



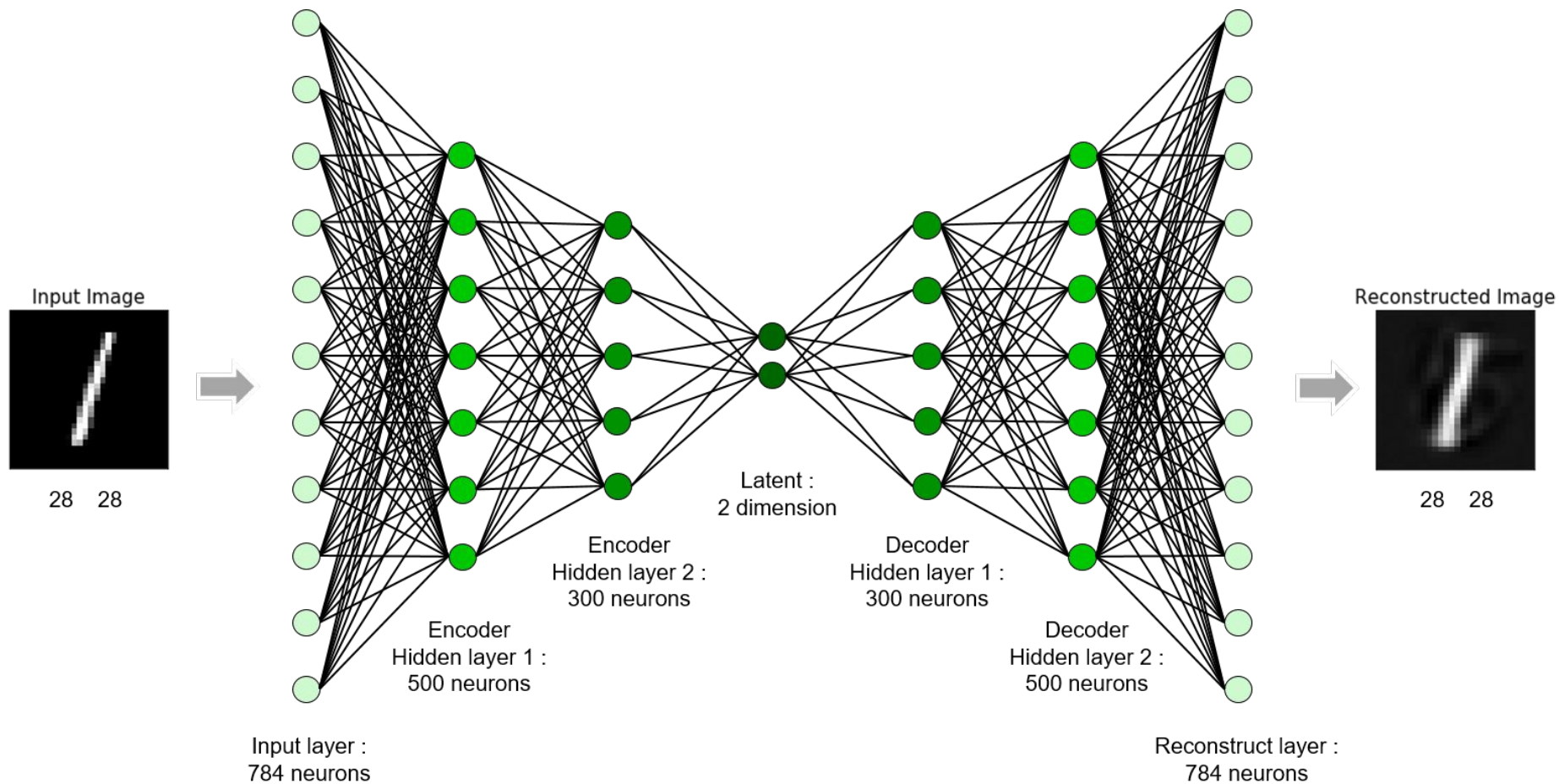
Autoencoders

Brief introduction



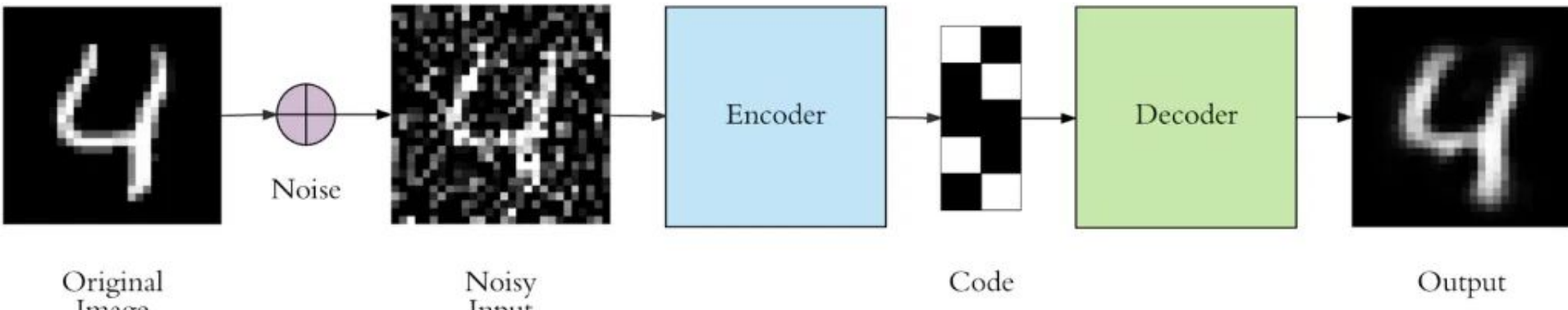
Basics

- Optimally characterising your data is fundamental in building a good machine learning algorithm. This largely boils down to feature selection.
- Autoencoders provide a means to compress large data sets and characterising them in terms of a reduced parameter space.
- An autoencoder is made up of two pieces:
 - **Encoder:** A fully-connected/convolutional (neural) network that compresses the initial data into **latent variables/ vector** at what is called the **bottleneck layer**.
 - **Decoder:** A fully-connected/convolutional (neural) network that reconstructs the output data.
- The network is trained by comparing output with the input data and minimising the 'reconstruction' loss.



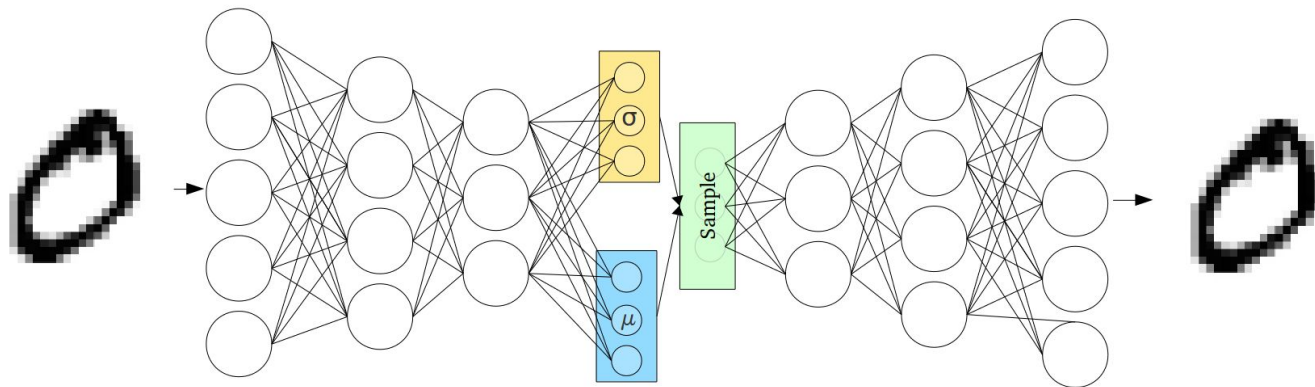
Applications

- Reducing bandwidth used by mobile phones (Google project).
- Image segmentation, e.g. self-driving cars use this to identify relevant information.
- Noise reduction.
- Neural inpainting, e.g. removing watermarks.
- Anomaly detection.



Variational autoencoders

- Instead of mapping input data to a fixed latent vector, we map to a distribution.
- In practice we assume some form for this distribution. In the case of a Gaussian, we map to a 'mean' vector and a 'standard deviation' vector.





Variational autoencoders II

- The loss function is made up of expectation of reconstruction loss and the KL divergence that forces the distribution to be close to a normal distribution.

$$\mathcal{L} = \mathbb{E}_{q(z|X)}[\log p(X|z)] - \beta D_{KL}[q(z|X)||p(z)]$$

- The network performs a sampling operation after the bottleneck and before the decoder.
- For normal VAE, hyperparameter $\beta=1$. [See *Irina Higgins et al 2016*.]
- Can be used for image generation for example.