TECHNISCHE UNIVERSITÄT DRESDEN

Fakultät für Elektro- und Informationstechnik, Professur für Grundlagen der Elektrotechnik und Elektronik

FliK Modul 2020

Autoencoder and VAE

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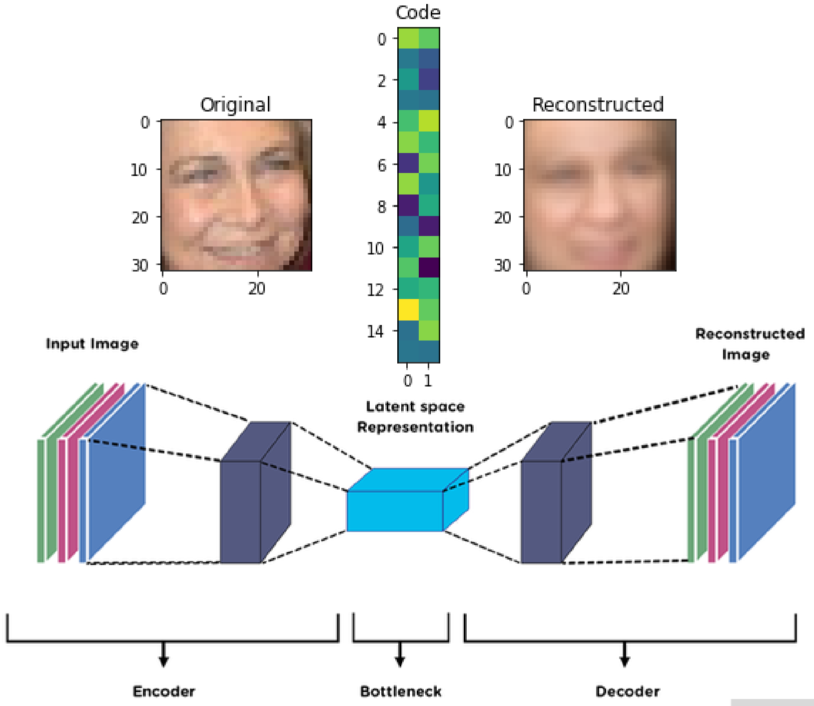
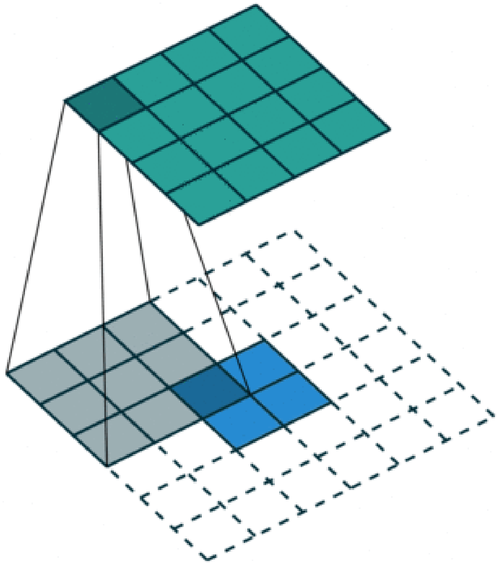
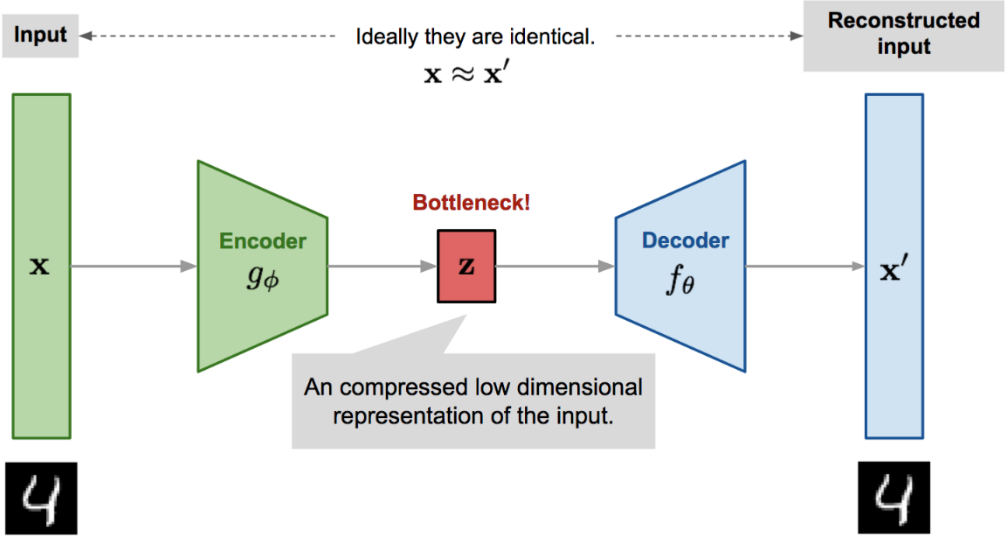
Autoencoder

Autoencoder use a different approach to solve neural network tasks. They usually try to **reconstruct** an e.g. an image through a bottleneck in the architecture. In CNN based Autoencoders the bottleneck is achieved by a series of **downsampling** (encoder) and upsamling /**transposed convolutions** (decoder)



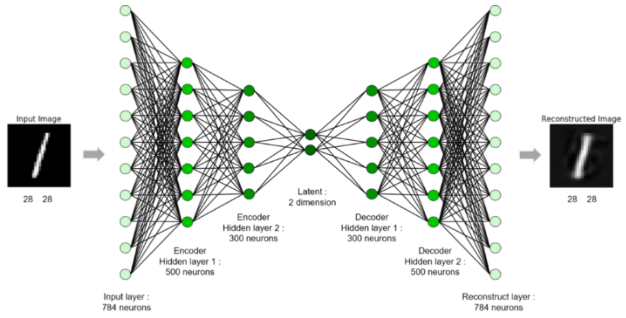
transposed convolutions



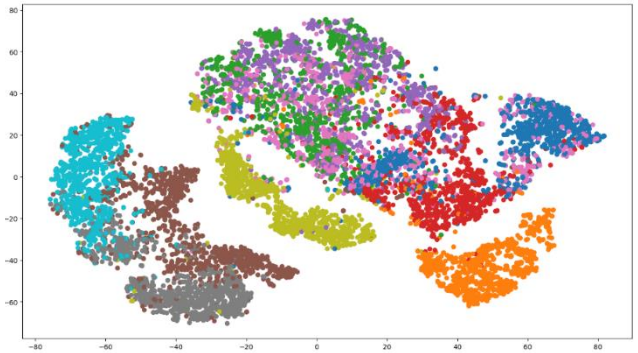


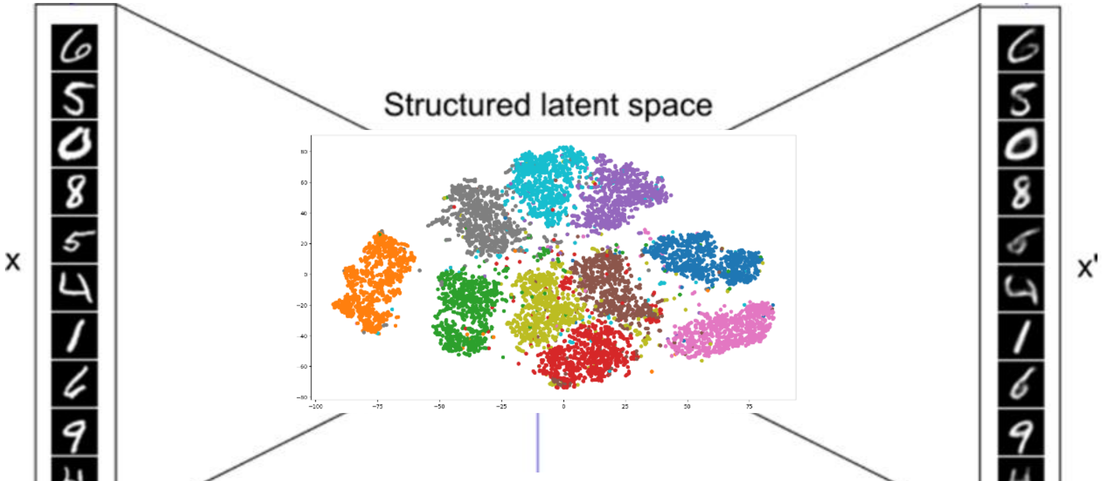
Autoencoder

The goal here is to receive a **latent representation** that best **explains the data**, requiring no supervised training at all! Autoencoder can be built by using **many Neural Network types**. Here we is one build up with standard Feed Forward Layers (e.g. Sigmoid Neurons)



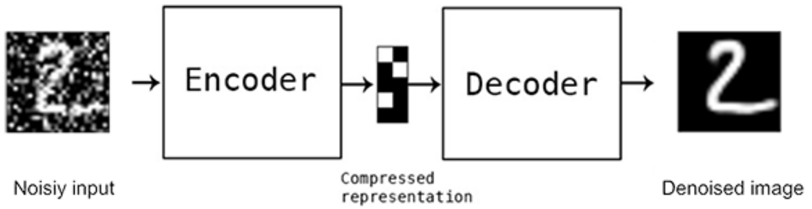
t-SNE pre AE encoder





t-SNE post AE encoder

The data prio to the AE doesn’t look nice at all! But **after passing** the **encoder** it is **well structured**! We will replicate those plots in the next exercise. A typical **use case** of an Autoencoder is **denoising**!

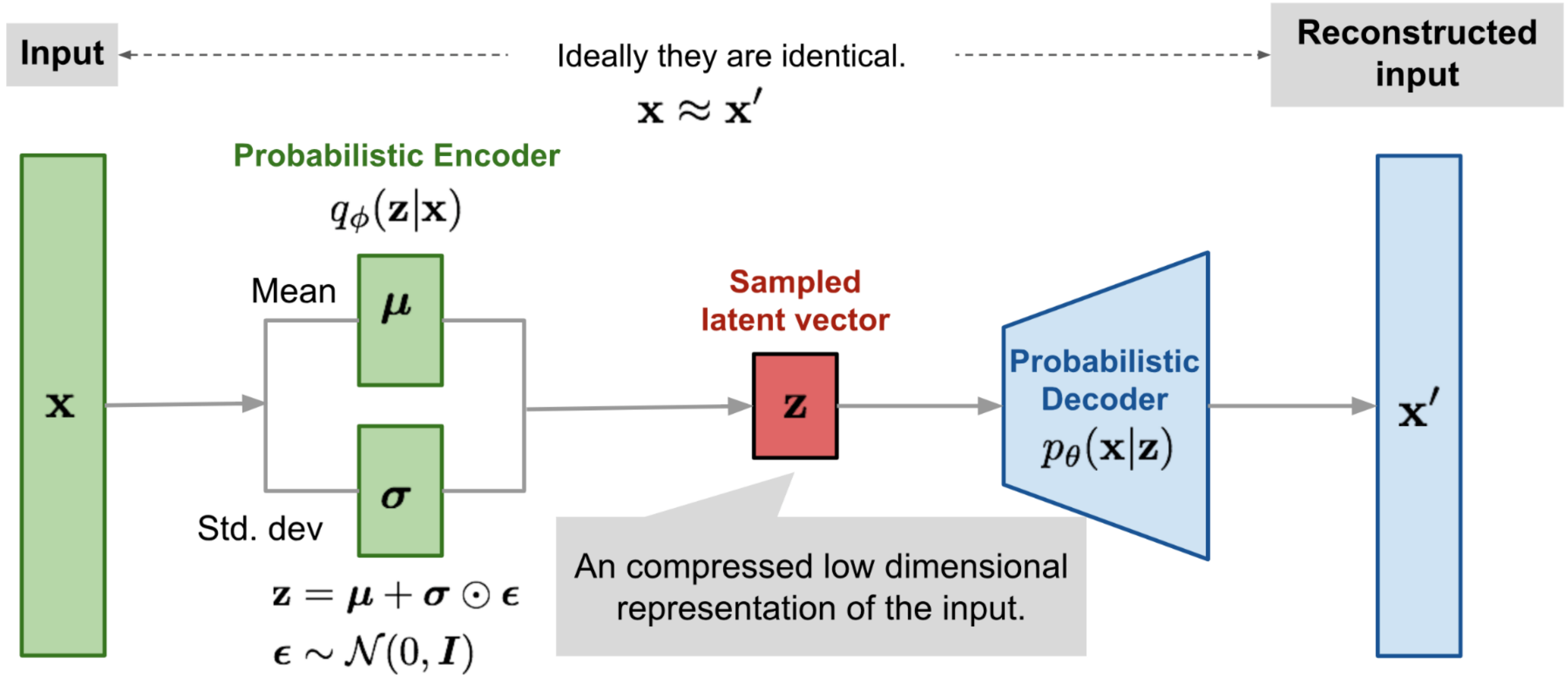


10. Exercise

Let‘s train our first Autoencoder for MNIST and FashionMNIST!

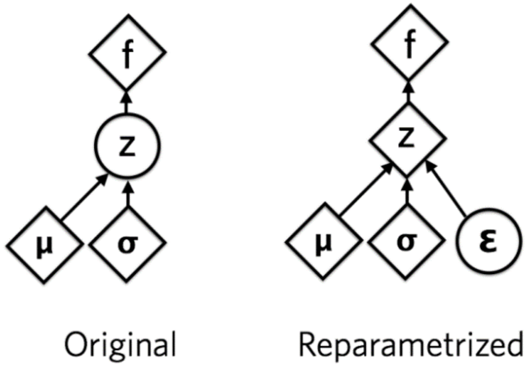
VariationalAutoencoder

Generative modeling instead of discriminative! Autoencoder is trying to estimate mu and sigma of a distribution!



Variational Autoencoder
Reparametrisation Trick

We can't backprogate though this network anymore as we pleased in the past. We need to use the **Reparametrisation Trick** by Kingma to so, because we can't backprop over a sampling process.



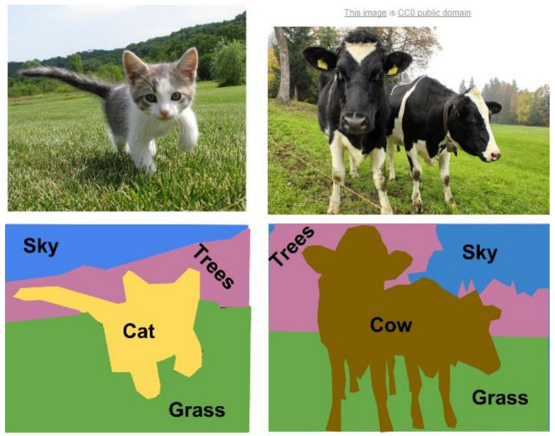
$$\text{Reparametrization Trick}: z = \mu + \sigma * \epsilon; \quad \epsilon \sim \mathcal{N}(0,1)$$

The trick is to **factor out** the sampling. Just multiplicate mu and sigma calculated by the network with a **predefined** (already sampled) image with mu =1 and sigma =0. The sampled image stay's the same over the hole training process it is a dummy just **scaled** by the **mu** and **sigma calculated** by the **network**! ☺

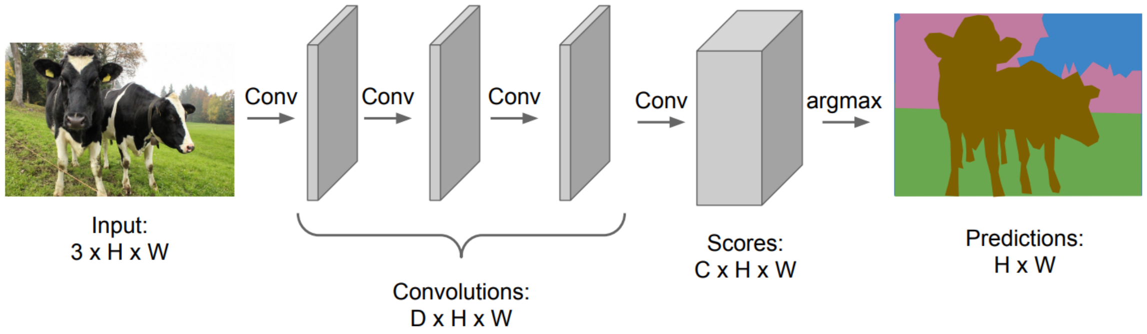
11. Exercise

Let‘s train our first Variational Autoencoder!

Image Segmentation

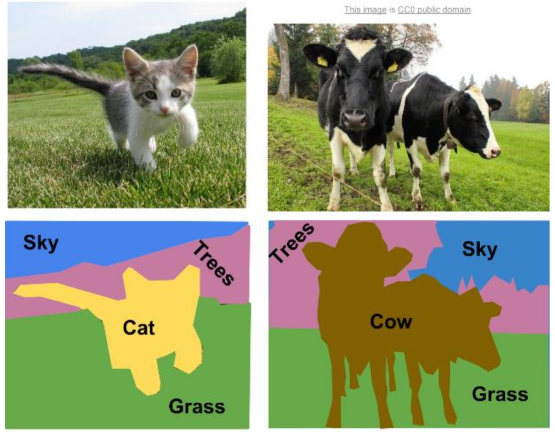


Today, Autoencoders have gained popularity in the task of **Image Segmentation**. For this task, **every pixel** is **labeled** with a class label, e.g. cow, tree, grass sky or cat. Thus we do **not care** about **detecting** any object, only about the label of all the pixels of the image.

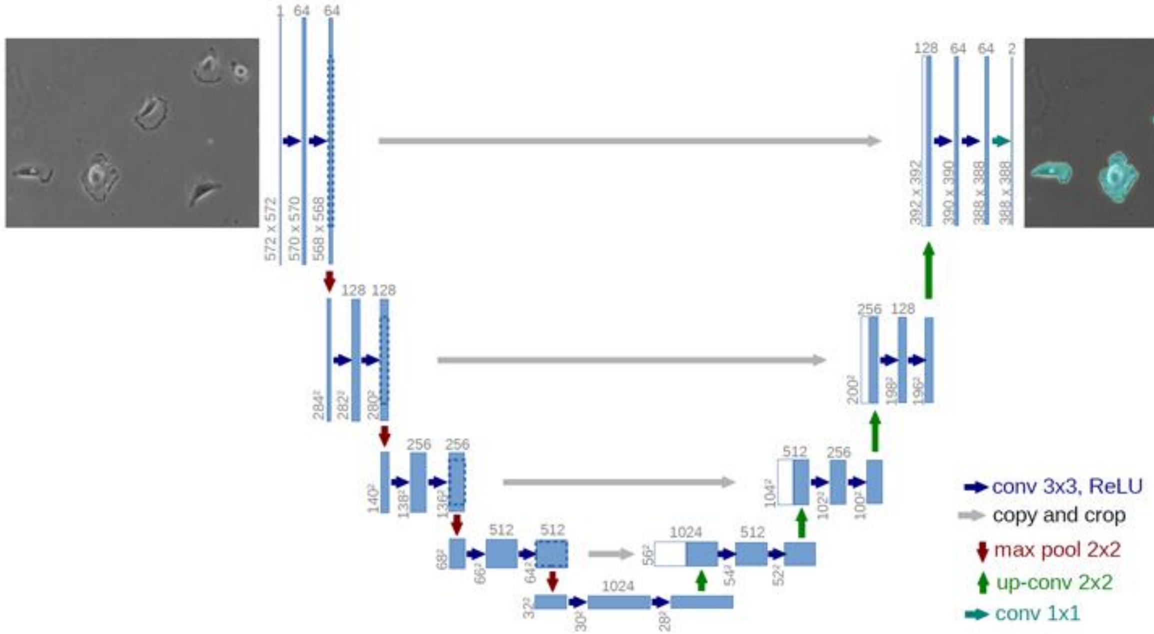


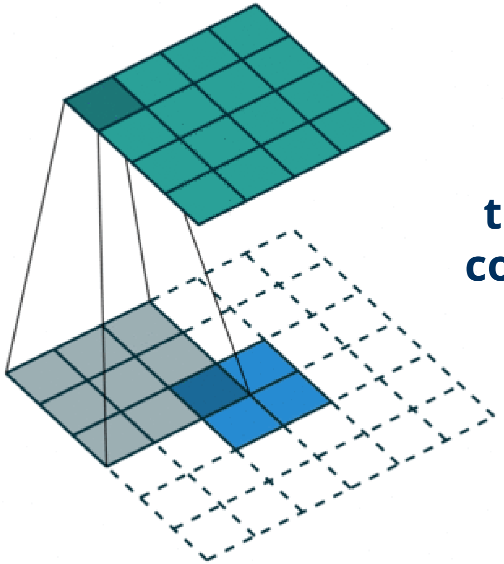
How about we **train** a fully convolutional network (=no MLP layer at the end) to make predictions for each pixel **all at once**? The problem with this approach is that (again) convolutions at the original image resolution will be **very expensive** and would take a lot of **memory**.

U-Net



Like an Conv. Autoencoder this architecture consists of a contracting path (**encoder**) to capture context and a symmetric expanding path (**decoder**). There are also **short-cut** paths which allows the network to propagate context information to higher resolution layers. But **in contrast** to the standard AE, **U-Net** uses a **supervised** mapping. The shape gives this network its U-Net name.





transposed convolutions

Extra

If time, train U-Net for cell segmentation in Uni-Warwick dataset!