Denoising Diffusion Probabilistic Models for Orthophotos

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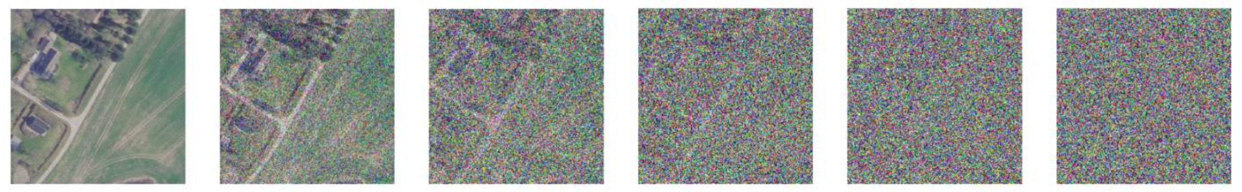
Introduction, motivation and dataset

Based on Ho et al. (2020)[1], this project seeks to build a diffusion model in PyTorch using orthophotos, closely following the authors' approach.

The decision to use orthophotos is motivated by the desire to explore how a diffusion model performs within the remote sensing domain, as geospatial data plays an increasingly critical role in environmental monitoring.

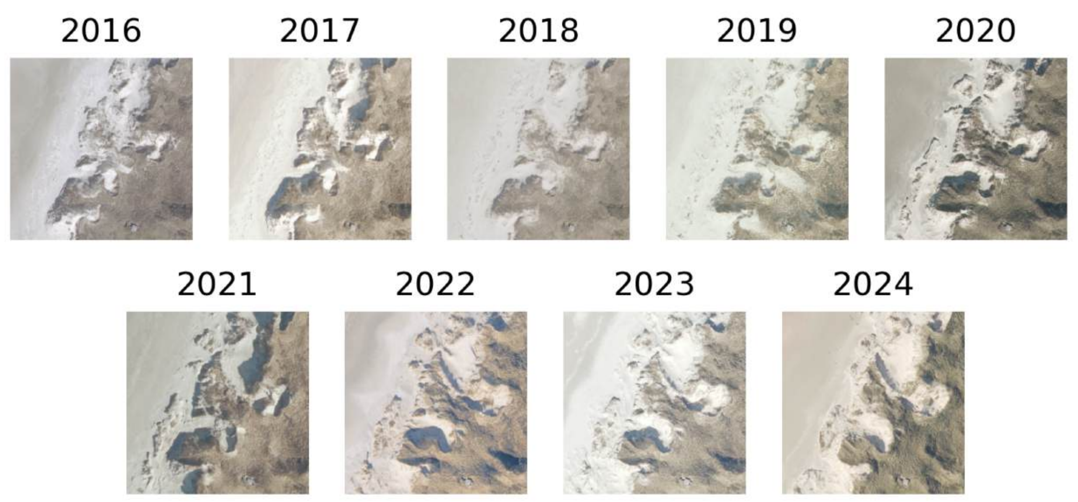
$$x_0 \rightarrow x_1 \rightarrow \ldots \rightarrow x_T$$



$$x_0 \leftarrow x_1 \leftarrow \ldots \leftarrow x_T$$

The dataset:

- Orthophotos of protected nature habitats in Denmark[2]
- Each image is tied to a geographical location, with a total of 358,910 different locations
- Each location has 9 images, one taken in the spring every year from 2016 to 2024
- RGB images with size 256x256 pixels, covering an area of 128x128 meter
- 1 pixel corresponds to an area of 50x50 cm
- Collected from an API monitored by Klimadatastyrelsen

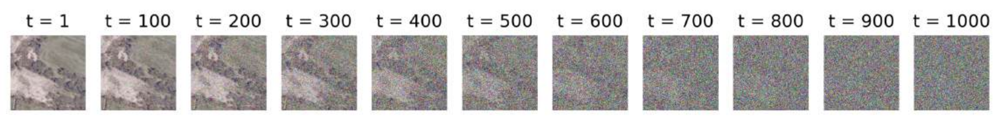


The forward process

The forward process is a Markov chain that gradually adds Gaussian noise to the input image x_0 step by step with a variance defined by $\beta_1, \ldots, \beta_T$. The process will produce a sequence of noisy image samples $x_1, \ldots, x_T$.

$$\underbrace{q(x_t|x_{t-1})}_{\text{Distribution of the noised images}} = N(\underbrace{x_t}_{\text{Output}}; \underbrace{\sqrt{1-\beta_t}x_{t-1}}_{\text{Mean } \mu_t}, \underbrace{\beta_t \mathbf{I}}_{\text{Variance } \Sigma_t})$$

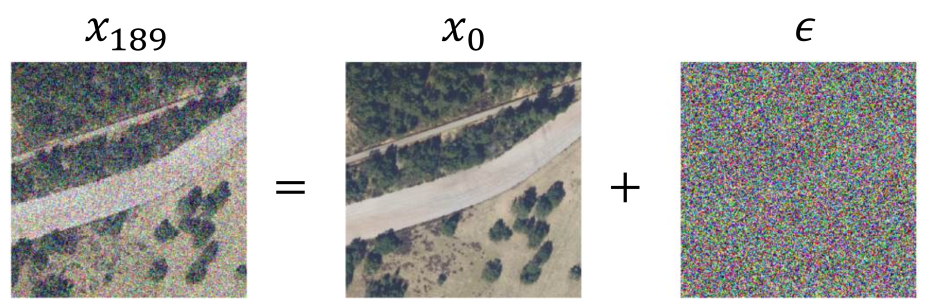
Like the authors Ho et al. (2020)[1], I set $T = 1000$ and linearly increase $\beta_1 = 0.0001$ to $\beta_T = 0.01$.



Alternative methods for noise scheduling exist, such as the cosine schedule, which is commonly used because it introduces noise at a slower rate[3].

The forward process admits sampling x_t at an arbitrary timestep t in closed form. By defining $\alpha_t = 1 - \beta_t$ and $\bar{\alpha}_t = \prod_{i=1}^{t} \alpha_i$, the closed form formula ultimately looks like:

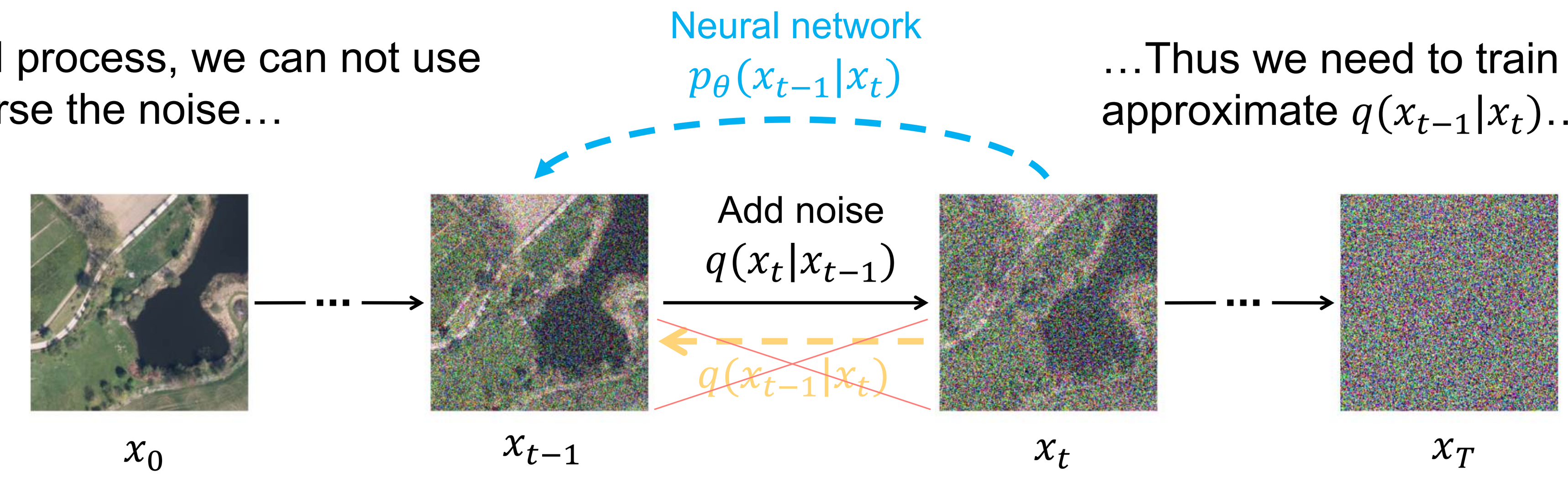
$$\boxed{x_t} = \sqrt{\bar{\alpha}_t}\boxed{x_0} + \sqrt{1-\bar{\alpha}_t}\boxed{\epsilon}$$



The reverse process

Unlike the forward process, we can not use $q(x_{t-1}|x_t)$ to reverse the noise…

…Thus we need to train a neural network to approximate $q(x_{t-1}|x_t)$…

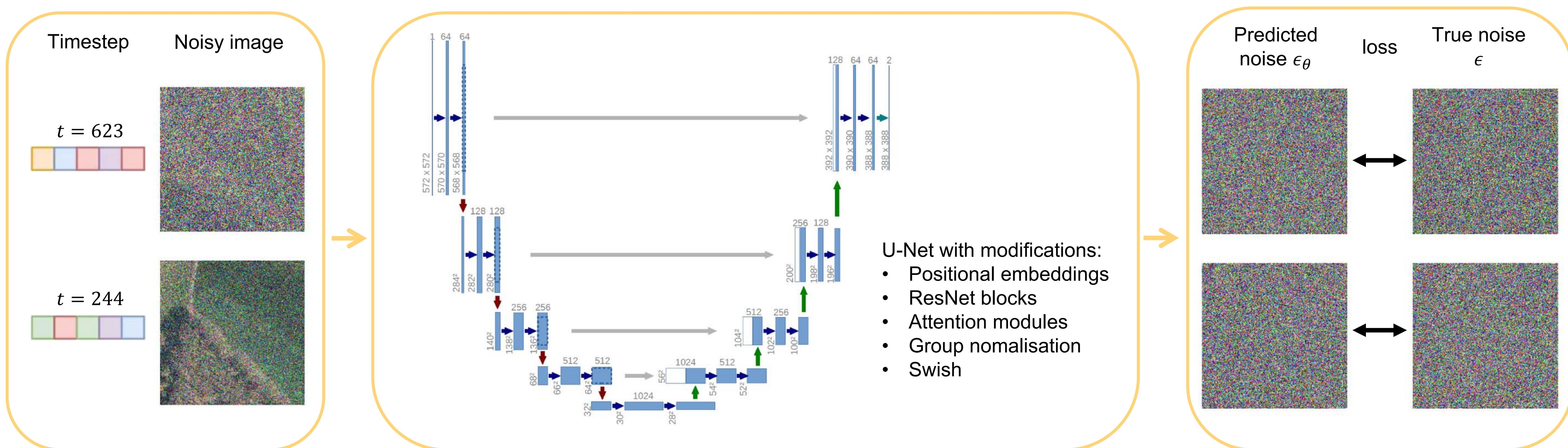


…It turns out, after doing a lot of math, p_θ is Gaussian in the form of $p_\theta(x_{t-1}|x_t) = N\left(x_{t-1}; \mu_\theta(x_t,t), \mathbf{\Sigma}_\theta(x_t,t)\right)$. Hence, we need to find $\mu_\theta(x_t,t)$ and $\mathbf{\Sigma}_\theta(x_t,t)$. The mean $\mu_\theta(x_t,t)$ is given by $\mu_\theta(x_t,t) = \frac{1}{\sqrt{\alpha_t}}\left(x_t - \frac{1-\alpha_t}{\sqrt{1-\bar{\alpha}_t}}\epsilon_\theta(x_t,t)\right)$. Fixing the variance $\mathbf{\Sigma}_\theta(x_t,t)$ to a constant $\sigma_t^2 = \tilde{\beta}_t = \frac{1-\bar{\alpha}_{t-1}}{1-\bar{\alpha}_t}\beta_t$, makes $\epsilon_\theta(x_t,t)$ the only learnable part of the reverse process.

Model

$$L_{simple} = \mathbb{E}_{t,x_0,\epsilon}[||\epsilon - \epsilon_\theta(\sqrt{\bar{\alpha}_t}x_0 + \sqrt{1-\bar{\alpha}_t}\epsilon, t)||^2]$$

Timestep encoding



Sampling and preliminary results

$$x_{t-1} = \frac{1}{\sqrt{\alpha_t}}\left(x_t - \frac{1-\alpha_t}{\sqrt{1-\bar{\alpha}_t}}\epsilon_\theta(x_t,t)\right) + \sigma_t \mathbf{z}, \text{ where } \mathbf{z} \sim N(\mathbf{0}, \mathbf{I})$$

References

[1] Ho, J., Jain, A., & Abbeel, P. (2020). Denoising diffusion probabilistic models. arXiv. https://doi.org/10.48550/arXiv.2006.11239

[2] Miljø- og Ligestillingsministeriet. (03/03/2019). Bekendtgørelse af lov om naturbeskyttelse. Retsinformation. https://www.retsinformation.dk/eli/lta/2019/240

[3] Nichol, A. Q., & Dhariwal, P. (2021). Improved denoising diffusion probabilistic models. arXiv. https://doi.org/10.48550/arXiv.2102.09672