Bioinformatics LAB 9

Autoencoders

Prof.ssa Elisa Ficarra
Prof.ssa Santa Di Cataldo
Eng. Marta Lovino
Eng. Alessio Mascolini

Politecnico di Torino
DAUIN
Dept. of Control and Computer Engineering

LAB 9 - Objectives

Objectives

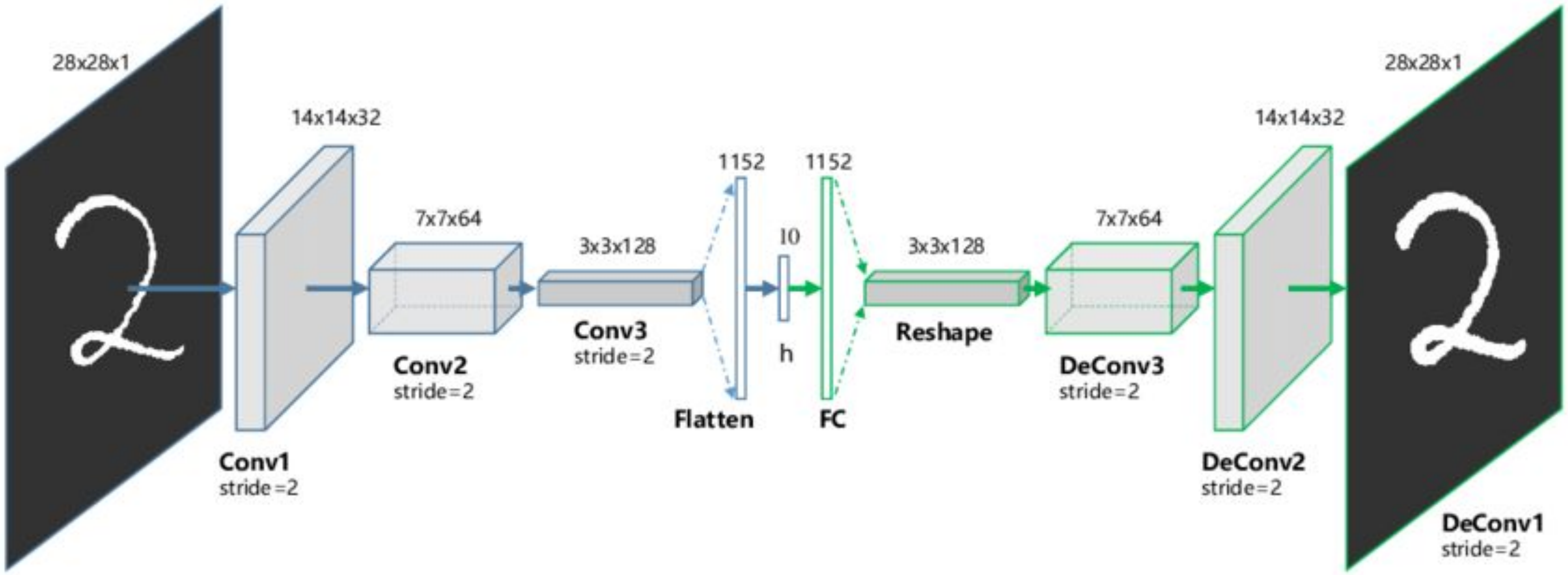
- Autoencoder
- Latent space interpolation
- Variational Autoencoder
- Reparametrization Trick
- VQ-VAE

Autoencoder

Encoder-Decoder architecture

An Autoencoder encodes an image as a point in a latent space and decodes the point to the same image

A bottleneck ensures the network learns a compressed representation of the data



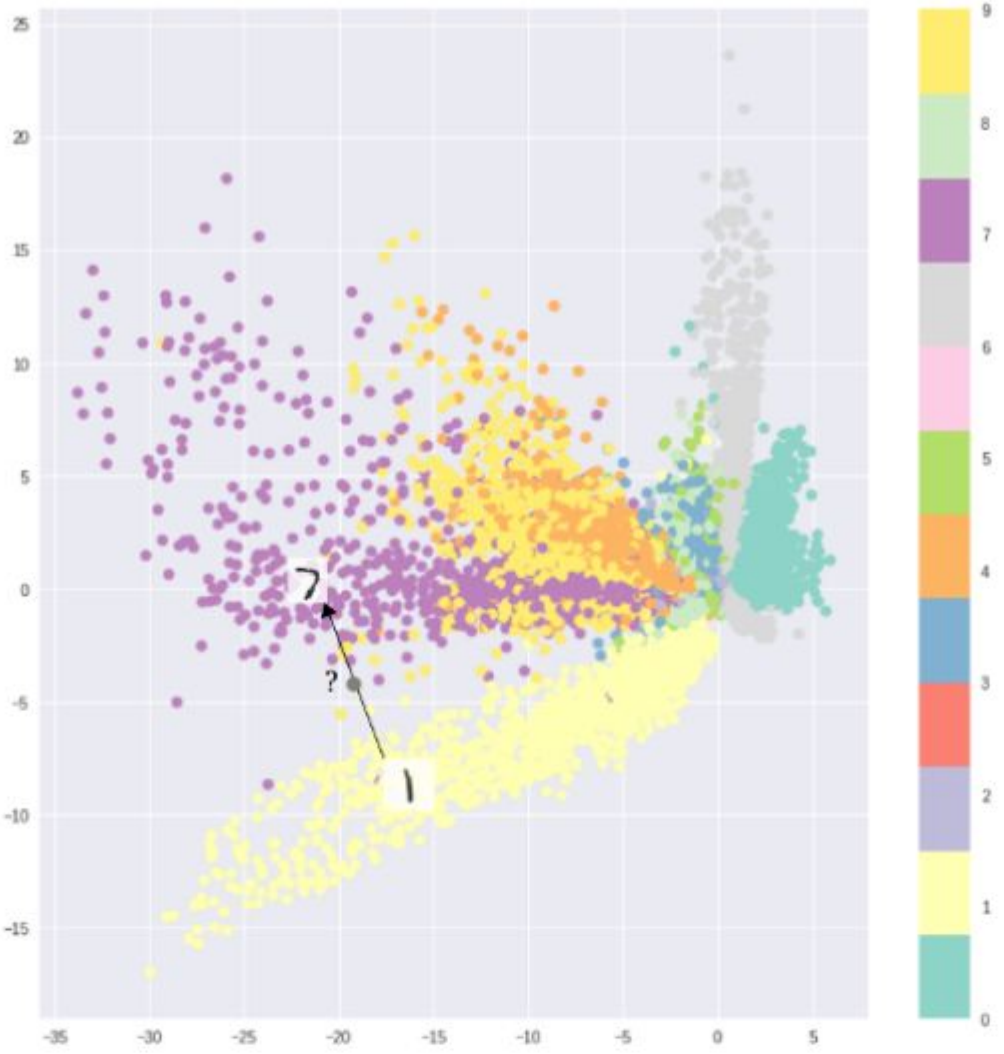
Latent Space Interpolation

Why do we need a latent space?

A good latent space keeps similar images close and different images far

Useful for tasks such as:

- Synthetic samples
- Clustering
- Outlier detection
- Segmentation



Variational Autoencoder

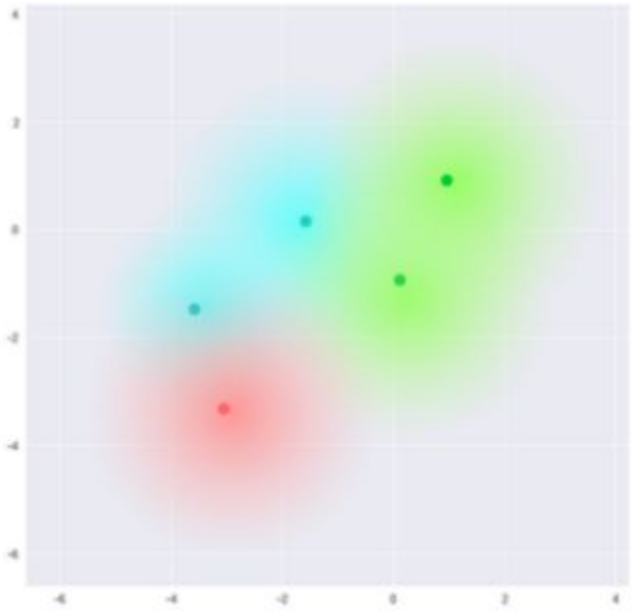
Variational inference: we assume the distribution family, usually a normal distribution, and use KL divergence to shape the distribution.

We can force the autoencoder to cluster data as normal distributions. How?
We assume a prior N(0,1)
The encoder predicts a posterior (μ and σ) instead of a point.

Then we sample a point from the distribution given by the encoder and feed it to the decoder.

Normally the encoder will just learn to set the σ to 0 and become a standard autoencoder, we can avoid this by using KLD, which will “pull” our distribution towards our prior.

We are also forcing the covariance matrix to be 0 off the diagonal, which makes our features disentangled

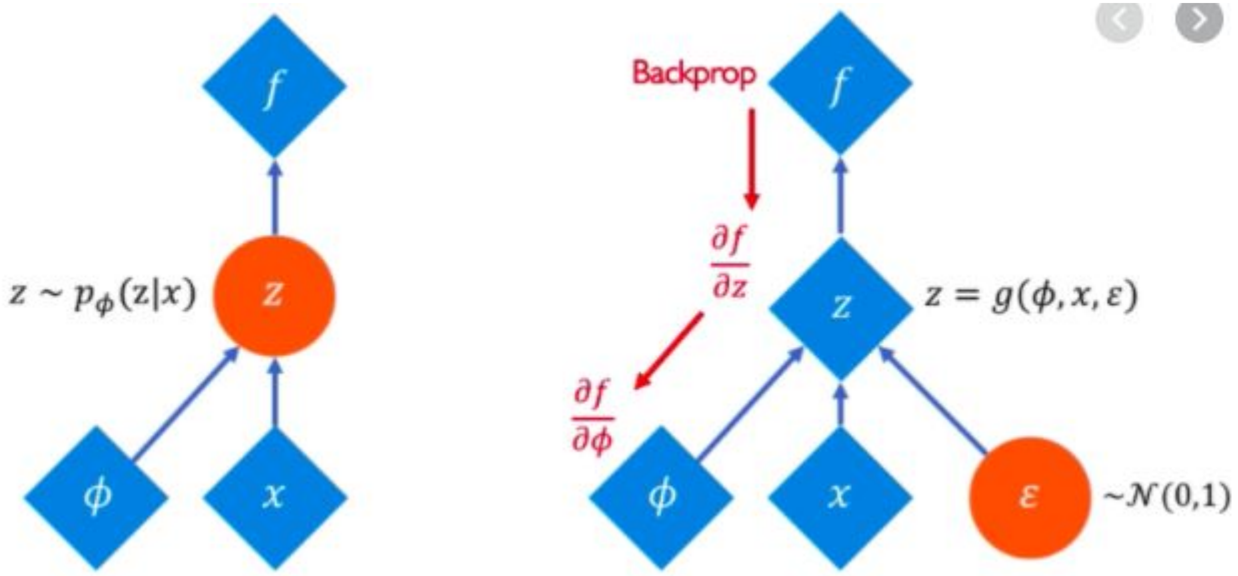


Reparametrization trick

- We can't propagate gradients through the sampling operation, so we make our sampling determinist by defining it as μ + εσ. ε is stochastic, but we don't care as we have no need to backpropagate through that part of the network

KLD term:

$$\frac{1}{2}\sum_{j=1}^{J}\left(1+\log((\sigma_j)^2)-(\mu_j)^2-(\sigma_j)^2\right)$$



VQ-VAE

A powerful decoder may learn to ignore the latent space if it does not provide strong enough information during training, this phenomenon is known as “posterior collapse”: The encoder learns the ideal posterior imposed by the KLD term, and the decoder learns the prior. The latent space becomes useless.

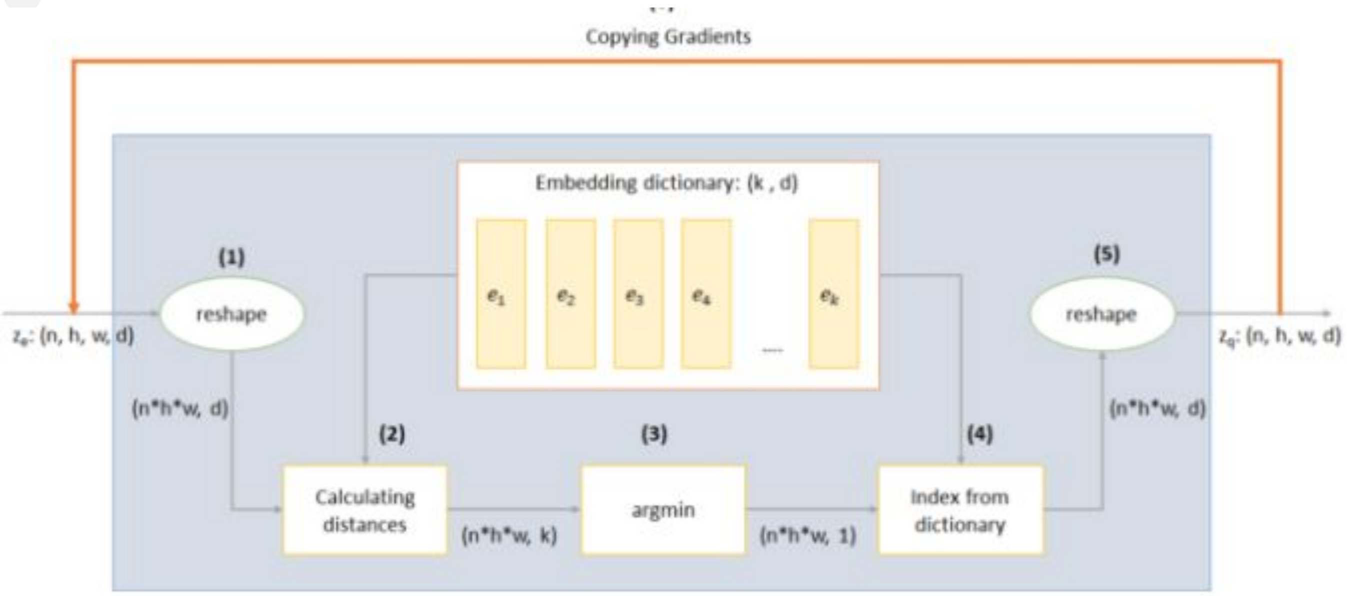
Normal distribution may not be the best in many cases, data is often best described by discrete classes. This technique also forces the latent space to be meaningful, increasing the decoder’s reliance on it.

VQ-VAE

The reconstruction loss gradients flow through the whole network, bypassing the vector quantization.

The encoder and chosen quantized vector get pulled towards each other by an additional l2 loss.

Sampling from the latent space is not possible without additional techniques.



LAB 9 - Assignments

Assignment 1: Traditional Autoencoder

- Install tensorflow-datasets (already installed on colab)
- import the colorectal_histology dataset

```
images = tfds.load(name='colorectal_histology',split='train',as_supervised=True)
images = images.batch(16)
images = images.map(lambda img,lab: (tf.image.convert_image_dtype(img, dtype=tf.float32),lab))
images = images.map(lambda img,lab: (img,img))
```

- Build an autoencoder
- Data is 150x150, use `tf.keras.layers.experimental.preprocessing.Resizing` to resize
- Remember how to build an image decoder from Lab 7
- Use MSE as loss
- Train the autoencoder

Assignment 2: Autoencoder with perceptual loss

- Instead of using just MSE, initialize a VGG16 model pretrained on imagenet using `tf.keras.applications.VGG16`
- Optimise the sum of the previous loss and a small contribution (0.1) from the MSE in the feature space of VGG16 as the new loss (`tf.keras.applications.vgg16.preprocess_input` requires data in the [0,255] range)
- Compare the results

Assignment 3: Variational Autoencoder

- Use 2 fully connected layers for the latent space, one for the mean and one for the variance
- Use the reparametrization trick to sample from the distribution
- Feed the sampled vector to the decoder
- loss = reconstruction loss + β KLD (formula in slide 7)
- What happens if β is too high?

LAB9 – Take home message

- Autoencoders do not require labels
- MSE smooths out images
- VAEs assume the prior of the latent space is N(0,1)
- The posterior is a normal distribution as well, since normal distributions are closed under conditioning
- VQ-VAE alleviate posterior collapse, at the expense of a discrete latent space
- Variational inference assumes the distribution family to make intractable problems tractable

Questions?

Remember:
no question is
stupid