Diffusion Models

How AI Learns to Create Images from Noise

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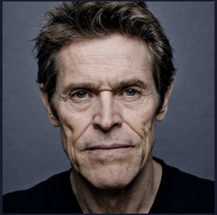
CSE 200: Technical Writing and Presentation
Bangladesh University of Engineering and Technology

Outline

What Problem Are We Solving?

Real face



AI-generated face *(Sora)*

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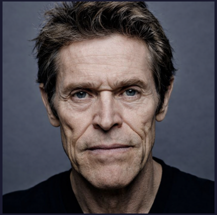

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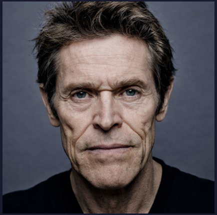

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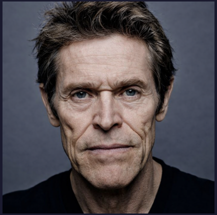

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Diffusion models provide a *stable, high-quality* solution.

The Core Idea: Learning by Destroying

Clean Image

contains
all the detail

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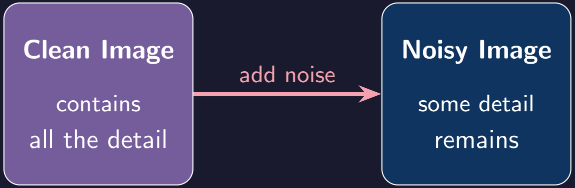

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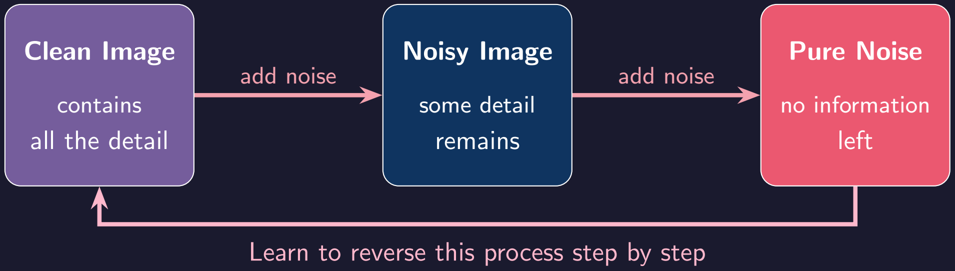

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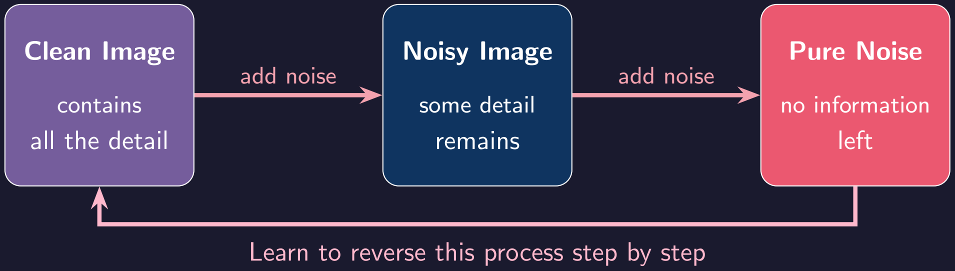

We Essentially Have Two Diffusion Processes

- 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

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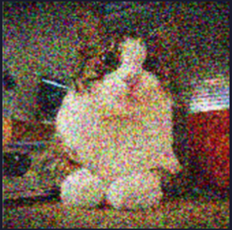

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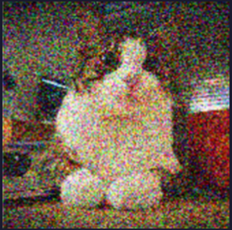

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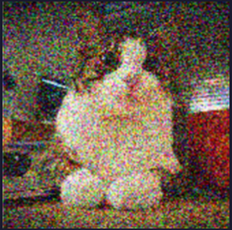

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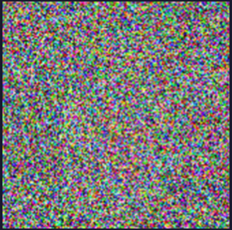

Pure Noise

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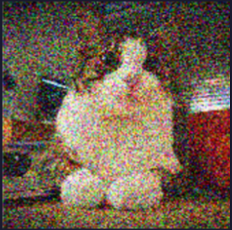

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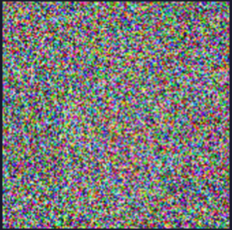
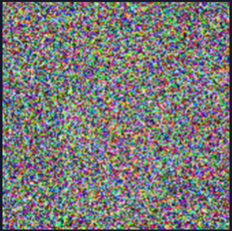


Pure Noise

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



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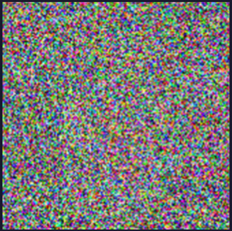

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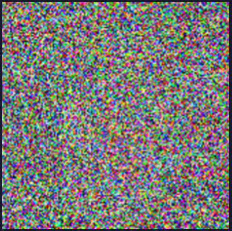

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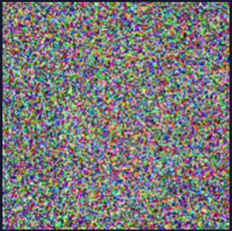

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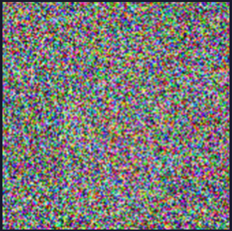

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How Generation Works

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

Training

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But how does the model learn this reverse process?

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4. Compare the prediction to the **actual noise**, minimize the error

Key Insight & Why It Works

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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

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

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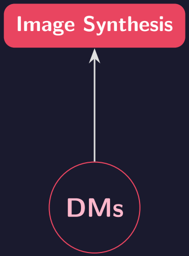
But where is Diffusion Models actually applied?

Applications



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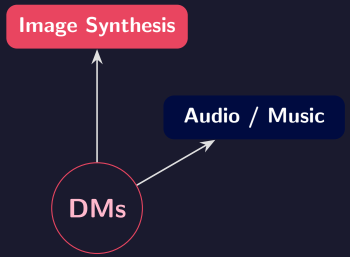

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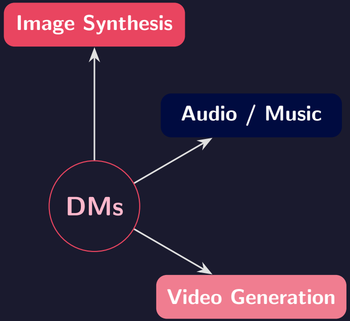

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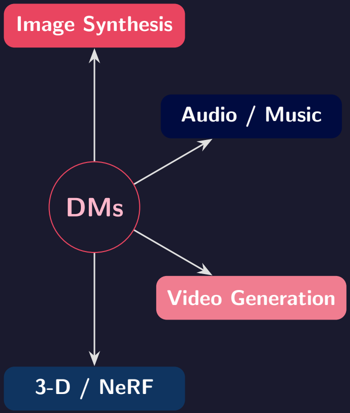

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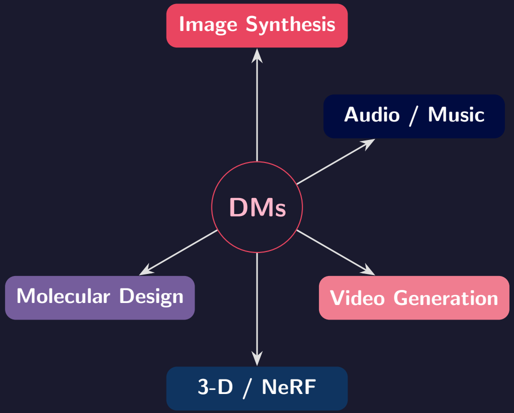

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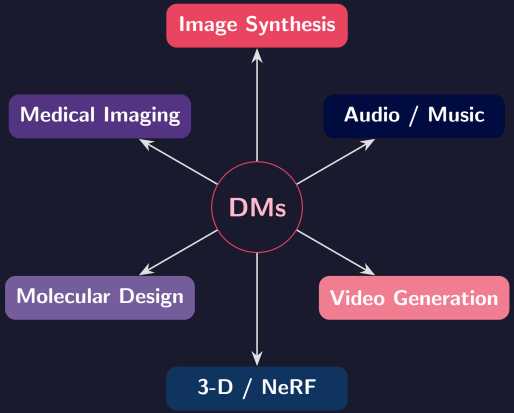

Some Real-World Tools Powered by Diffusion

Midjourney

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DALL·E

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OpenAI Sora

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- **Large model size:** not easy to run on consumer hardware

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- 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.