

Diffusion Models

How AI Learns to Create Images from Noise

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Roadmap

Motivation

Forward Process

Reverse Process

Training & Score Matching

Applications

Conclusion

- **10 min talk**

Speaker 1 (Anindya Biswas) 3 min

Speaker 2 (Tasnim Tamal) 3 min

Speaker 3 (Din Mohammad) 3 min

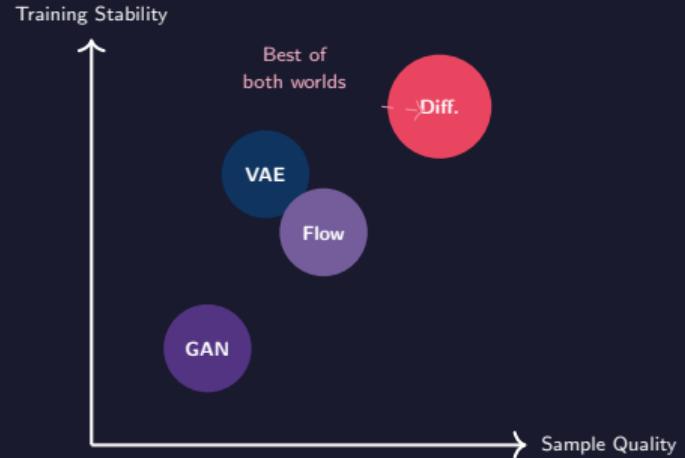
Buffer / Transition 1 min

Why Diffusion Models?

In One Line

A diffusion model learns to **turn random noise into meaningful data** (like realistic images).

- **GANs**: high quality, but training is often unstable
- **VAEs**: stable and fast, but outputs can look blurry
- **Flows**: mathematically clean, but architecture is restricted
- **Diffusion**: stable training + very strong output quality



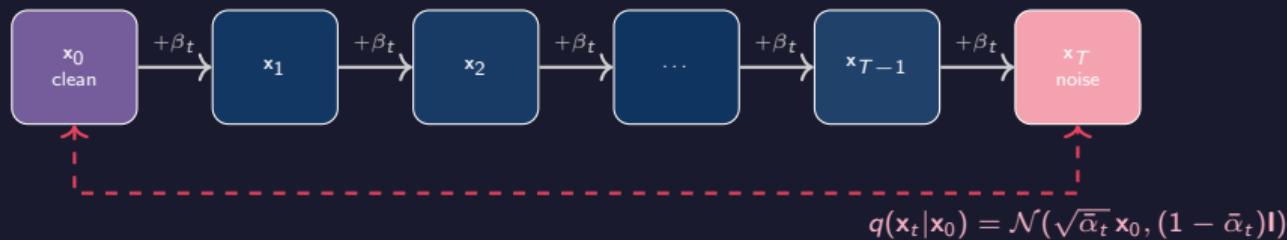
Used in tools like DALL·E 3, Stable Diffusion, and Sora

The Forward (Noising) Process

Key Idea

Gradually corrupt data \mathbf{x}_0 into pure Gaussian noise \mathbf{x}_T through a fixed Markov chain.

$$q(\mathbf{x}_t | \mathbf{x}_{t-1}) = \mathcal{N}\left(\mathbf{x}_t; \sqrt{1 - \beta_t} \mathbf{x}_{t-1}, \beta_t \mathbf{I}\right)$$



Plainly: start from a real sample and add a little noise repeatedly until almost all information is gone.

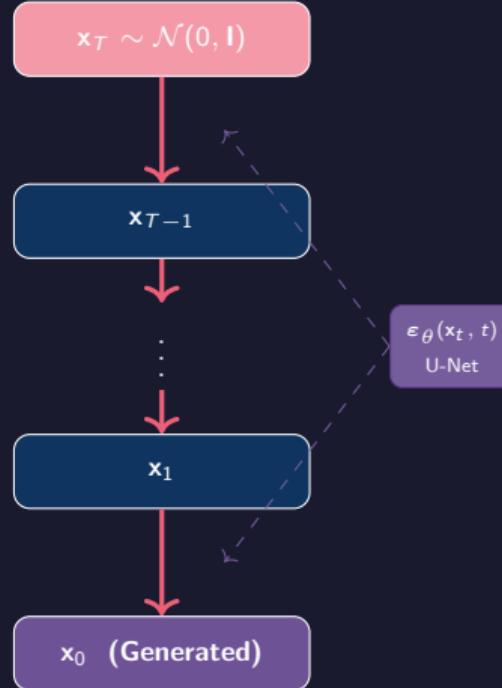
The Reverse (Denoising) Process

Goal: Learn $p_\theta(\mathbf{x}_{t-1}|\mathbf{x}_t)$ to reverse the noise.

A **neural network** ϵ_θ predicts the noise present at each step:

$$\mathbf{x}_{t-1} \approx \mathbf{x}_t - \text{predicted noise}$$

- Backbone: usually a **U-Net**
- Input: noisy sample \mathbf{x}_t and timestep t
- Repeat to gradually recover clean data



Training Objective

Training Idea (Simple Version)

$$\mathcal{L}_{\text{simple}} = \mathbb{E}_{t, \mathbf{x}_0, \boldsymbol{\varepsilon}} \left[\left\| \boldsymbol{\varepsilon} - \boldsymbol{\varepsilon}_\theta \left(\sqrt{\bar{\alpha}_t} \mathbf{x}_0 + \sqrt{1 - \bar{\alpha}_t} \boldsymbol{\varepsilon}, t \right) \right\|^2 \right]$$

Algorithm — Training

1. Sample $\mathbf{x}_0 \sim q(\mathbf{x}_0)$



2. Sample timestep $t \sim \mathcal{U}\{1, T\}$



3. Sample $\boldsymbol{\varepsilon} \sim \mathcal{N}(0, \mathbf{I})$



4. Compute noisy sample \mathbf{x}_t



5. Minimise $\|\boldsymbol{\varepsilon} - \boldsymbol{\varepsilon}_\theta(\mathbf{x}_t, t)\|^2$

What this loss means

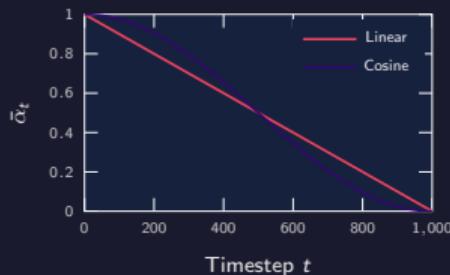
- We add known noise to a clean sample
- The model guesses that exact noise
- If the guess is close, the model is learning correctly
- After training, we remove noise step by step

Key insight: learning to denoise is enough for generation.

Noise Schedule & Sampling Speed

Noise Schedules

- *Linear*: increase noise at a constant rate
- *Cosine*: keeps more structure early on
- *Learned*: schedule is optimized by data

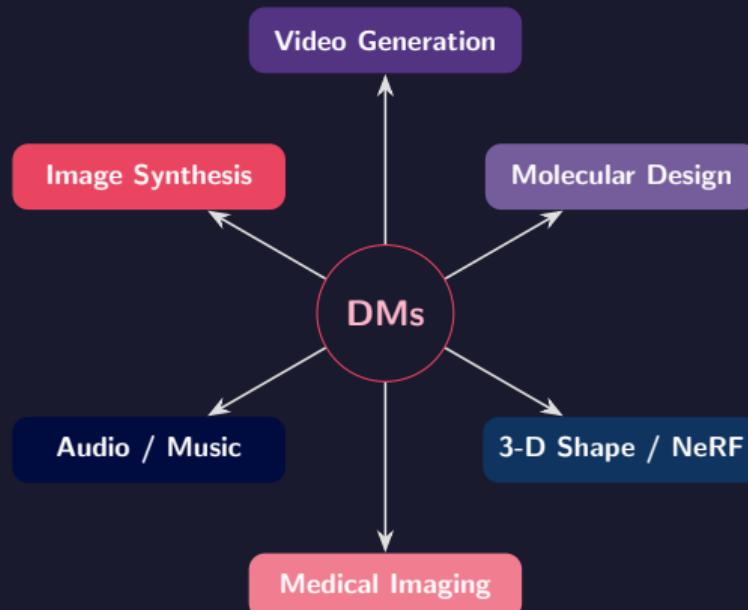


Accelerated Sampling

- DDPM: $T = 1000$ steps (slow)
- **DDIM** (Song et al., 2020): deterministic, ~ 50 steps, same quality
- **DPM-Solver**: ~ 20 steps
- **Consistency Models**: 1–2 steps!

Speed-quality trade-off is an active research frontier.

Applications & Variants



Conditional Generation

- **Classifier guidance:** steer outputs toward a target label
- **Classifier-free:** no separate classifier required
- **Text conditioning:** prompt-driven image generation

Notable: Stable Diffusion (latent space), DALL·E 3 (GPT captions), Sora (video)

Takeaways & Open Challenges

- Key Takeaways

- Diffusion = iterative **denoising**
- Training objective is **simple MSE**
- Grounded in **score matching** theory
- Sets **state-of-the-art** across modalities

- Open Challenges

- Slow sampling (active research)
- High compute cost
- Evaluation metrics (FID, CLIP-S)
- Alignment & safety of generated content

Core Formula to Remember

$$\mathcal{L} = \mathbb{E}_{t, \mathbf{x}_0, \boldsymbol{\varepsilon}} \left[\left\| \boldsymbol{\varepsilon} - \boldsymbol{\varepsilon}_\theta(\sqrt{\bar{\alpha}_t} \mathbf{x}_0 + \sqrt{1 - \bar{\alpha}_t} \boldsymbol{\varepsilon}, t) \right\|^2 \right]$$

Thank You!

Thanks for listening

References

- [1] J. Ho et al. “**Denoising diffusion probabilistic models**”. In: *Proceedings of the 34th International Conference on Neural Information Processing Systems*. NIPS '20. Vancouver, BC, Canada: Curran Associates Inc., 2020.
- [2] Y. Song and S. Ermon. “**Generative modeling by estimating gradients of the data distribution**”. In: *Advances in neural information processing systems* 32 (2019).
- [3] J. Song et al. “**Denoising diffusion implicit models**”. In: *arXiv preprint arXiv:2010.02502* (2020).
- [4] A. Q. Nichol and P. Dhariwal. “**Improved denoising diffusion probabilistic models**” . In: *International conference on machine learning*. PMLR. 2021, pp. 8162–8171.