# Generative AI

# Generative vs Discriminative Models

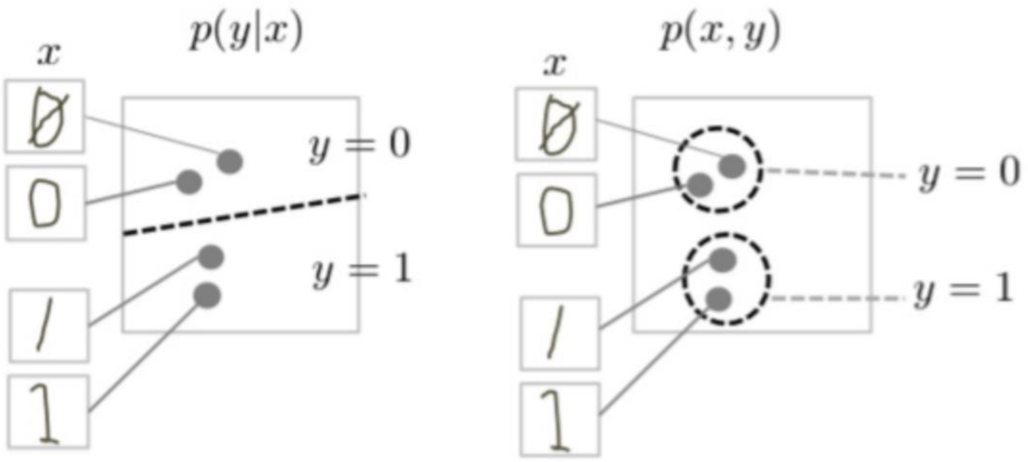
generative models: predict joint probability $P(Y, \boldsymbol{X})$ (what allows to create new data samples) or directly generate new data samples

or just $P(\boldsymbol{X})$ → unsupervised (or self-supervised) learning

discriminative models: predict conditional probability (or probability distribution for regression) $P(Y|\boldsymbol{X})$ or directly output (label for classification, real value for regression)

task of generative models more difficult: model full data distribution rather than merely find patterns in inputs to distinguish outputs

discriminative model generative model

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# Data Generation

generative models can be used for discriminative tasks (although potentially inferior to direct discriminative methods)

but generative methods do more than discriminative ones: model full data distribution

→ allows generation of new data samples (can be images, text, video, audio, code like SQL or Python, proteins, materials, time series, structured data, …)

large (auto-regressive) language models examples of generative models

# Deep Learning for Generative AI

Depending on the application, there are currently two dominant approaches for generative AI:

- text generation: LLMs

- image synthesis: diffusion models (usually conditioned on text by transformers)

note the difference between image synthesis and multimodal understanding in LLMs

# Image Synthesis

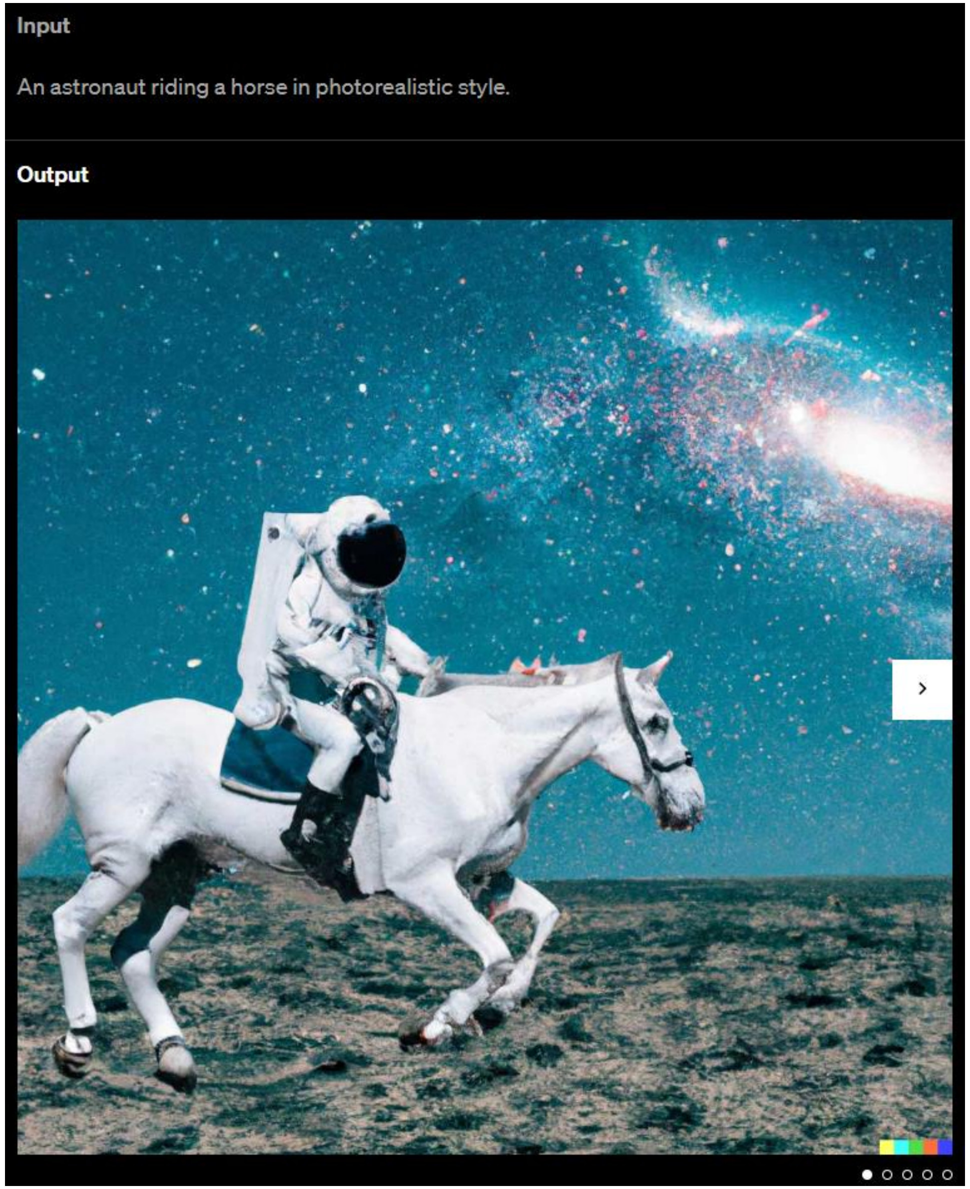
idea: generate new images as variations of training data

condition generation on text prompts: text-to-image

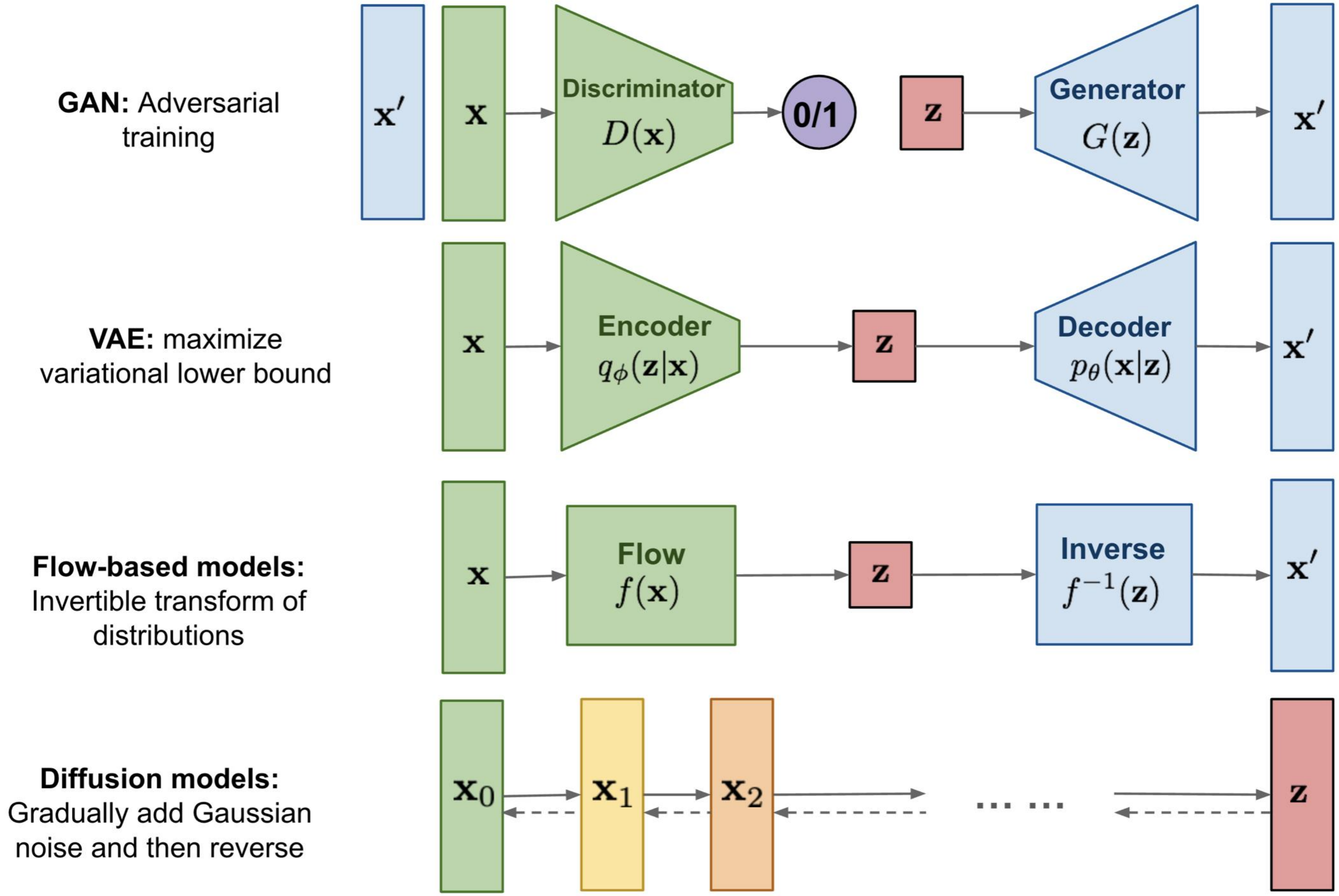
trade-off between diversity and fidelity

SOTA: (guided) diffusion models

example: DALL-E 2



# Different Models Types for Image Synthesis




two neural networks playing a zero-sum game

learn variational distribution (not just replicating inputs)

more complex distributions by applying change-of-variable technique (need for specialized architecture)

chain of denoising autoencoders

→ generalization: [flow matching]

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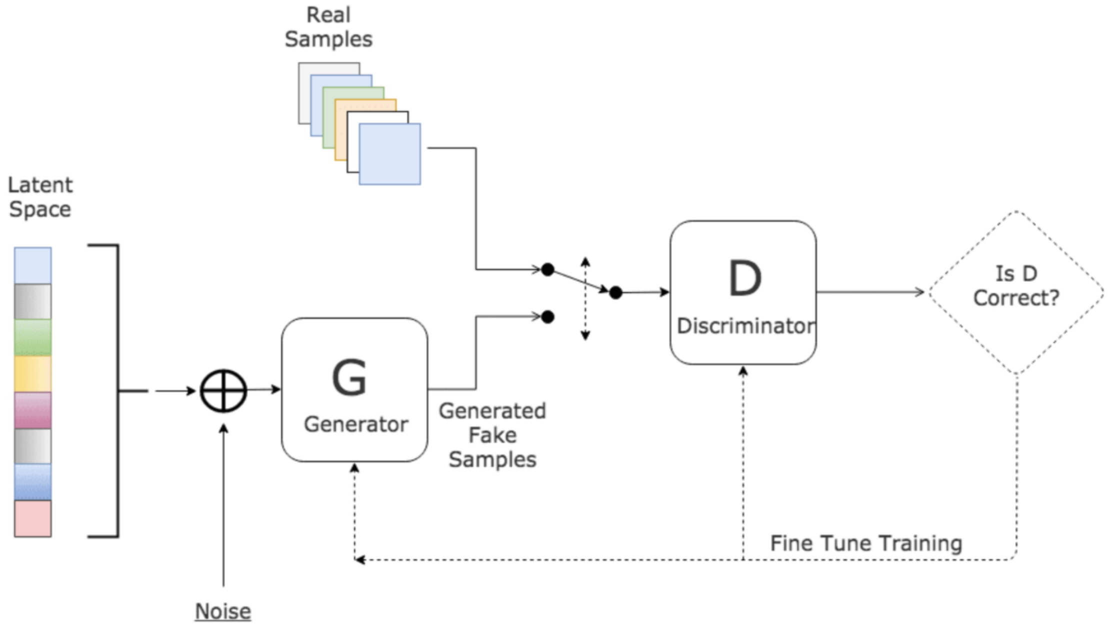
# Generative Adversarial Networks (GAN)

two neural networks playing a zero-sum game:

- the generator network G generating new (fake) samples
- the discriminator network D trying to distinguish between real and fake samples

indirect training via D: G not trained directly to minimize reconstruction error of real samples, but to fool D → self-supervised approach

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common loss for generator and discriminator:

$$L(\boldsymbol{x}_i) = E_{\boldsymbol{x}\sim p_r(\boldsymbol{x})}[\ln D(\boldsymbol{x}_i)] + E_{\boldsymbol{x}\sim p_g(\boldsymbol{x})}\left[\ln\left(1 - D(\boldsymbol{x}_i)\right)\right]$$

G trying to minimize

D trying to maximize

# Side Note: Autoencoder

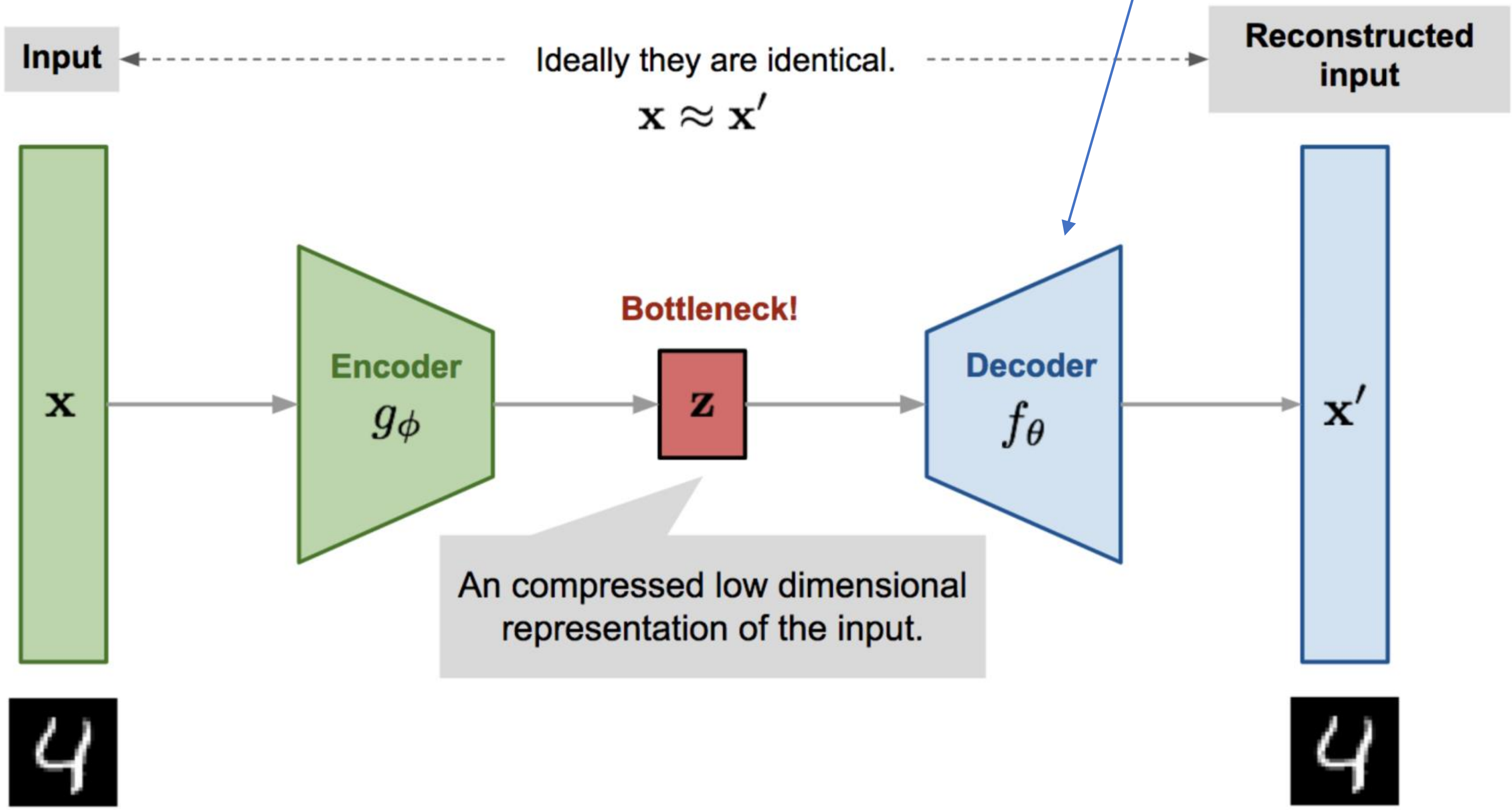
up-sampling, for example, by transposed convolutions

(deep) encoder network

(deep) decoder network

learned together by minimizing differences between original input and reconstructed input (expressed as losses)

compressed intermediate representation: dimensionality reduction

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# Variational Autoencoder (VAE)

goal: generation of variations of input data rather than compressed representation

→ learn variational distribution instead of identity function

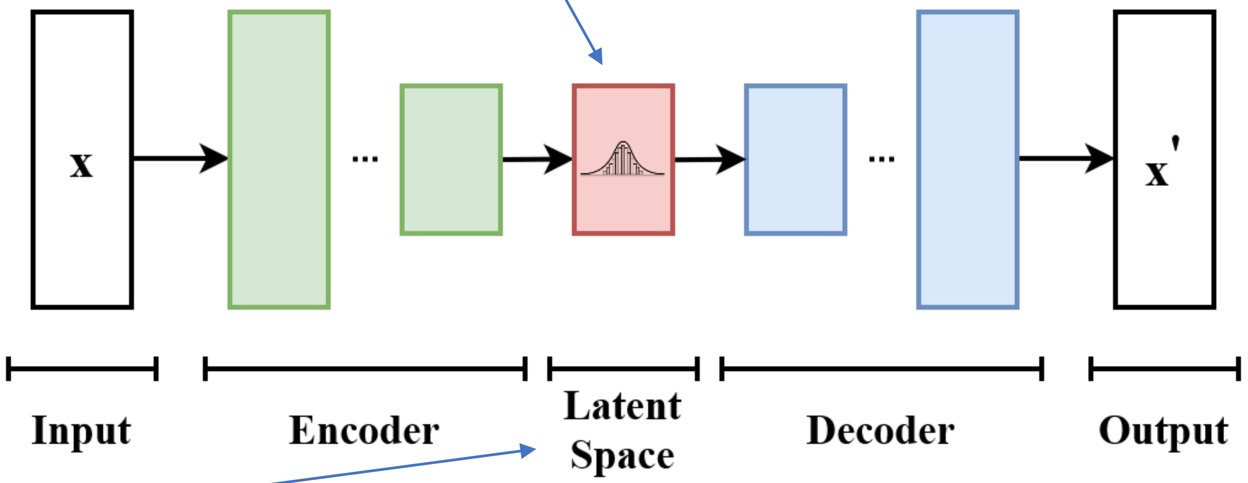
to be precise: parametrized variational distribution of latent encoding variables $\boldsymbol{z}$

prior (simple distribution, in usual VAE: Gaussian): $p_{\boldsymbol{\theta}}(\boldsymbol{z})$

posterior: $p_{\boldsymbol{\theta}}(\boldsymbol{z}|\boldsymbol{x}) = \dfrac{p_{\boldsymbol{\theta}}(\boldsymbol{x}|\boldsymbol{z})p_{\boldsymbol{\theta}}(\boldsymbol{z})}{\int p_{\boldsymbol{\theta}}(\boldsymbol{x}|\boldsymbol{z})p_{\boldsymbol{\theta}}(\boldsymbol{z})d\boldsymbol{z}}$

$p_{\boldsymbol{\theta}}(\boldsymbol{x})$: mixture of Gaussians

from which to sample

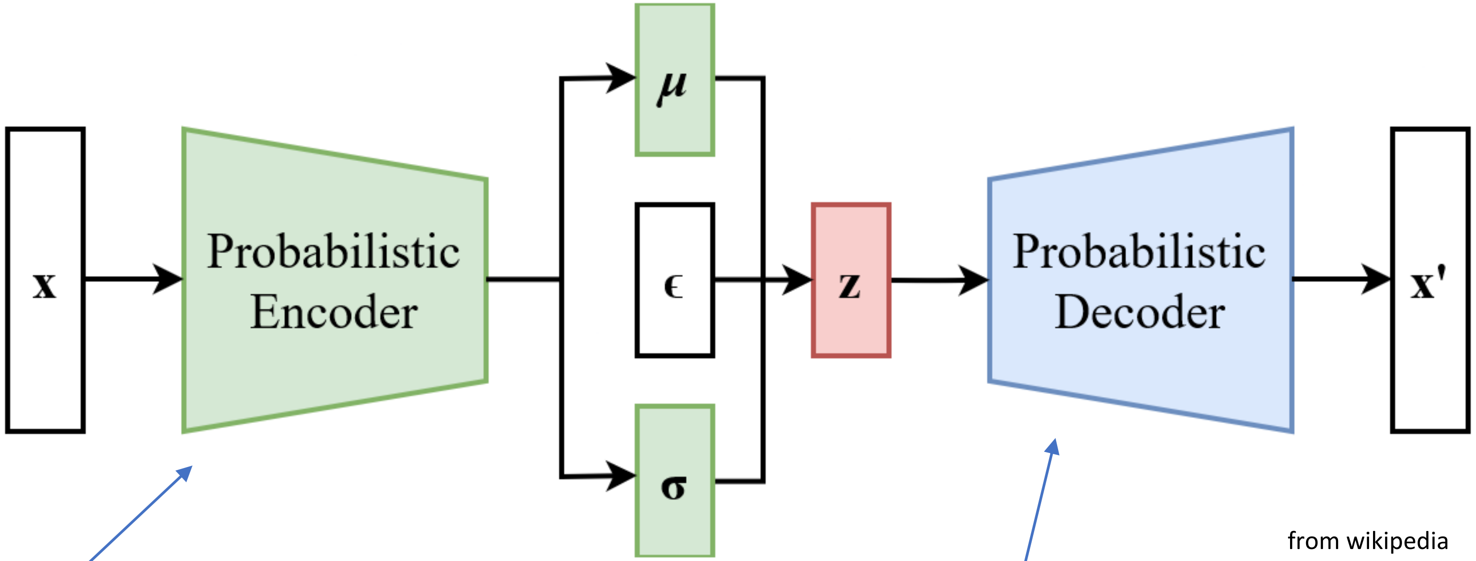



from wikipedia

Variational Bayesian Method

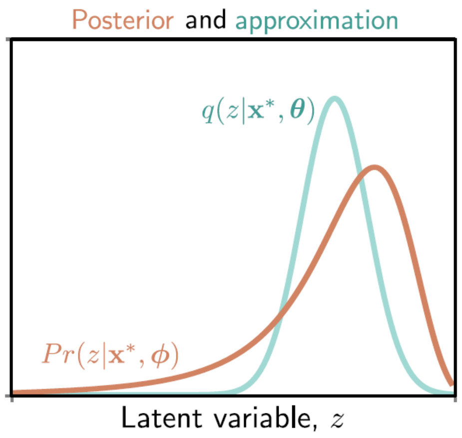
# Gaussian Approximation

learn mean and variance of multivariate Gaussian with diagonal covariance structure

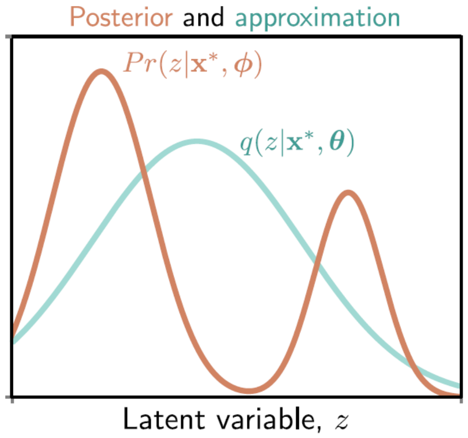


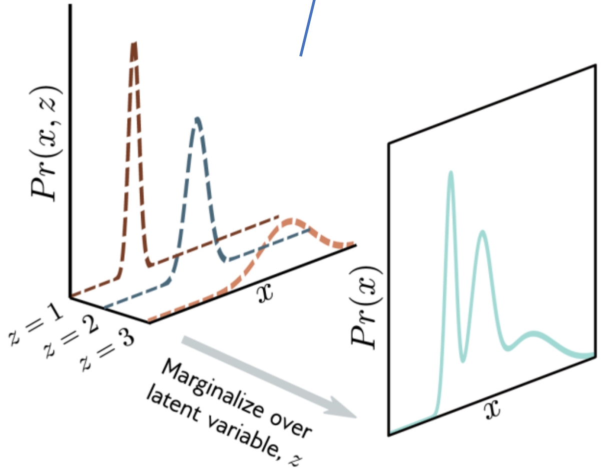

from wikipedia

good approximation:




poor approximation:

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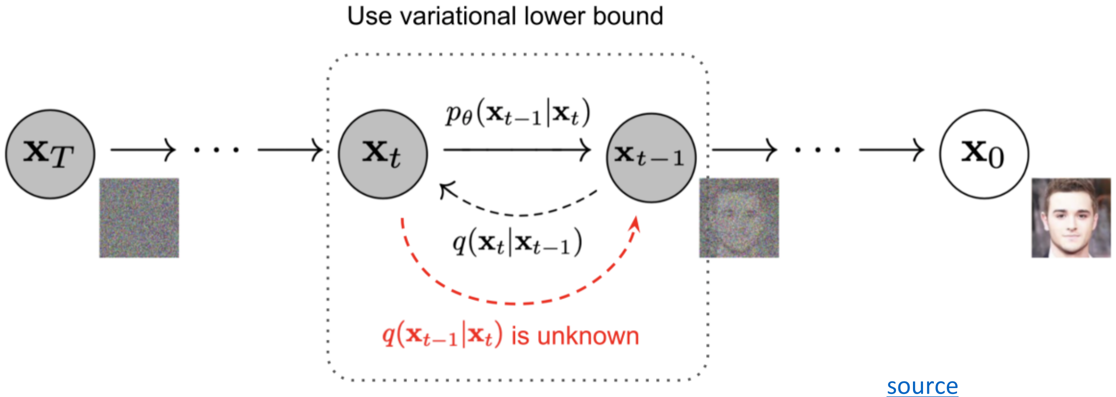
# Diffusion

training: distort training data by successively adding random noise, then learn to reverse this process (denoising)

generation: sample random noise and run through the learned denoising process

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advantages: easy to train, produce high-quality/realistic samples

can be interpreted as special case of hierarchical VAE (one latent variable generates another) with fixed encoder and latent space of same size as the data

→ more sophisticated latent space than just Gaussian mixture in VAE

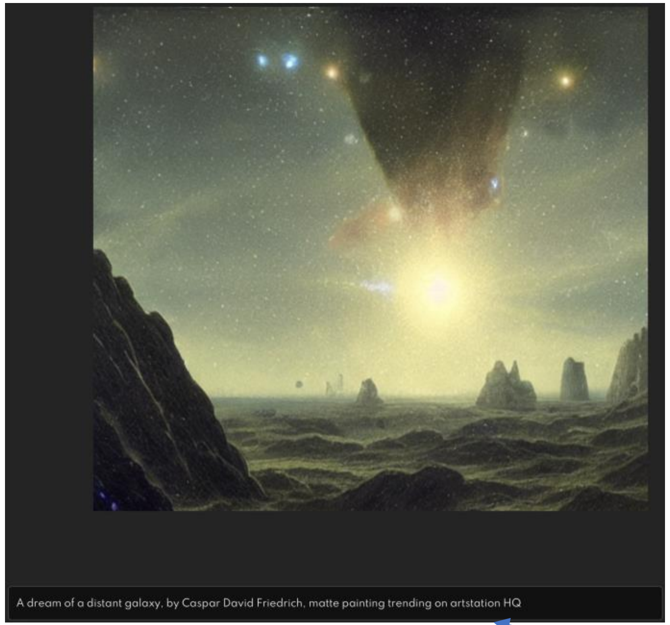
# Text-to-Image

plenty of applications: DALL-E, Stable Diffusion, ImageGen, Midjourney, ...

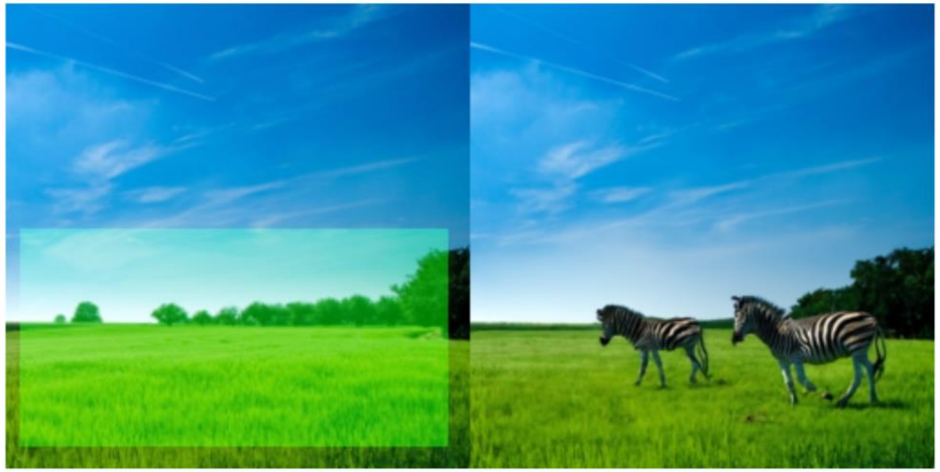
rather "translations"

also text-to-speech (VALL-E, Speech T5, ...) (and speech recognition, e.g., Whisper),
text-to-video (Make-A-Video, Lumiere, Sora, ...) → dynamics/physics understanding/simulation

web app for Stable Diffusion: DreamStudio




inpainting example (GLIDE ):



"zebras roaming in the field"

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prompt

# Assignments

- text classification: Kaggle Disaster Tweets

(prompt engineering or fine-tune a Transformers model)

- local LLM assistant with RAG: be creative ;)

(options: chat with pdf/website using langchain/llamaindex, Ollama for coding with CodeLlama or image understanding with Llava)