Diffusion Models

How AI Learns to Create Images from Noise

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Outline

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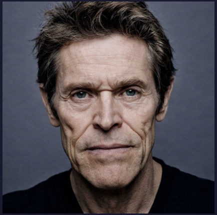
What Problem Are We Solving?

Real face

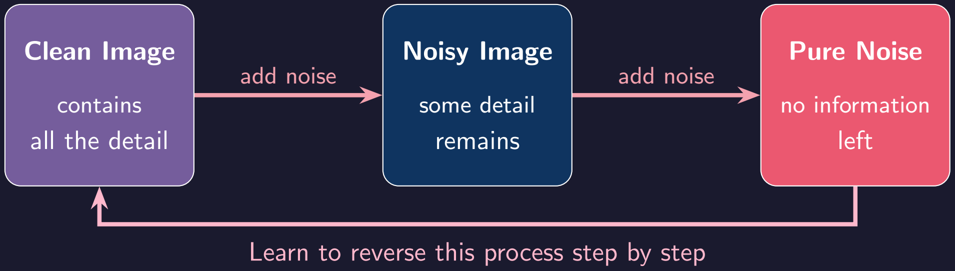


AI-generated face *(Sora)*

- Can a machine learn to **create new, realistic samples** that are *indistinguishable* from real data?
- In other words can it learn the underlying **probability distribution** of the data?

Diffusion models provide a *stable, high-quality* solution.

The Core Idea: Learning by Destroying

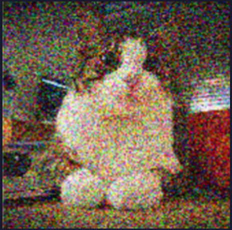


We Essentially Have Two Diffusion Processes

- The **Forward Diffusion Process** that gradually adds noise.
- The **Reverse Diffusion Process** that removes noise step by step.

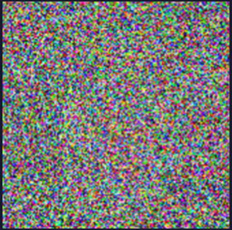
The Forward Diffusion Process: Adding Noise

Clean Image



Slightly Noisy

Heavily Noisy

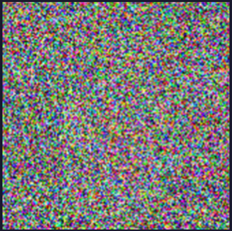


Pure Noise

What Happens

Take a real image and add a *tiny* bit of random noise. Repeat this hundreds of times until only noise remains.

The Reverse Diffusion Process: Removing Noise



Pure Noise

Slightly Less Noisy

Almost Denoised

Fully Denoised

How Generation Works

- Start from **pure noise**
- Predict and remove a little noise at each step
- Repeat until a realistic image appears

Training

To produce realistic images, the model must **learn** to **reverse** the noise process.

But how does the model learn this reverse process?

How Do We Train It?

1. Take a real image from the training set
2. Pick a random step and add the corresponding noise
3. Ask the neural network: *“what noise was added?”*
4. Compare the prediction to the **actual noise**, minimize the error

Key Insight & Why It Works

Key Insight

- We control the **noise process**
- Added noise is mathematically defined
- So the training signal is precise
- This makes the objective a well-defined *regression problem*

Why It Works

- The task is simplified into **small, predictable steps**
- Each stem only removes a tiny amount of noise
- Repeating simple steps reconstructs complex structure

Why Diffusion Models Work So Well

Advantages

- **Stable training**
- **High Quality Samples**
- **Good Diversity** (less mode collapse than GANs)
- **Flexible Conditioning** (text-to-image, video-generation, audio synthesis)
- **Strong Theoretical Foundation** (probabilistic modeling, score matching)

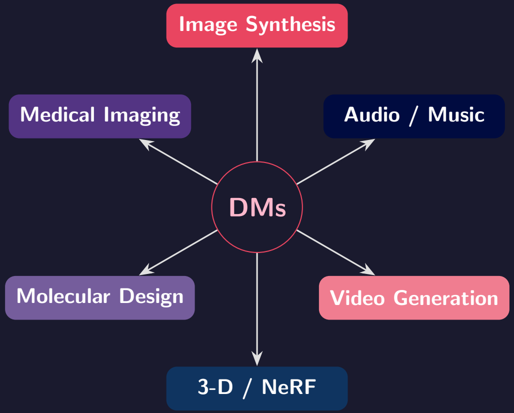
In practice, diffusion models combine reliability with strong output quality.

Summary

Diffusion models generate realistic data by learning the *underlying probability distribution* through reversing a *gradual, structured noise process.*

But where is Diffusion Models actually applied?

Applications



Some Real-World Tools Powered by Diffusion

Midjourney

DALL·E

OpenAI Sora

Current Limitations

- **Slow generation:** requires many denoising steps (hundreds to thousands)
- **High compute cost:** training requires significant GPU resources
- **Large model size:** not easy to run on consumer hardware

Open Challenges

- Can we make generation **faster**? (Active research area)
- How do we ensure generated content is **safe and ethical**?
- Can we extend to **longer videos** and **interactive content**?

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.