# Generative AI

Assignment 2:
Denoising Diffusion Probabilistic Models

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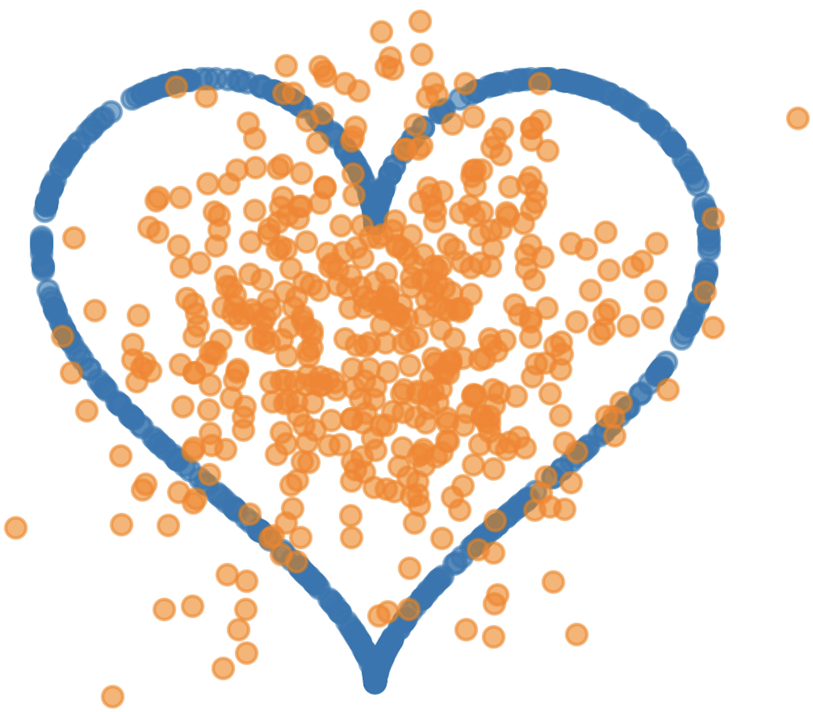

*Instructor: Evangelos Kalogerakis*

# 1 DDPM pipeline with Heart

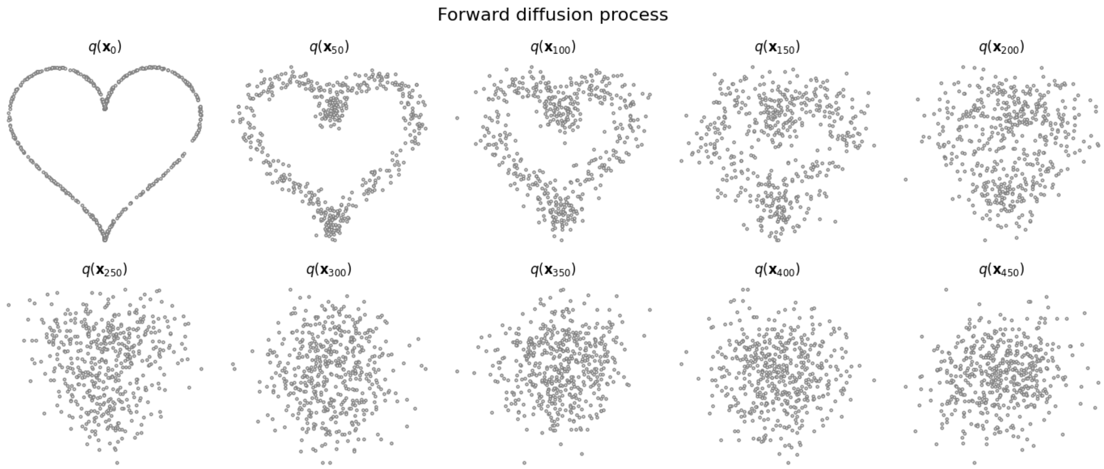


Figure 1: Visualization of the forward diffusion process applied to the heart-shaped point cloud. Each subplot shows $q(\mathbf{x}_t)$ for timesteps $t = 0, 50, 100, \dots, 450$, illustrating how the clean heart gradually becomes unstructured Gaussian noise.

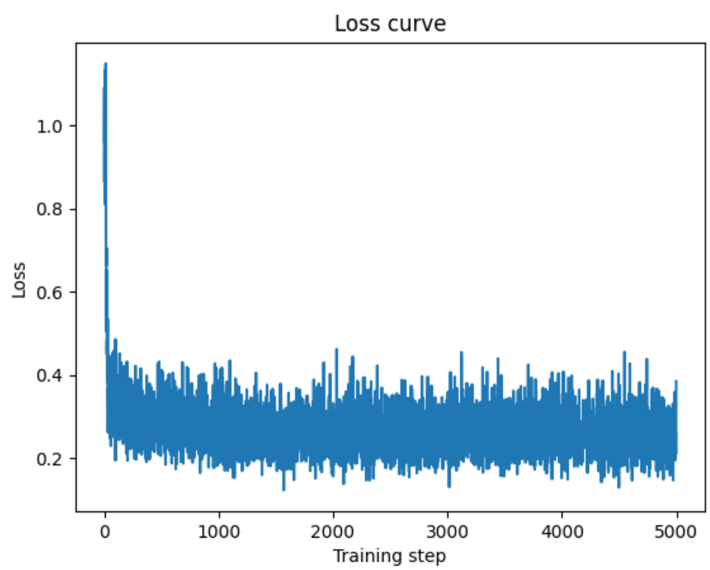


Figure 2: Training loss of the DDPM model over 5 000 iterations. The loss corresponds to the simplified noise-matching objective (MSE between true and predicted noise).

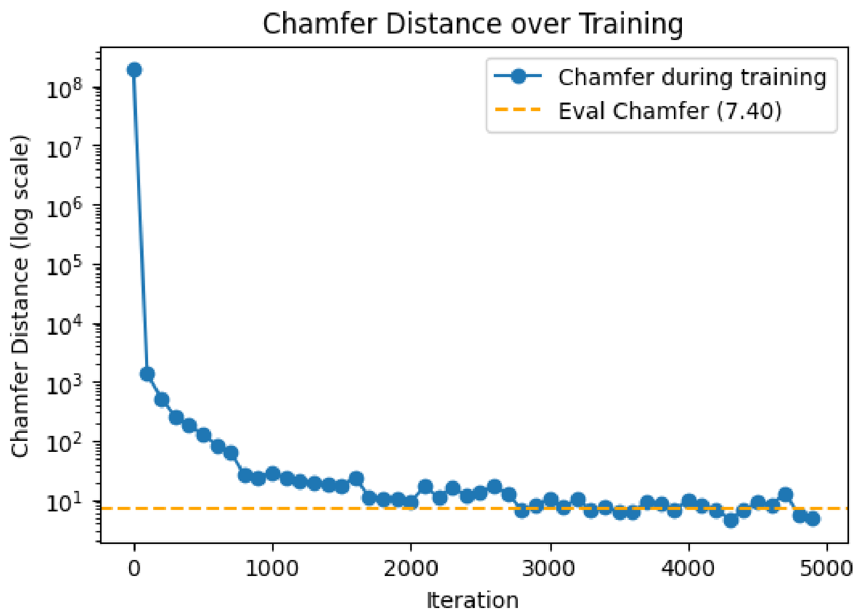


Figure 3: Log-scale plot of the Chamfer distance between generated and true point clouds at periodic checkpoints (every 100 steps). The dashed orange line marks the final evaluation Chamfer distance of 7.40.

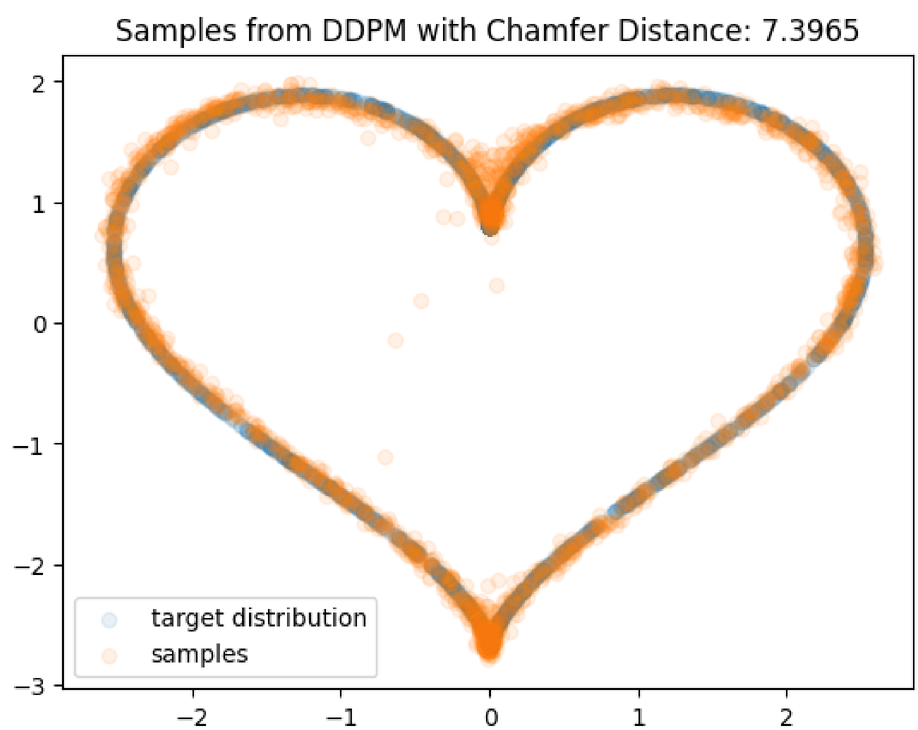


Figure 4: Overlay of 2 048 generated points (orange) and the true heart-shaped target distribution (blue) after full reverse diffusion. The computed Chamfer distance at this final checkpoint is 7.40.

# 2 Image Diffusion

The 64×64 unconditional DDPM was trained on the AFHQ dataset (cats, dogs, and wildlife) for 100 000 steps on an NVIDIA RTX 3060 GPU (about 28 h). We logged both the training loss and periodic sample snapshots; after training we generated 500 images for evaluation.

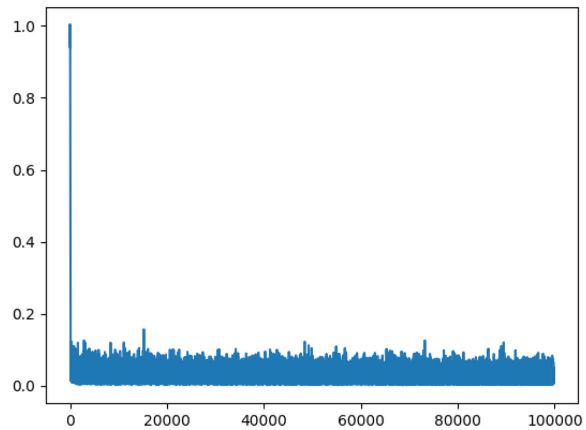


Figure 5: Training loss of the AFHQ DDPM over 100 000 diffusion steps on the RTX 3060. The objective is the MSE between true and predicted noise.

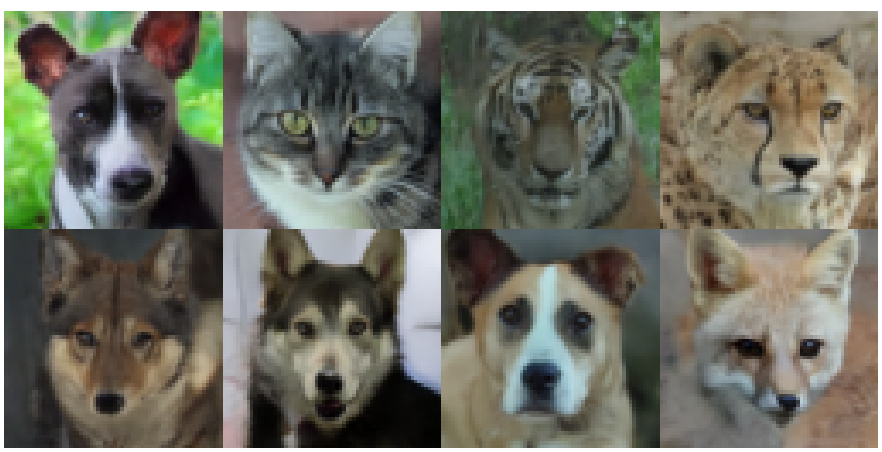

Figure 6: Eight randomly selected 64×64 samples generated by the DDPM after full reverse diffusion.

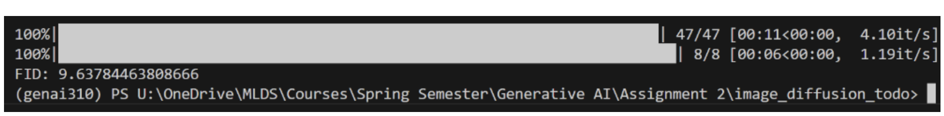


Figure 7: FID computation against the full AFHQ validation set, measured as 9.64 (lower is better).