# Image Generation with Diffusion Models

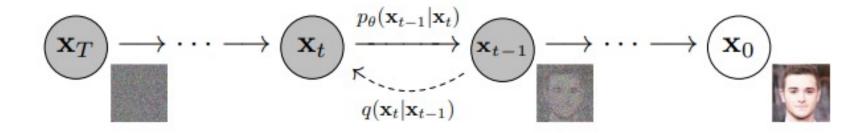
Lambda

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## Denoising Diffusion Probabilistic Model

- Adding (Gaussian) noise to image
- Neural network: learns to predict noise at each small step
- Image generation: start from pure noise -> denoise step-by-step

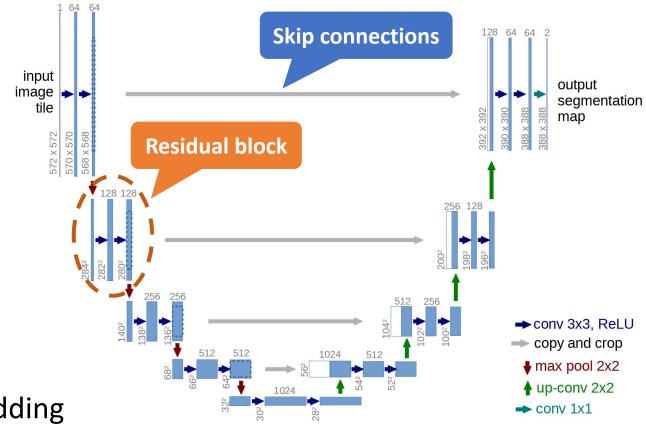


#### **Related Work & Sources:**

- [1] J. Ho, A. Jain, and P. Abbeel. Denoising diffusion probabilistic models. URL <a href="https://arxiv.org/abs/2006.11239">https://arxiv.org/abs/2006.11239</a>
- [2] N. Rogge and K. Rasul. The annotated diffusion model, 2022. URL https://huggingface.co/blog/annotated-diffusion
- [3] A. Béres. Denoising diffusion implicit models, 2022. URL <a href="https://keras.io/examples/generative/ddim/">https://keras.io/examples/generative/ddim/</a>
- [4] A. K. Nain. Denoising diffusion probabilistic model, 2022. URL <a href="https://keras.io/examples/generative/ddpm/">https://keras.io/examples/generative/ddpm/</a>

## **Neural Network**

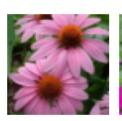
- Input:
  - noisy image
  - noise level
- Output: predicted noise at the level
- Architecture: U-NET
- Optimizations:
  - Multiple residual blocks per level
  - Group normalization
  - Sinusoidal time (noise level) embedding
  - Exponential moving average for weight update



Source: O. Ronneberger, P. Fischer, and T. Brox. U-net: Convolutional networks for biomedical image segmentation. 2015. URL <a href="http://arxiv.org/abs/1505.04597">http://arxiv.org/abs/1505.04597</a>

#### **Datasets**

- Oxford 102 Flower Dataset<sup>1</sup>
  - 8189 images of various kinds of flowers
- Oxford-IIIT Pet Dataset<sup>2</sup>
  - 7349 images of cats and dogs
- Scaled down and cropped to 64\*64 pixels
- 80%/20% split used for training/validation sets





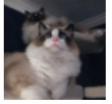












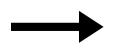
<sup>&</sup>lt;sup>1</sup> https://www.robots.ox.ac.uk/~vgg/data/flowers/102/

<sup>&</sup>lt;sup>2</sup> https://www.robots.ox.ac.uk/~vgg/data/pets/

## **Evaluation**

- Solution written in Jupyter Notebook, wrapped in Docker container
- Training

- GTX 1070



Smaller, overfit training: 6-8 hours

Training on full dataset: 36 hours

Measured metrics:

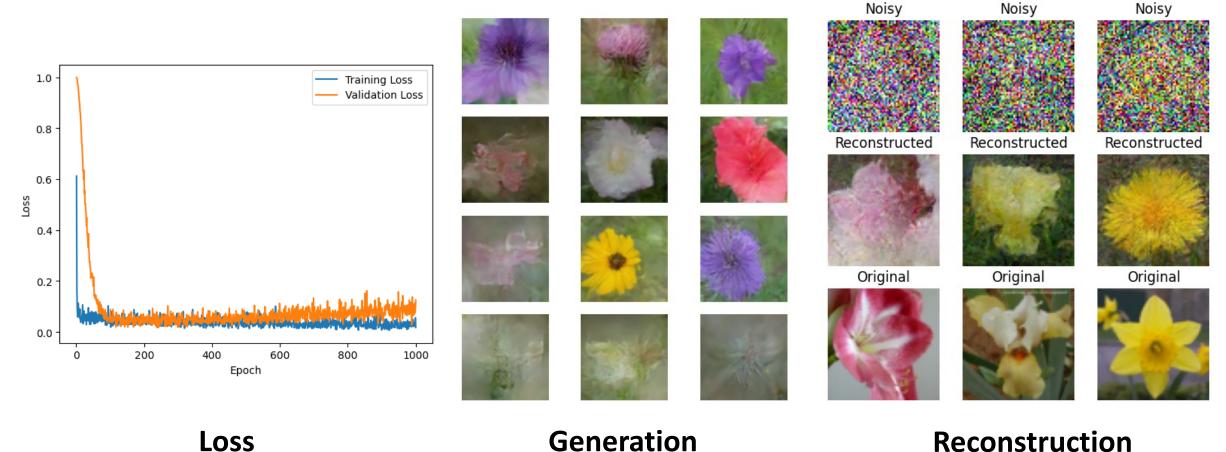
- 1000 epochs

- training loss
- validation loss
- Kernel Inception Distance<sup>1</sup> (KID)
- Subjective evaluation: how *flower-like* are the generated images?

<sup>&</sup>lt;sup>1</sup> M. Bińkowski, D. J. Sutherland, M. Arbel, A. Gretton: Demistifying MMD GANs (<a href="https://arxiv.org/abs/1801.01401">https://arxiv.org/abs/1801.01401</a>)

# Overfitting the Model

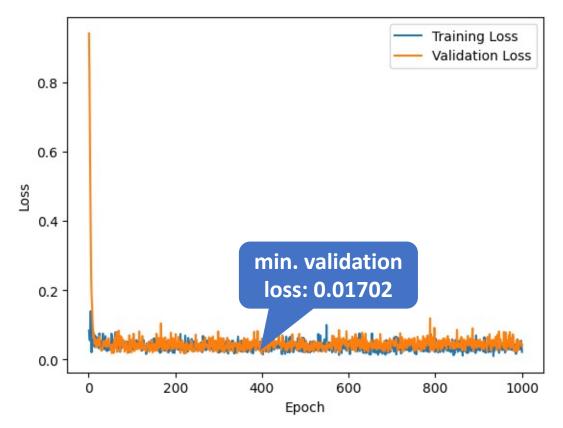
• smaller dataset: 1000-1000 training and validation images



Generation Reconstruction

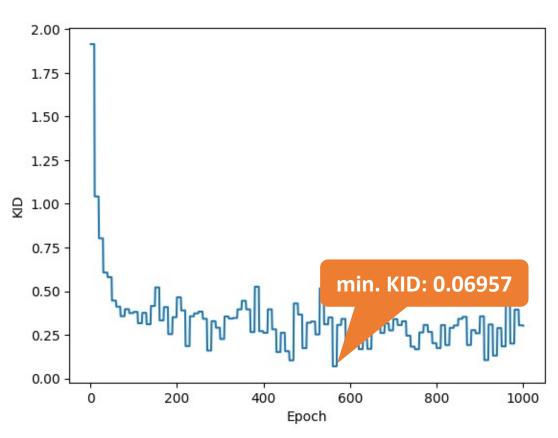
## Training on Full Dataset

**Loss** measured every epoch



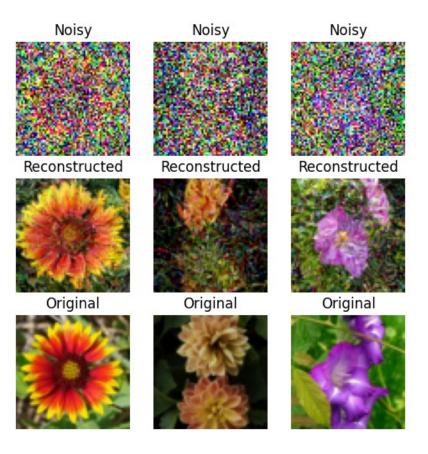
#### **Kernel Inception Distance**

measured every 10 epochs



## **Best KID Model**





**Generation** 

Reconstruction

## **Generated Pets**

• smaller dataset: 1000-1000 training and validation images



**Best KID Model** 

**Overfit Model** 

## Summary

- Familiarized ourselves with diffusion models
- Implemented denoising diffusion process and U-Net
- Trained the model on 2 datasets
- Evaluated the models based on 2 metrics: loss and KID
- Containerized the solution in Docker
- Created flower generating Gradio demo<sup>1</sup>
- Lessons learned: output activation function, group normalization
- Future work: further improve net (attention), complex noise schedule

