

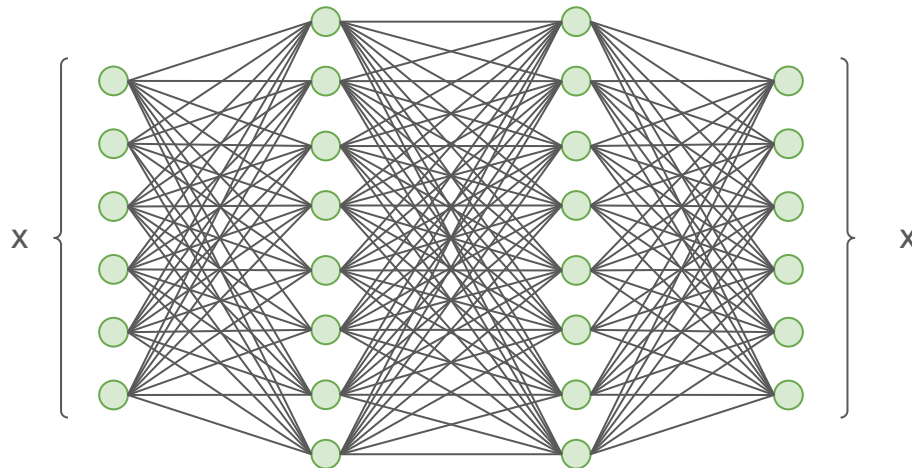
Variational AutoEncoders

Thanos Tagaris

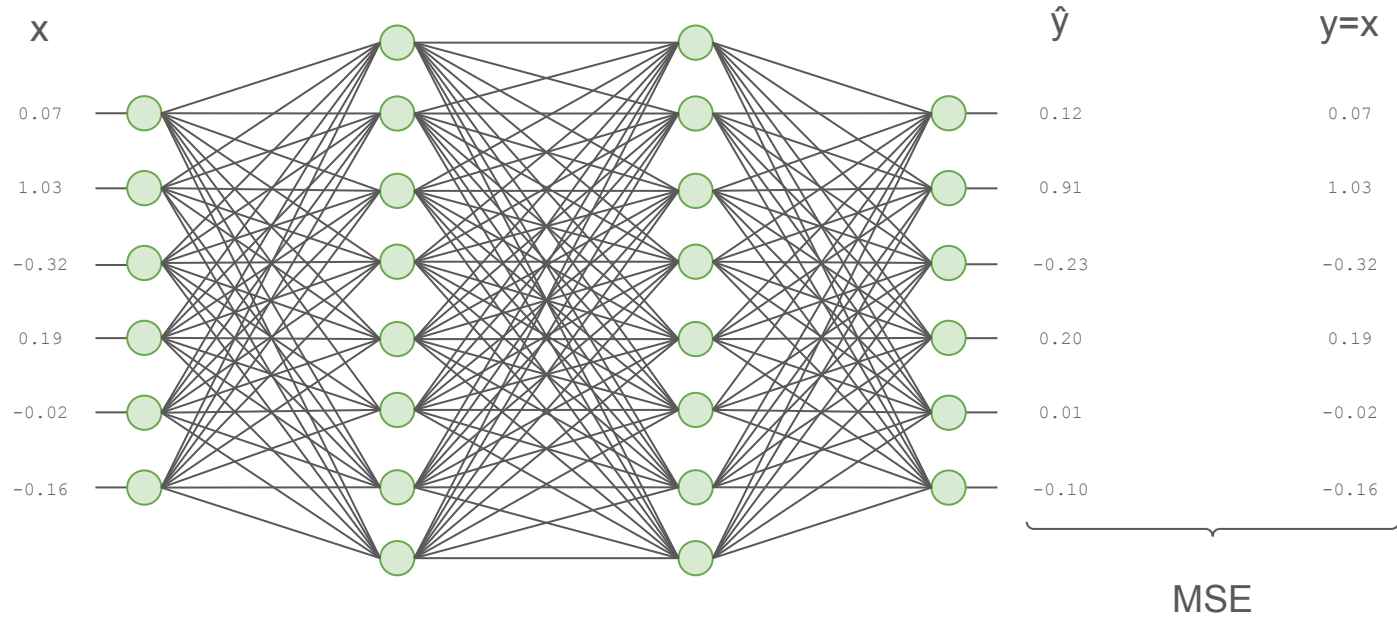
Generative Neural Networks: AutoEncoders

AutoEncoders (AE)

- A Neural Network architecture that has the same shape for its input and output
- Trained in an unsupervised manner
- This leads to a **generative** training

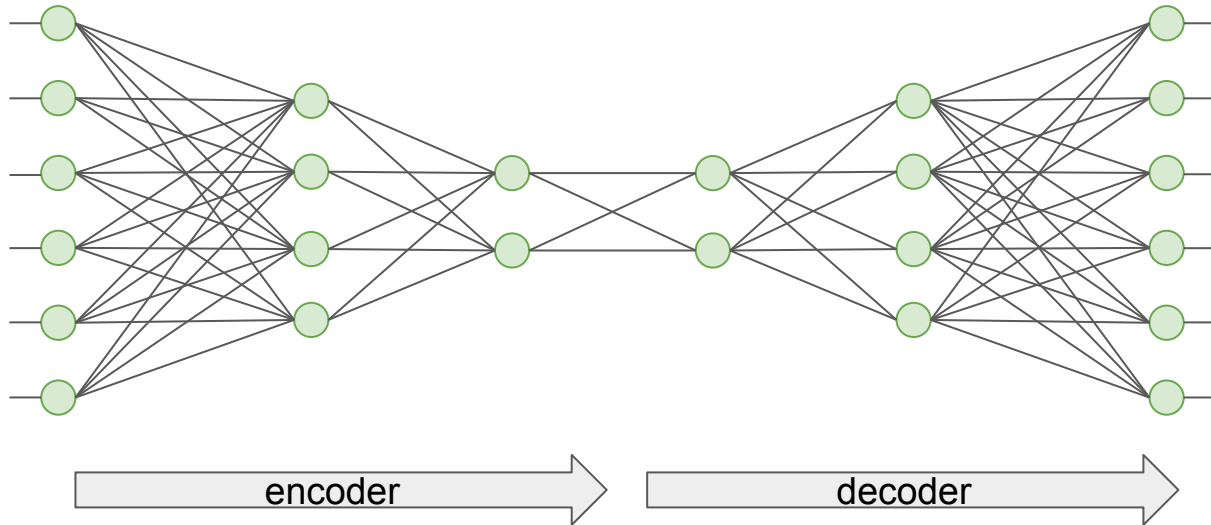


AutoEncoders (AE)



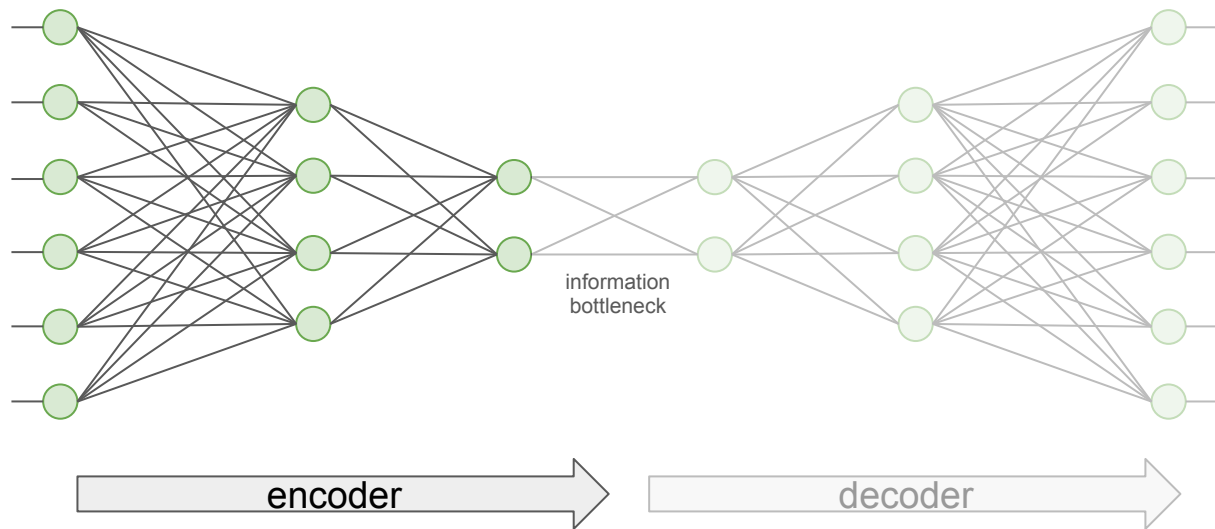
AutoEncoders (AE)

- One thing was inaccurate in the previous depictions
- Autoencoders need to *shrink* the input dimensions to *compress* the input information
- Else they could just learn to copy the information from input directly to output



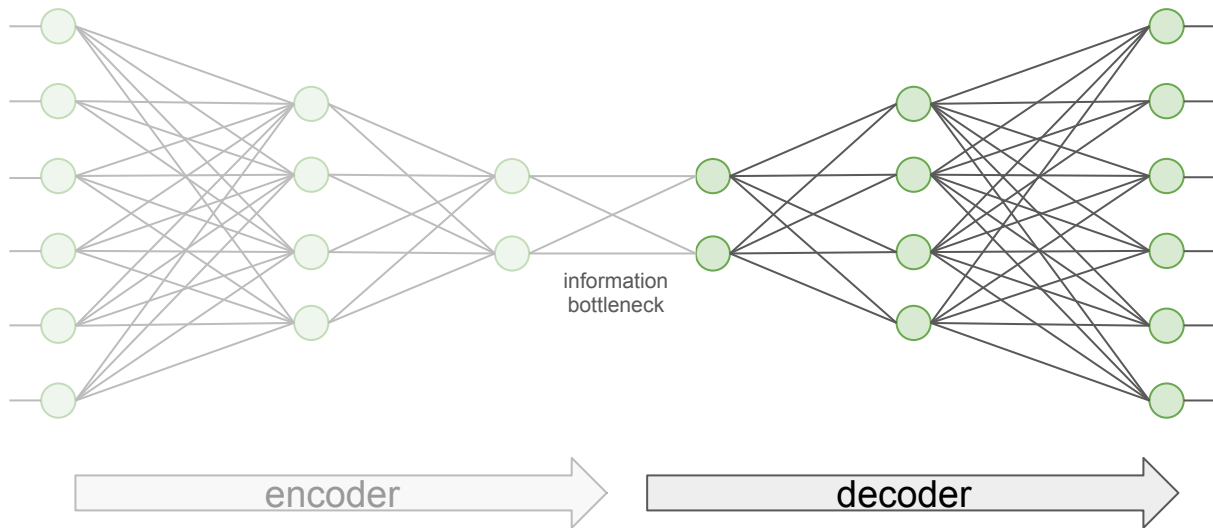
Encoding

- The task of the autoencoder is to essentially *reconstruct* the original input
- The encoder compresses the most **useful information** on how to do this
- Due to the information shrinkage, it can't capture all the details.



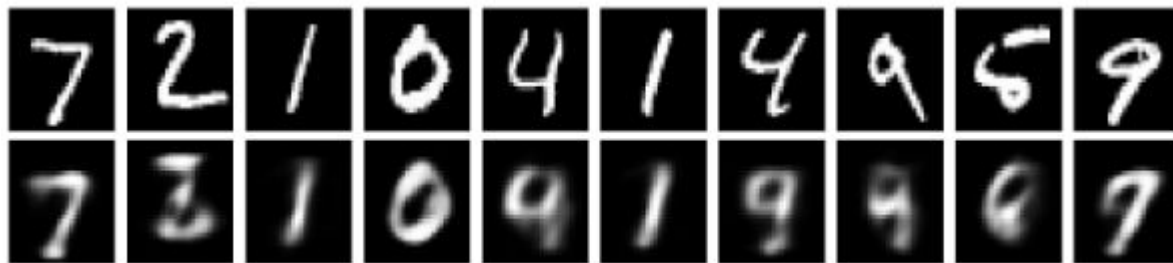
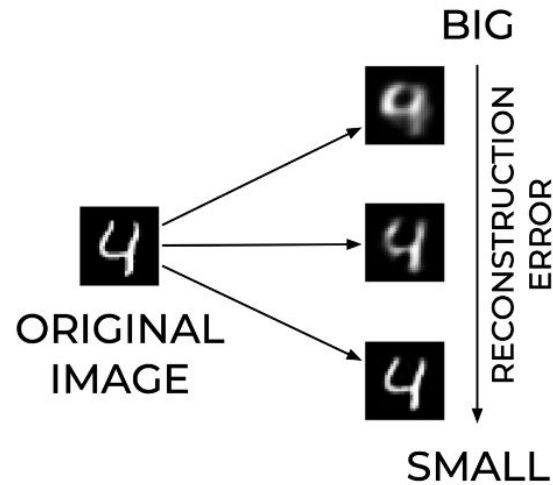
Decoding

- The decoder takes the compressed vector as its input and needs to fill in all the missing details.
- To do this it needs to understand some fundamental properties about how the input data's underlying distribution.
- This is what makes it **generative**.



Input Reconstruction

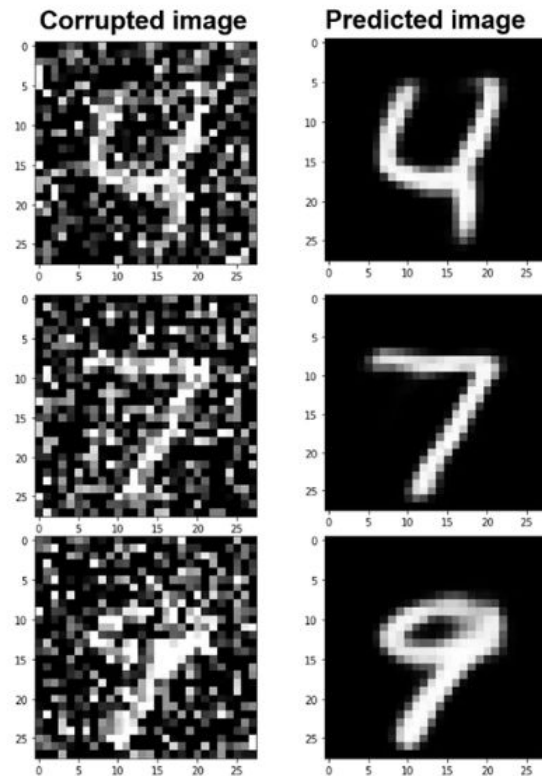
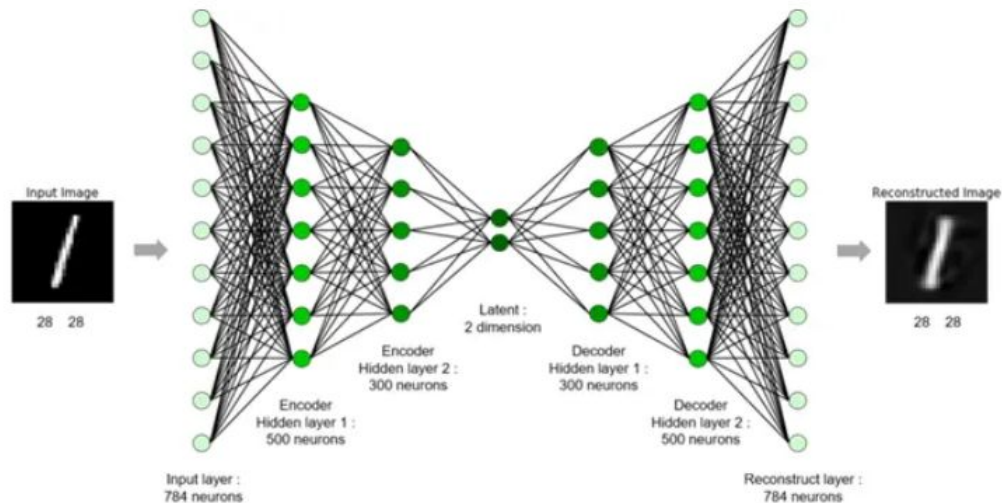
- An autoencoder can work on any modality (images, audio, text, etc.)
- Again, to be able to reconstruct its input, it needs to learn the distribution of its inputs
- ... it needs to be **generative**



Demo

Build a convolutional autoencoder
on the MNIST dataset

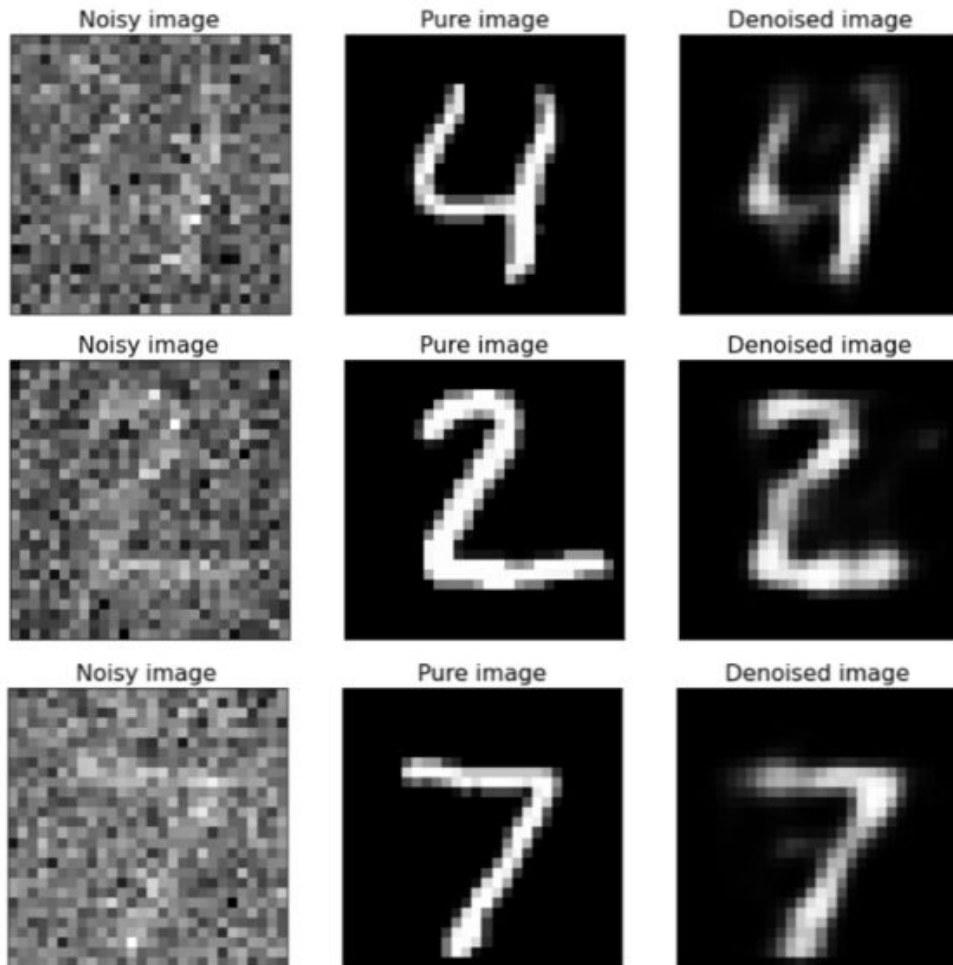
Denoising Autoencoders



Denoising Autoencoders

even harder examples...

This process forces the autoencoder to look beyond the input noise and learn the true **underlying distribution**

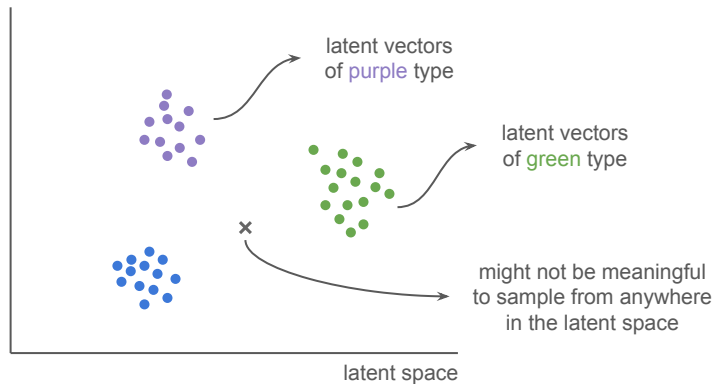
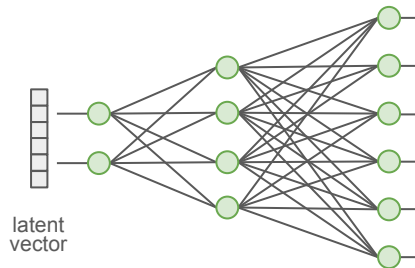


Demo

Try to train the previously created
AutoEncoder for denoising

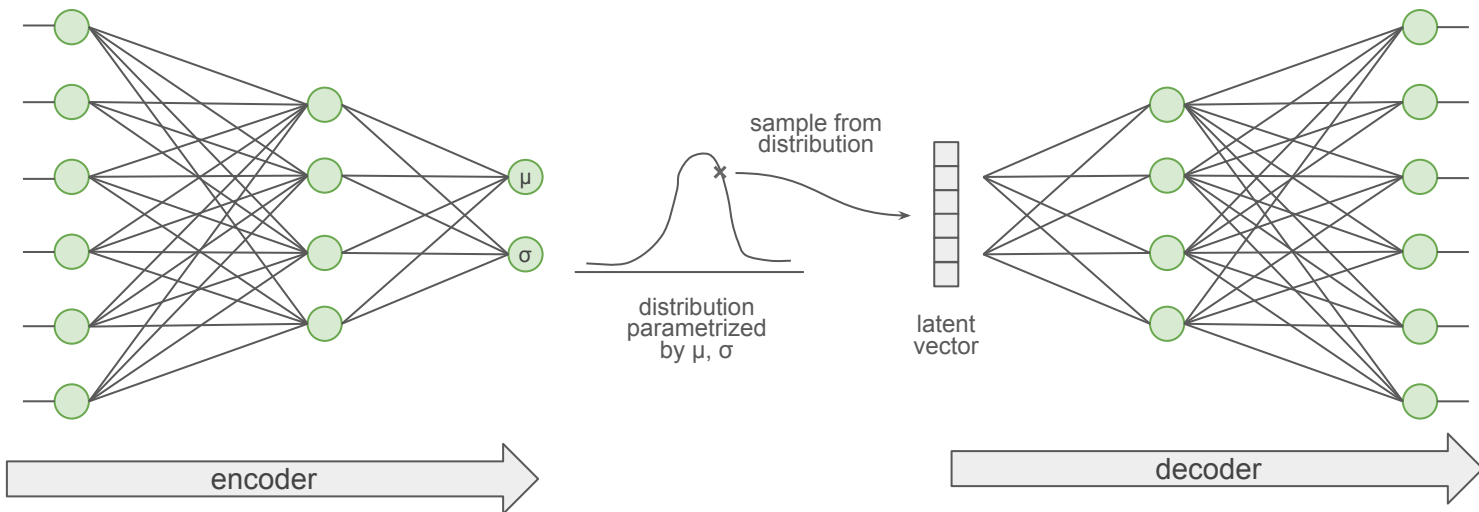
Using Autoencoders for Generative tasks

- So, we know that the decoding part of the AE is **generative**.
- What do we need to do to make it generate something?
 - supply it with a latent vector
- How do we know what values to choose in the latent vector?
 - we can't
 - can we randomly choose a vector?



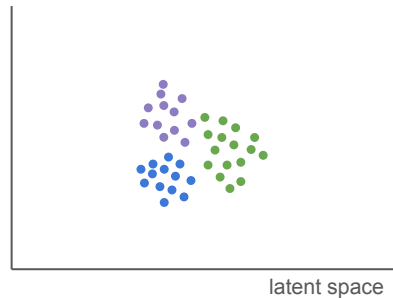
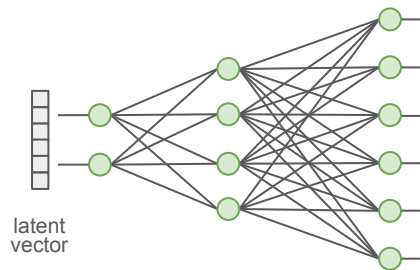
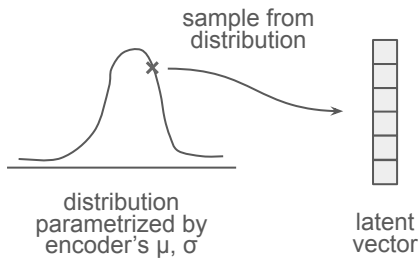
Variational AutoEncoders (VAE)

- Idea: instead of learning the latent vectors deterministically, learn the **distribution** from which they are sampled.
- Encoder will learn the parameters of this **distribution** (e.g. μ , σ in normal distribution)
- Decoder will reconstruct output from a latent vector, sampled from this **distribution**



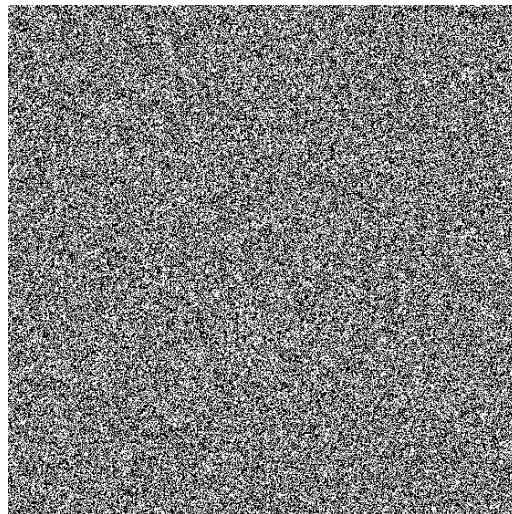
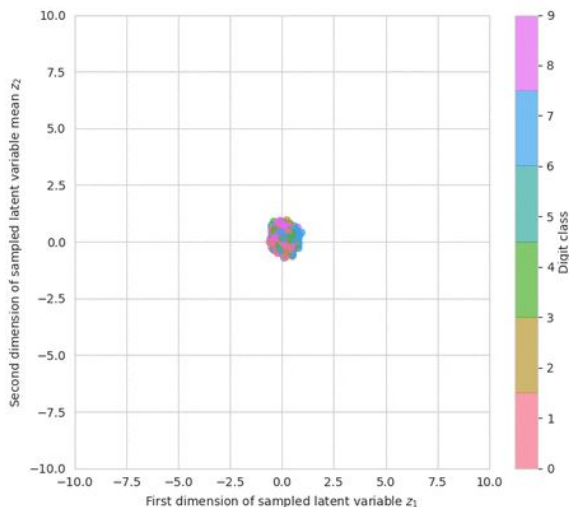
Using VAEs for Generative tasks

- So, how does a VAE help us with our **generative** tasks?
 - In deterministic AEs we didn't know how to select the latent vector
 - In VAEs, we know the distribution from which latent vectors can be sampled
- **Generative** process:
 - Step 1: sample a latent vector from the distribution
 - Step 2: supply latent vector to the decoder
- VAE's training objective leads them to have a more continuous latent space



VAE: training details

- Trained with ELBO loss function. Two terms:
 - Reconstruction loss
 - Regularization term to constrain latent distribution to “follow” a prior (e.g. gaussian)



Evidence Lower Bound

$$\begin{aligned}\log p_{\theta}(x^{(i)}) &\geq \mathcal{L}(\theta, \phi; x^{(i)}) \\ &= E_{q_{\phi}(z|x^{(i)})}[-\log q_{\phi}(z|x) + \log p_{\theta}(x|z)] \\ &= \underbrace{-D_{KL}(q_{\phi}(z|x^{(i)})||p_{\theta}(z))}_{\text{KL diversion to keep}} + \underbrace{E_{q_{\phi}(z|x^{(i)})}[\log p_{\theta}(x|z)]}_{\text{likelihood}}\end{aligned}$$

KL diversion to keep
distribution close to a prior
distribution

likelihood