

# Deep Generative Models

## Lecture 14

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AI Masters

2024, Spring

# Recap of previous lecture

## SDE basics

Let define stochastic process  $\mathbf{x}(t)$  with initial condition  $\mathbf{x}(0) \sim p_0(\mathbf{x})$ :

$$d\mathbf{x} = \mathbf{f}(\mathbf{x}, t)dt + g(t)d\mathbf{w},$$

where  $\mathbf{w}(t)$  is the standard Wiener process (Brownian motion)

$\mathbf{w}(t) - \mathbf{w}(s) \sim \mathcal{N}(0, (t - s)\mathbf{I})$ ,  $d\mathbf{w} = \epsilon \cdot \sqrt{dt}$ , where  $\epsilon \sim \mathcal{N}(0, \mathbf{I})$ .

## Langevin dynamics

Let  $\mathbf{x}_0$  be a random vector. Then under mild regularity conditions for small enough  $\eta$  samples from the following dynamics

$$\mathbf{x}_{t+1} = \mathbf{x}_t + \eta \frac{1}{2} \nabla_{\mathbf{x}_t} \log p(\mathbf{x}_t | \theta) + \sqrt{\eta} \cdot \epsilon, \quad \epsilon \sim \mathcal{N}(0, \mathbf{I}).$$

will comes from  $p(\mathbf{x}|\theta)$ .

The density  $p(\mathbf{x}|\theta)$  is a **stationary** distribution for the Langevin SDE.

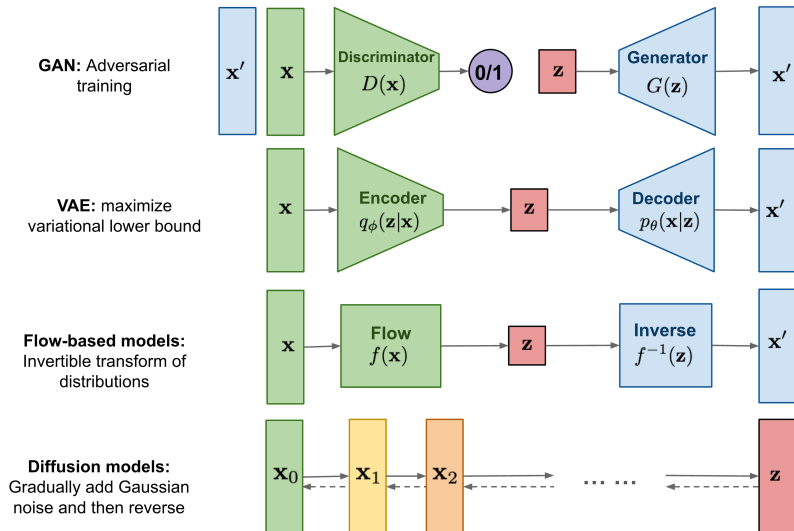
# Outline

1. The worst course overview

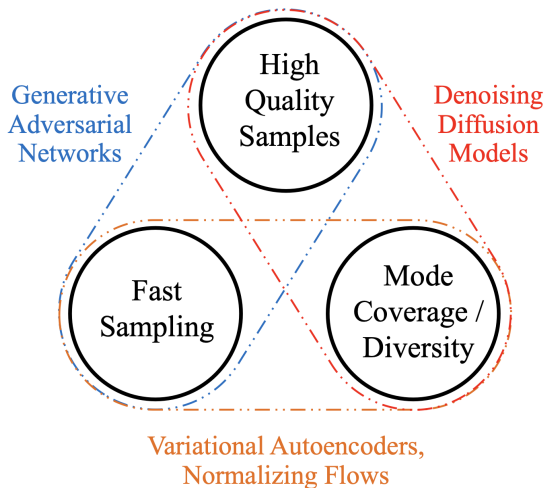
# Outline

1. The worst course overview

# The worst course overview :)



# The worst course overview :)



Xiao Z., Kreis K., Vahdat A. Tackling the generative learning trilemma with denoising diffusion GANs, 2021

# The worst course overview :)

Model	Efficient	Sample quality	Coverage	Well-behaved latent space	Disentangled latent space	Efficient likelihood
GANs	✓	✓	✗	✓	?	n/a
VAEs	✓	✗	?	✓	?	✗
Flows	✓	✗	?	✓	?	✓
Diffusion	✗	✓	?	✗	✗	✗

# Summary

