

Diffusion Models

How AI Learns to Create Images from Noise

Presented by: *Anindya, Tamal and Din*

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CSE 200: Technical Writing and Presentation

Bangladesh University of Engineering and Technology

Outline

Introduction

Core Idea

Forward Diffusion Process

Reverse Diffusion Process

Training

Insights

Applications

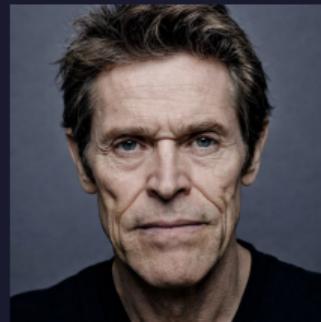
Limitations & Challenges

Conclusion

What Problem Are We Solving?



Real face

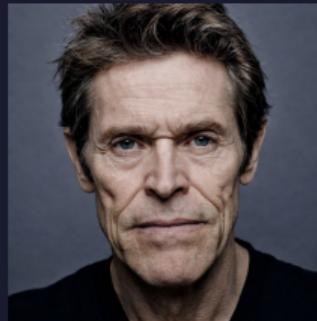


AI-generated face (*Sora*)

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- Can a machine learn to **create new, realistic samples** that are *indistinguishable* from real data?

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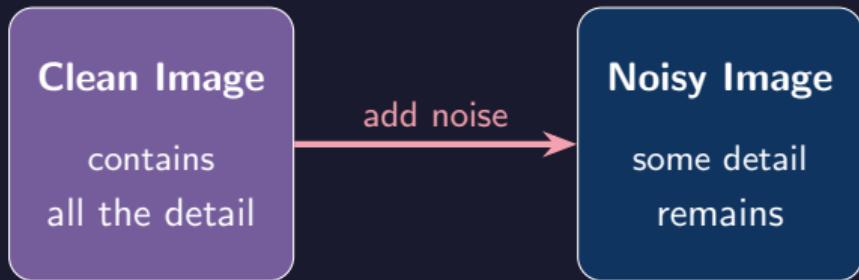
Diffusion models provide a *stable, high-quality* solution.

The Core Idea: Learning by Destroying

Clean Image

contains
all the detail

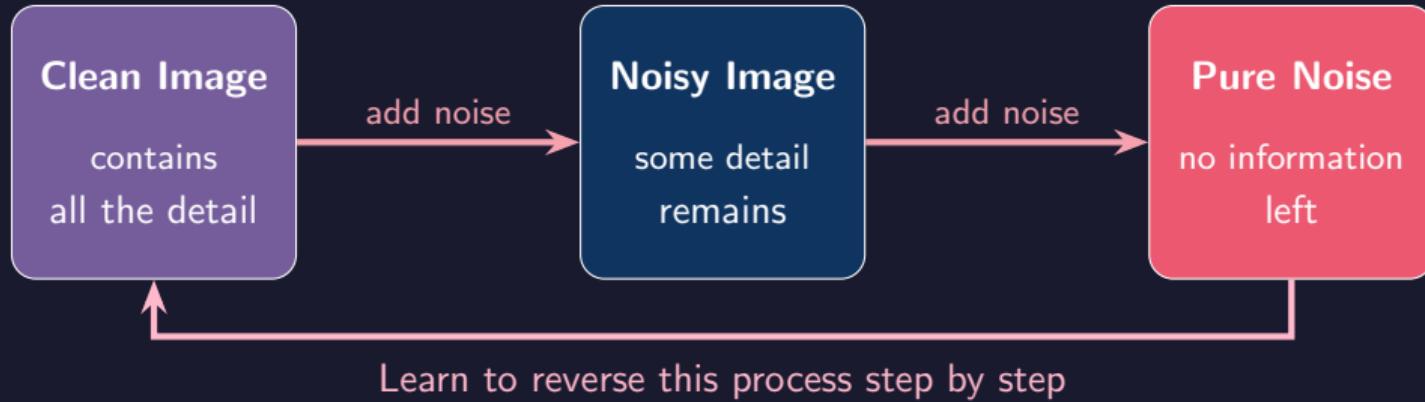
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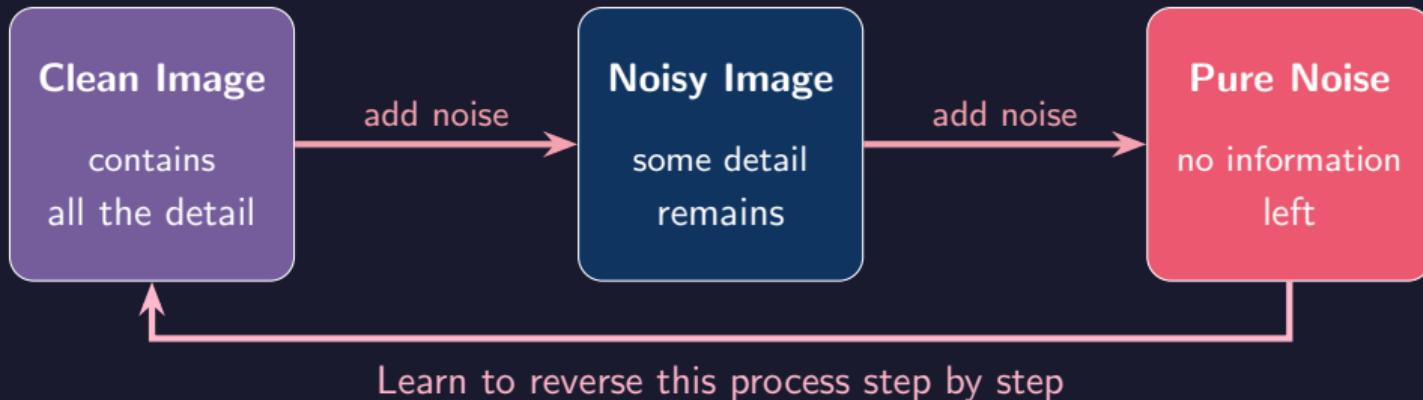
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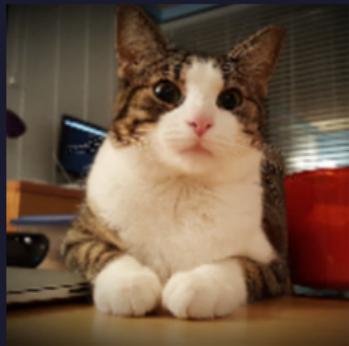
The Core Idea: Learning by Destroying



We Essentially Have Two Diffusion Processes

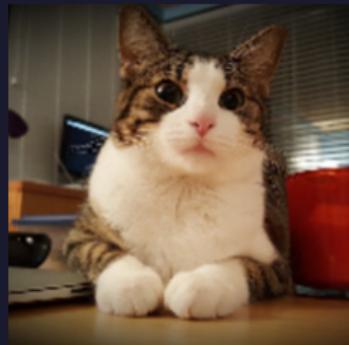
- The **Forward Diffusion Process** that gradually adds noise.
- The **Reverse Diffusion Process** that removes noise step by step.

The Forward Diffusion Process: Adding Noise



Clean Image

The Forward Diffusion Process: Adding Noise

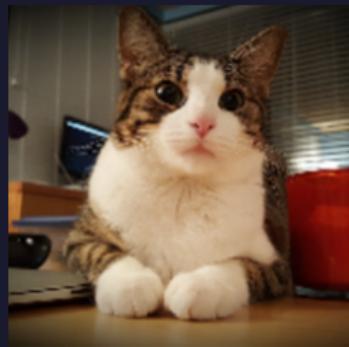


Clean Image



Slightly Noisy

The Forward Diffusion Process: Adding Noise



Clean Image

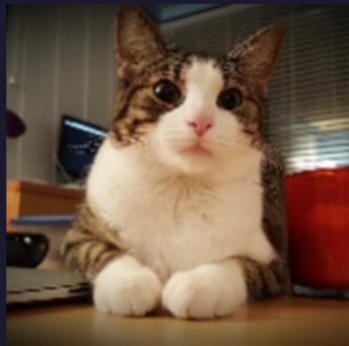


Slightly Noisy



Heavily Noisy

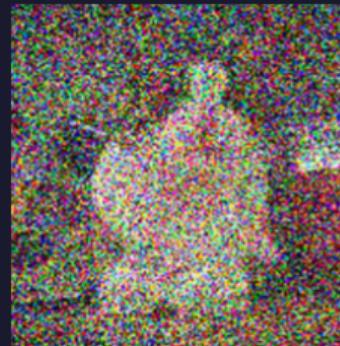
The Forward Diffusion Process: Adding Noise



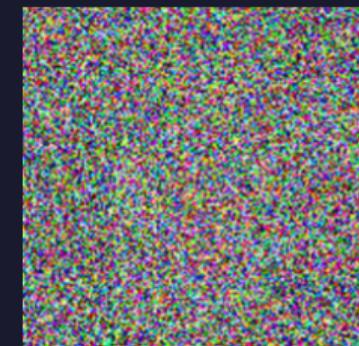
Clean Image



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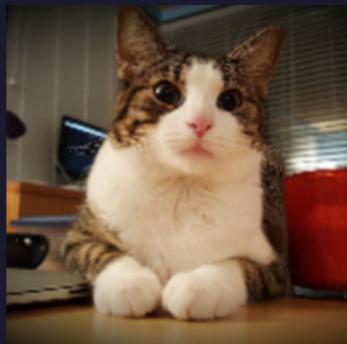


Heavily Noisy



Pure Noise

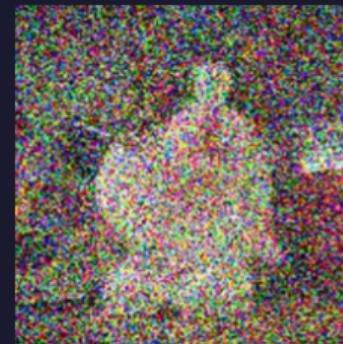
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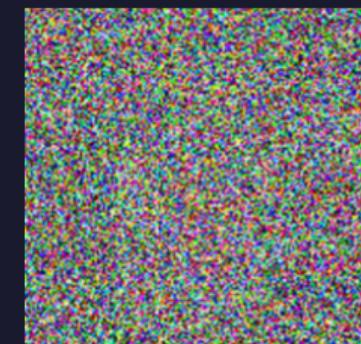
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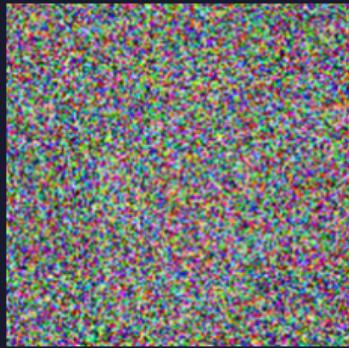


Pure Noise

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



Pure Noise

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Pure Noise

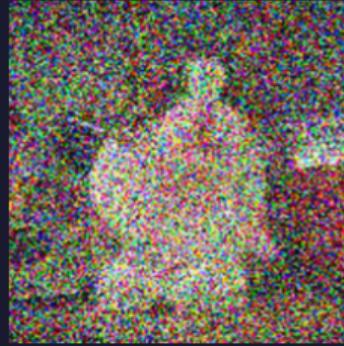


Slightly Less Noisy

The Reverse Diffusion Process: Removing Noise



Pure Noise



Slightly Less Noisy

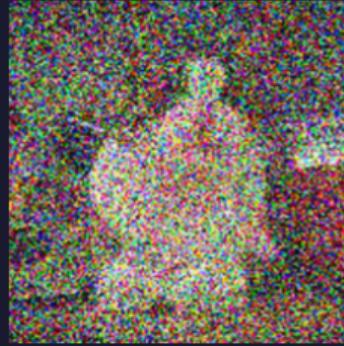


Almost Denoised

The Reverse Diffusion Process: Removing Noise



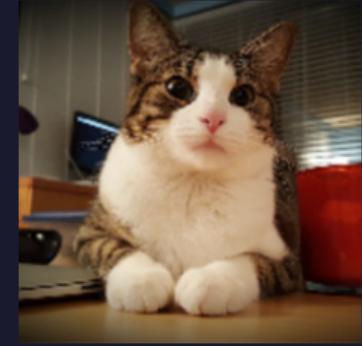
Pure Noise



Slightly Less Noisy

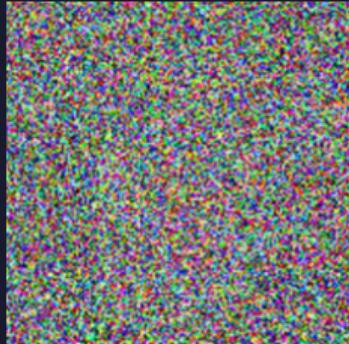


Almost Denoised

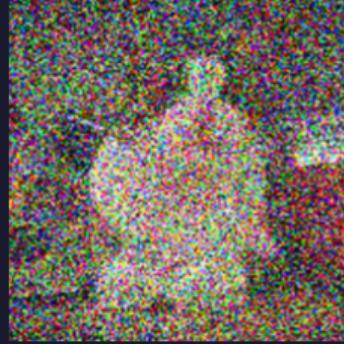


Fully Denoised

The Reverse Diffusion Process: Removing Noise



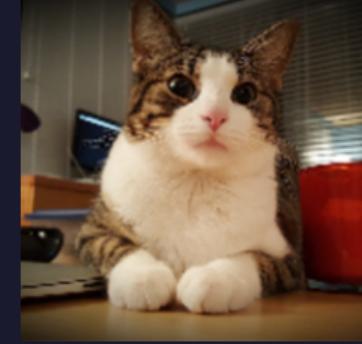
Pure Noise



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.

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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.

Summary

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

Summary

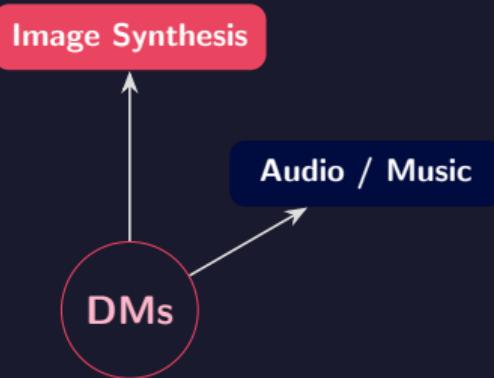
Diffusion models generate realistic data by learning the *underlying probability distribution* through reversing a *gradual, structured noise process*.

But where is Diffusion Models actually applied?

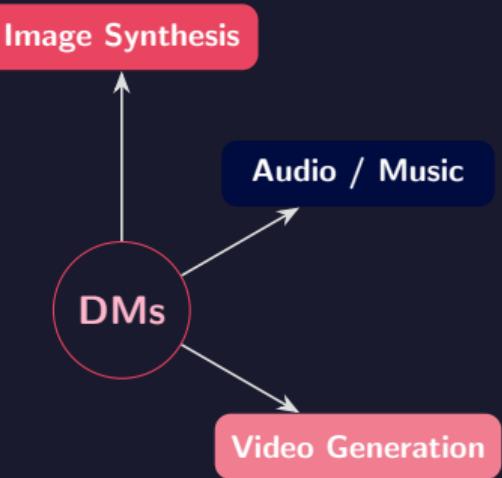
Applications



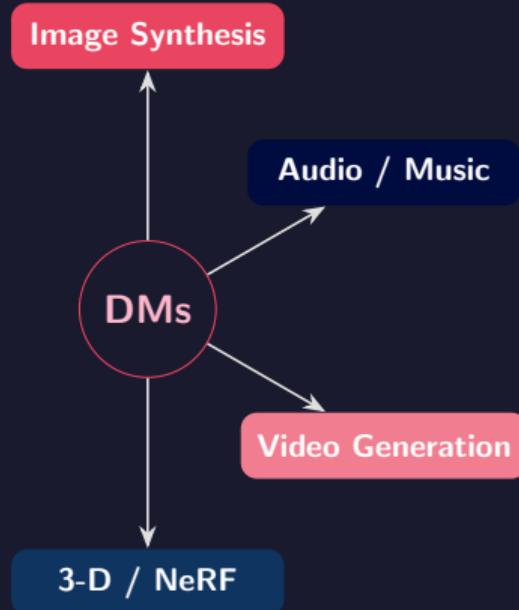
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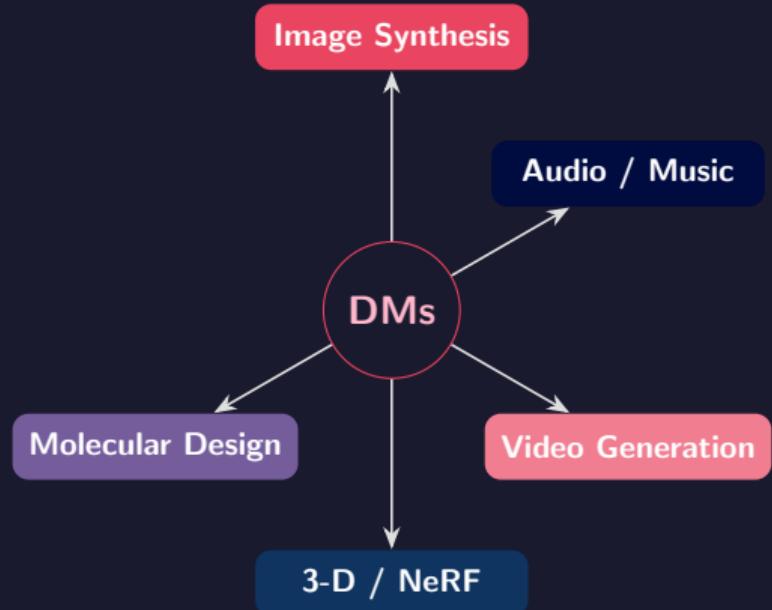
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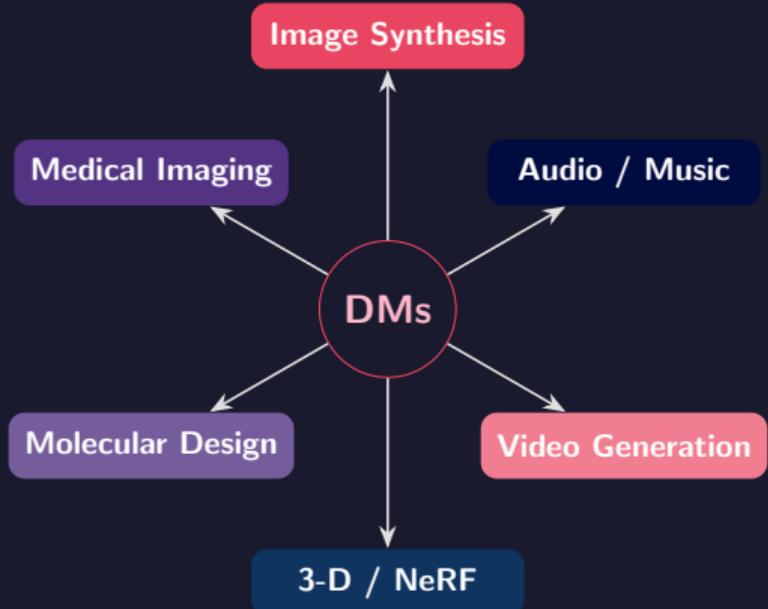
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Applications



Some Real-World Tools Powered by Diffusion



Midjourney

Some Real-World Tools Powered by Diffusion



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DALL-E

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OpenAI Sora

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- **Slow generation:** requires many denoising steps (hundreds to thousands)

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- **High compute cost:** training requires significant GPU resources
- **Large model size:** not easy to run on consumer hardware

Open Challenges

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- 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.