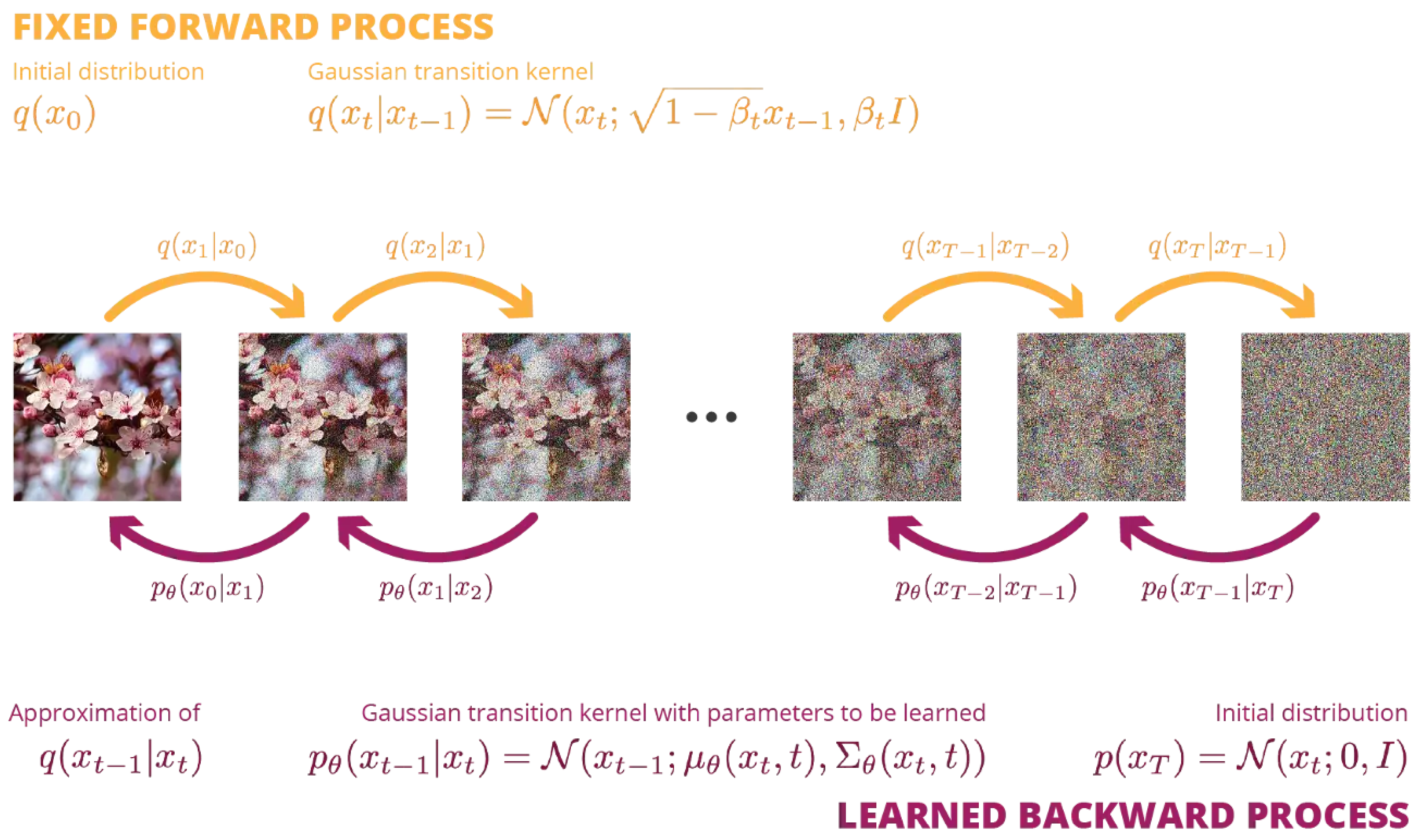
Reverse Diffusion process

- We will not get into details, but learning the reverse diffusion step implies Bayesian inference, KL divergence and so on.
- As we have the images at t and $t + 1$, it should be possible to learn, right?



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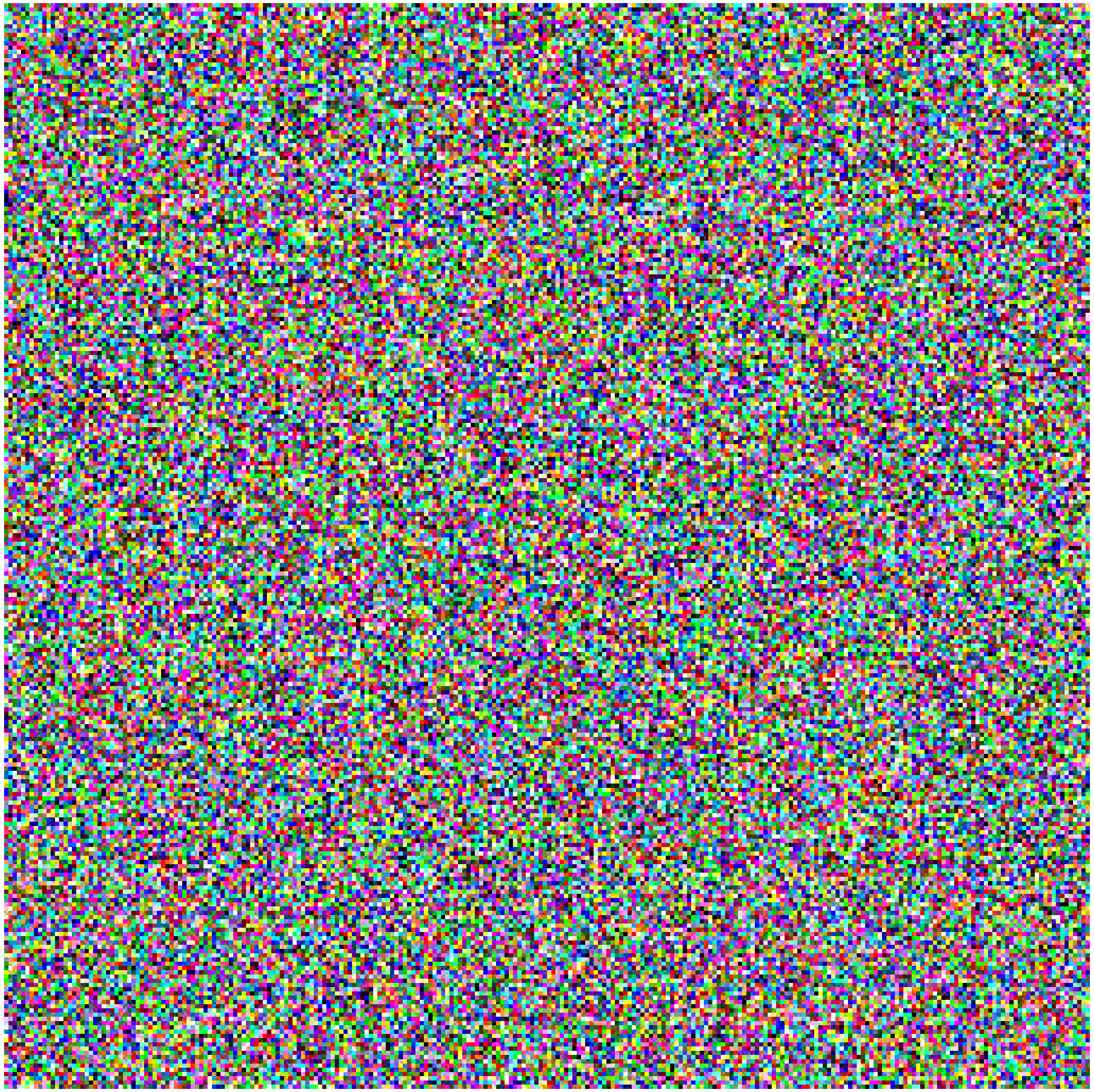
Probabilistic diffusion models



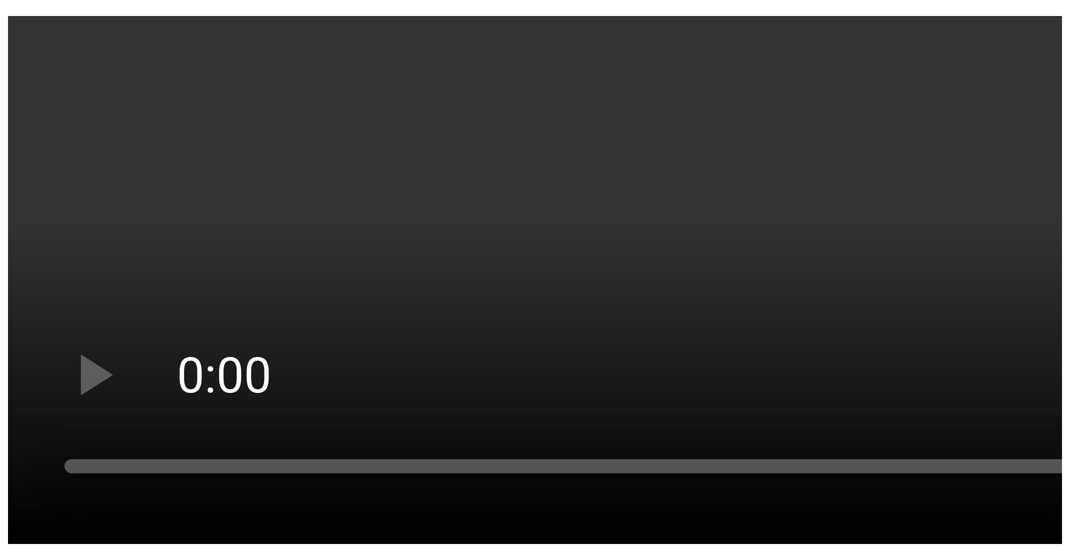
Source: http://adityaramesh.com/posts/dalle2/dalle2.html

2 - Dall-e

Dall-e

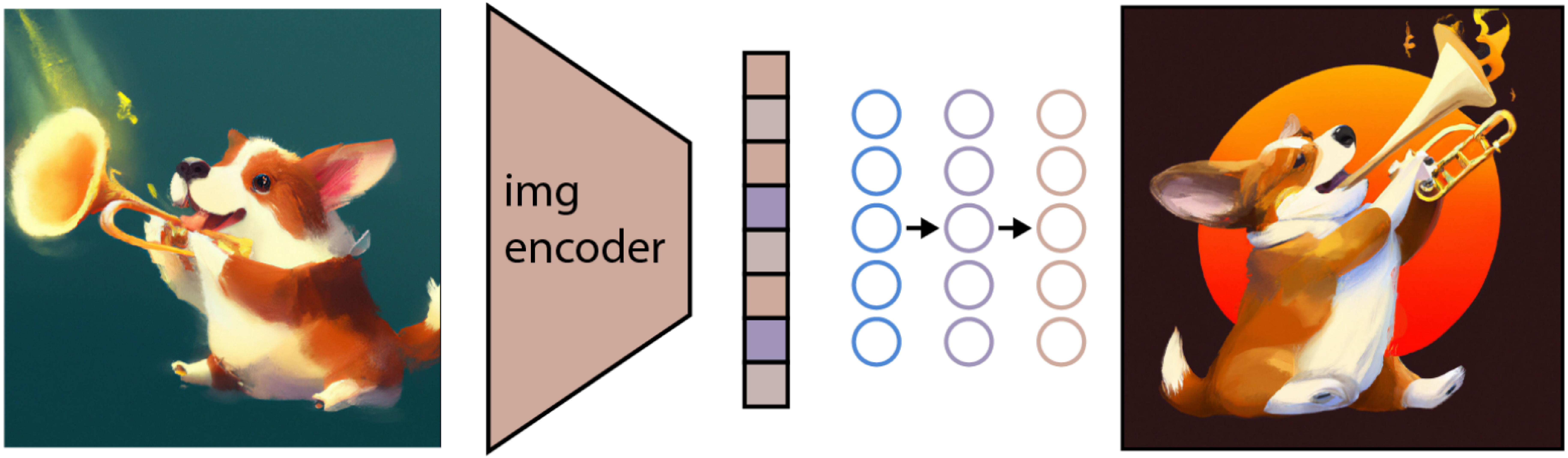
Source: https://towardsdatascience.com/understanding-diffusion-probabilistic-models-dpms-1940329d6048

CLIP: Contrastive Language-Image Pre-training



GLIDE

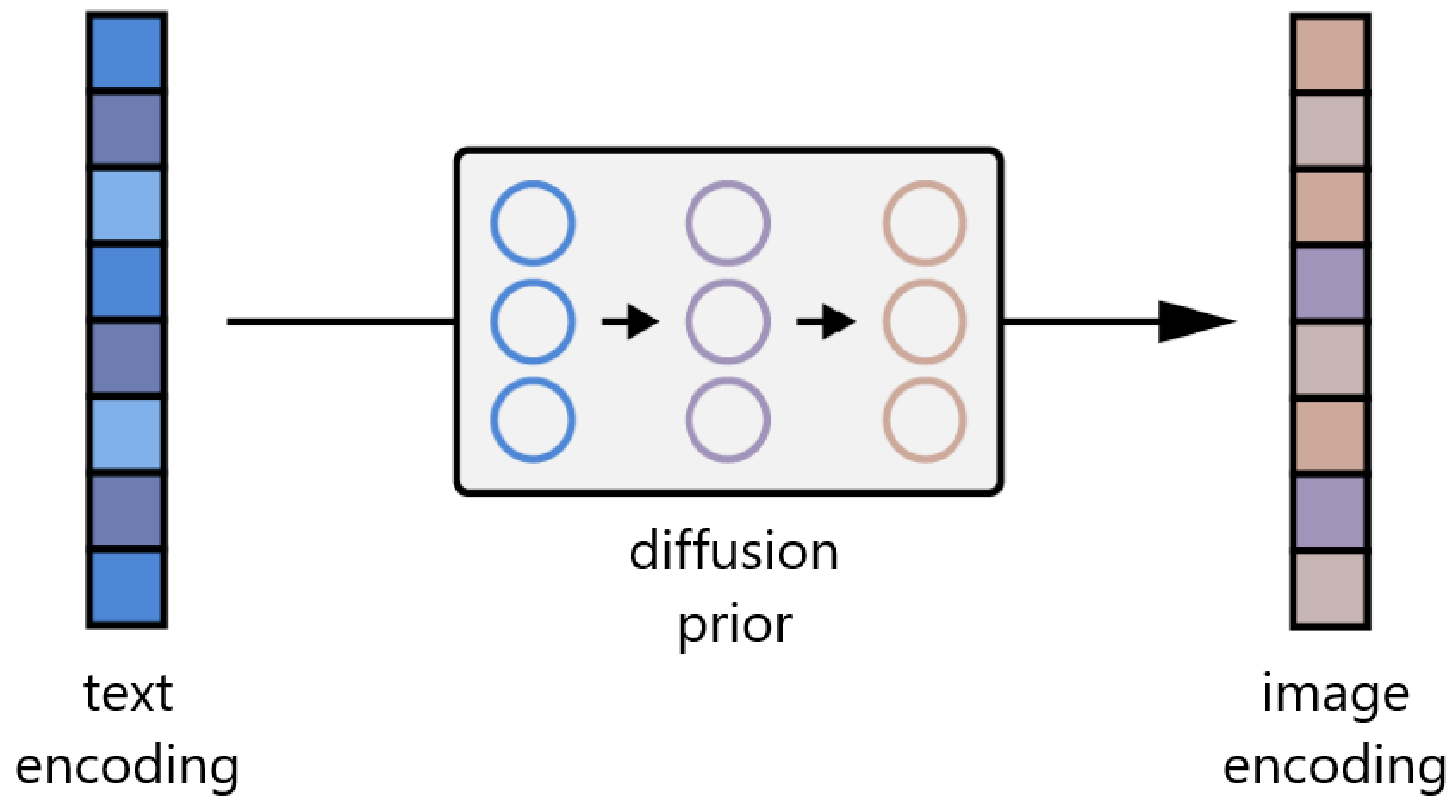
- GLIDE is a **reverse diffusion process** conditioned on the encoding of an image.



Source: https://www.assemblyai.com/blog/how-dall-e-2-actually-works/

Dall-e

- A prior network learns to map text embeddings to image embeddings:



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- Complete Dall-e architecture: