# Generating Bulbasaurs using DDPM Project 4 - Statistical deep learning MT7042

Florence Hugh & August Jonasson

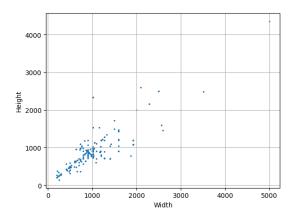
2025-01-17

#### Introduction



#### **Exploratory analysis**

- $\bullet~\approx 200$  images of varying resolution and #channels
- pre-processing required
- data augumentation



# Decay of the forward process

#### Transition density of the forward process

$$q(x_t|x_0) := \mathcal{N}(x_t; \sqrt{\overline{\alpha}_t}x_0, \sqrt{1-\overline{\alpha}_t} \mathbf{I}),$$

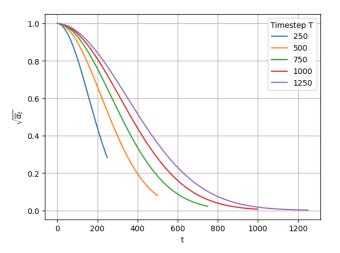
where  $x_t$  is the image at timestep t,  $x_0$  is the starting image, and

$$\overline{\alpha}_t = \prod_{i=1}^t \alpha_i.$$

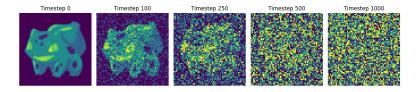
- What we need:  $q(x_T|x_0) \to \mathcal{N}(x_T; 0, I)$ , as  $T \to \infty$
- Crucial to control the decay of  $\sqrt{\overline{\alpha}_t}$ 
  - by choosing  $\{\alpha_t\}$  and T

#### Decay of the forward process

With linearly decaying  $\{\alpha_t\}$ , the decay of  $\sqrt{\overline{\alpha}_t}$  for different T

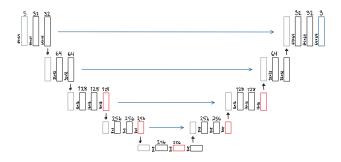


#### Forward noising process applied to a pre-processed image



#### Architecture

- U-Net
  - Capable of handling image segmentation



## Optimization problem

- Equivalent to a least-squares regression problem
  - ightharpoonup Response: Random generated noise  $\epsilon$
  - Predictor: Time-step t & image x<sub>t</sub>
- Hence, minimization of

$$||\epsilon - \epsilon_{\theta}(\sqrt{\overline{\alpha}_t}x_0 + \sqrt{1 - \overline{\alpha}_t}\epsilon, t)||_2^2, \quad \forall t \in \{1, \dots, T\}.$$

# Generating images

• 2000 epochs with Adam optimizer and MSE loss function

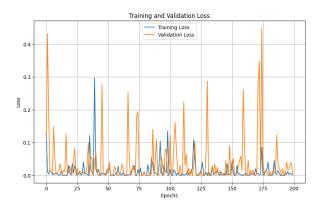
## Generating images

• 2000 epochs with Adam optimizer and MSE loss function



# Examining the training

- 80/20 split, different from the model that generated images
- What do we expect a healthy training to look like?



#### Alternative methods of validation

- Plausible vs novelty
- Quality of generated images

#### Fréchet inception distance

$$d_F(\mathcal{N}(\mu,\Sigma),\mathcal{N}(\mu',\Sigma'))^2 = ||\mu-\mu'||_2^2 + \operatorname{tr}\left(\Sigma + \Sigma' - 2(\Sigma\Sigma')^{\frac{1}{2}}\right),$$

Where  $\mathcal{N}(\mu, \Sigma)$  is the distribution of the original image set and  $\mathcal{N}(\mu', \Sigma')$  of the generated images.

## Possible improvements

- Monitoring the training
  - ▶ 90/10 split
  - Leave-one-out cross-validation
- How to handle overfitting
  - Add data augumentation
  - Dropout
  - $ightharpoonup L_1$  (Lasso) and  $L_2$  (Ridge) penalty