AUTOENCODER : ENCODER-DECODER

Machine Learning Course CS460

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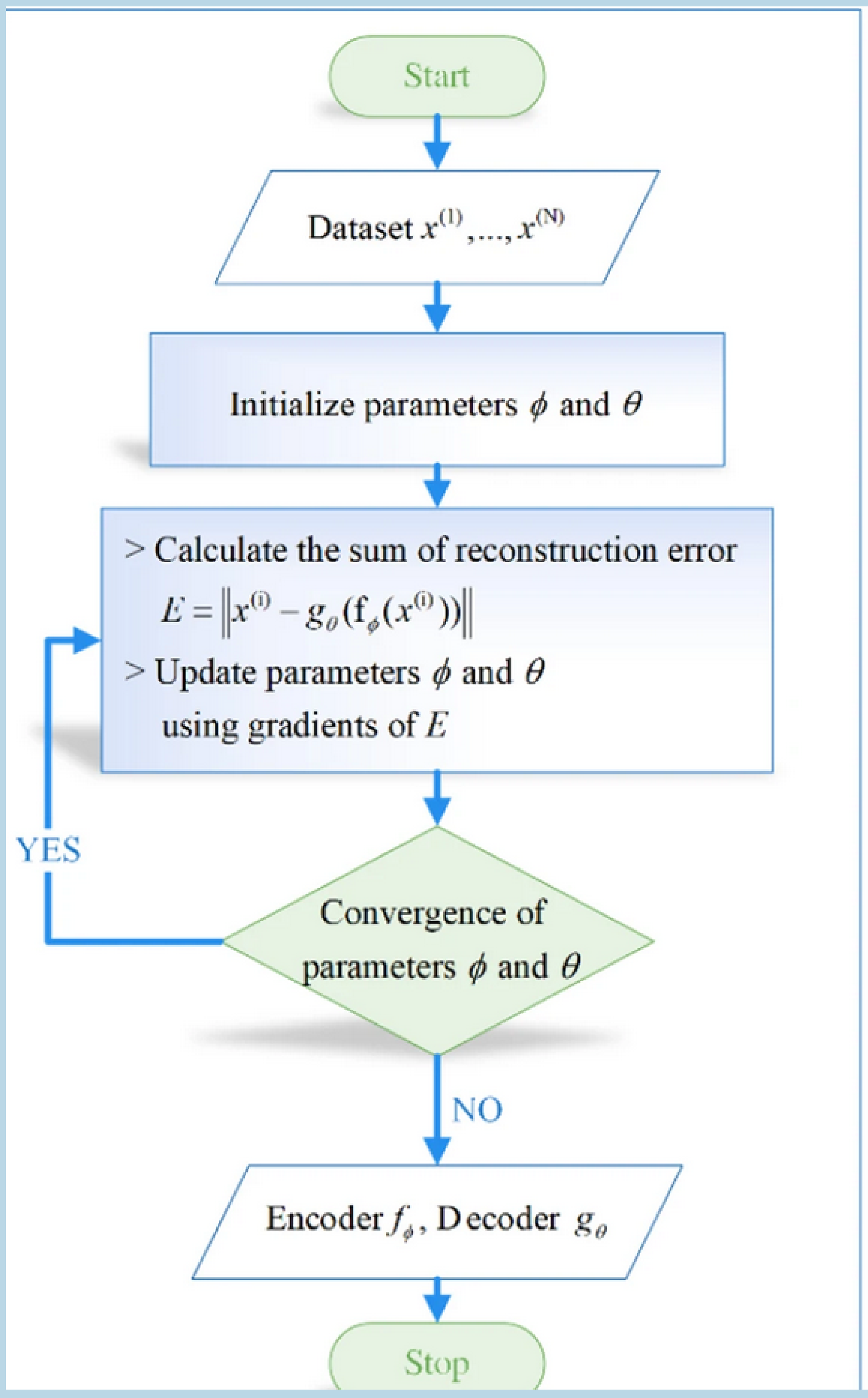
Types of Autoencoder

- **Denoising Autoencoder** : Denoising autoencoder works on a partially corrupted input and trains to recover the original undistorted image.
- **Sparse Autoencoder** : This contains more hidden units than the input but only a few are allowed to be active at once. This property is called the sparsity of the network.
- **Convulational Autoencoder** : The compression is achieved by applying convolutional layers to extract features from the input image and downsampling them to reduce the dimensionality.
- **Contractive Autoencoder**: It has a regularization term to prevent the network from learning the identity function and mapping input into the output.
- **Variational Autoencoder** :Variational autoencoders deal with this specific topic and express their latent attributes as a probability distribution, leading to the formation of a continuous latent space that can be easily sampled and interpolated. It allows us to learn smooth latent state representations of the input data.

Training



References

[1] orabi, H., Mirtaheri, S. L., Greco, S. (2023, January 4). Practical autoencoder based anomaly detection by using vector reconstruction error. Cybersecurity (Singapore).

[2] ttps://www.geeksforgeeks.org/auto-encoders/

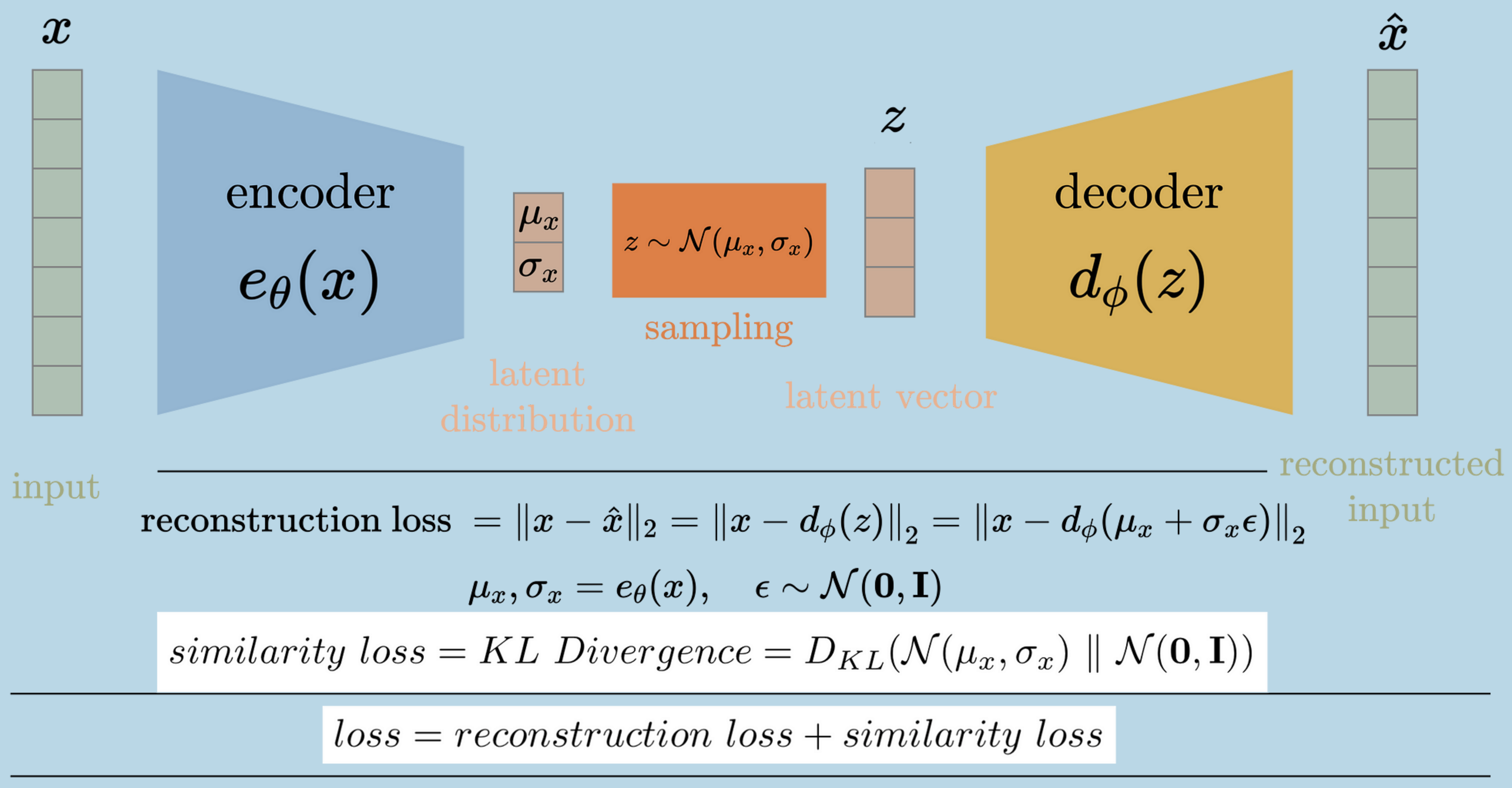
[3] ttps://en.wikipedia.org/wiki/Autoencoder

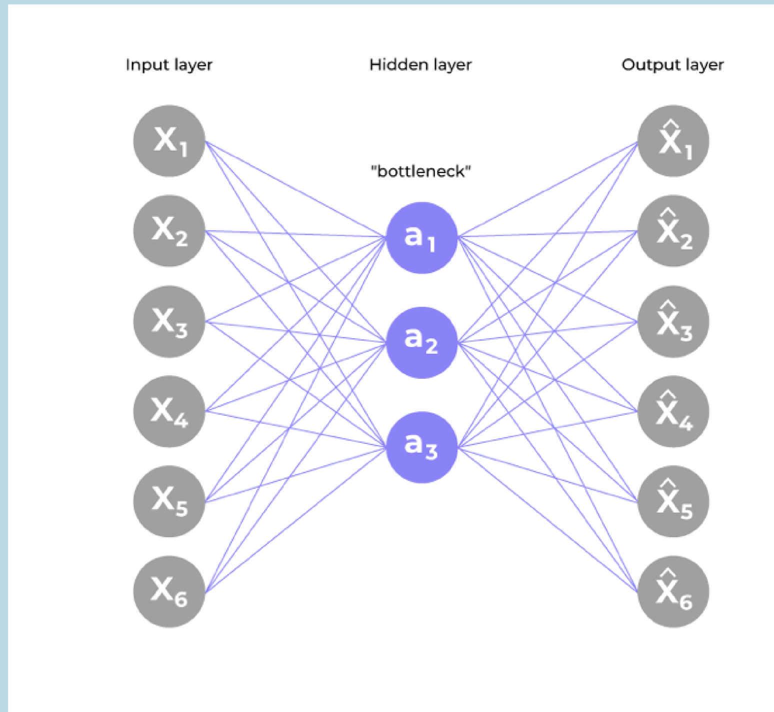
[4] ttps://analyticsdrift.com/creating-3d-images-from-2d-images-using-autoencoder/

[5] ttps://www.v7labs.com/blog/autoencoders-guide

Architecture of Autoencoder

Autoencoders are specialized class of algorithms that can learn efficient representations of input data with no need for labels. It is a class of artificial neural networks designed for unsupervised learning. This is accomplished using a two fold structure that consists of an **Encoder** and a **Decoder**.The encoder transforms the input data into a reduced dimensional representation, which is often referred to as **latent space** . The hidden layers progressively reduce the dimensionality of the input, capturing important features and patterns. The **bottleneck layer** is the final hidden layer, where the dimensionality is significantly reduced. This layer represents the compressed encoding of the input data and the decoder reconstructs the input.





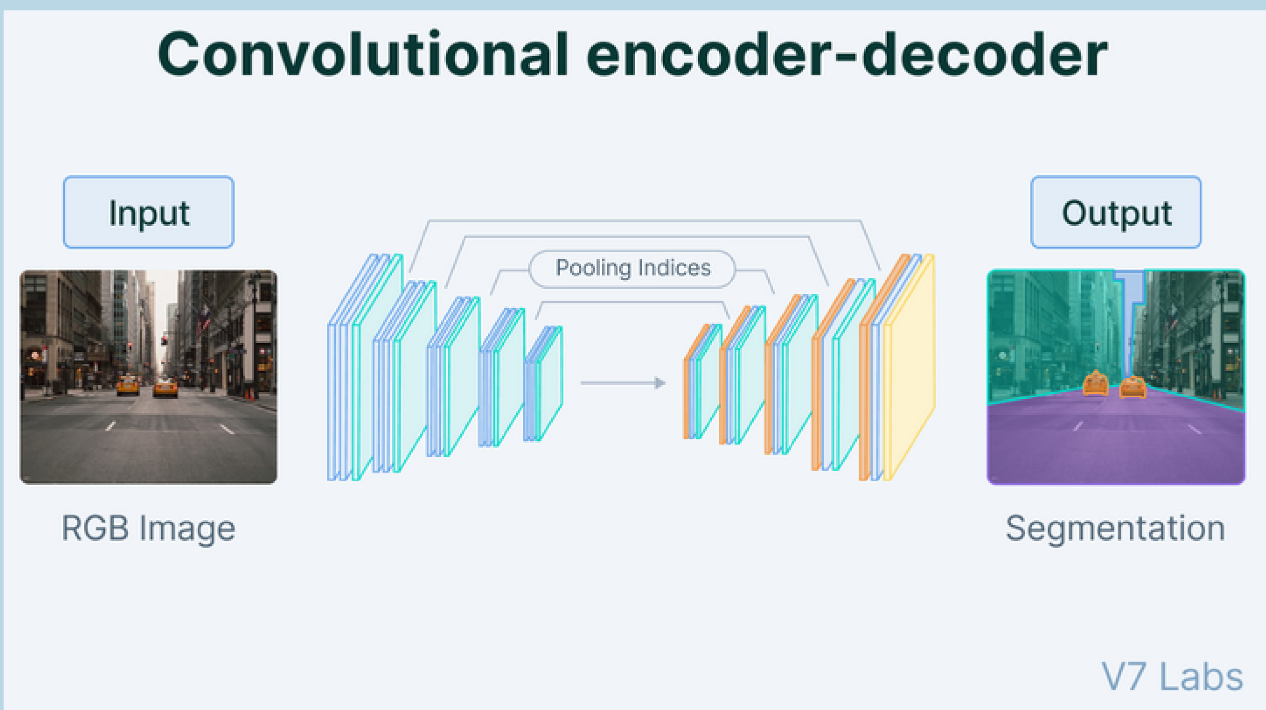
The loss function used during training is typically a **Reconstruction loss**, measuring the difference between the input and the reconstructed output. During training, the Autoencoder learns to minimize the reconstruction loss, forcing the network to capture the most important features of the input data in the bottleneck layer. The KL divergence loss prevents the network from learning narrow distributions and tries to bring the distribution closer to a unit normal distribution, Here N denotes the normal unit distribution and β denotes a weighting factor.

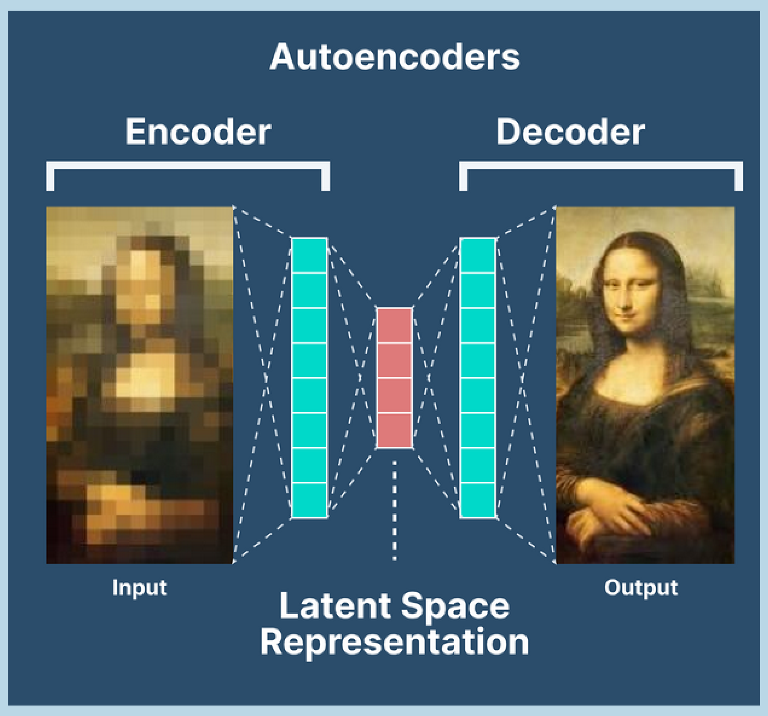
$$L = |x-\widehat{x}| + \beta \sum_i KL\left(q_j(z \mid x) \| N(0,1)\right)$$

Implementation of Autoencoder

Application of Autoencoder

- Feature extraction
- Dimension Reduction
- Missing value imputation
- Generate higher resolution data and colour the black and white input.
- Anomaly Detection





Case Study - Creating 3D image from 2D:

The researchers of the Visual Geometry Group, University of Oxford — Shangzhe Wu, Christian Rupprecht, and Andrea Vedaldi introduced unsupervised learning of symmetric deformable 3D objects from images in the wild. The idea behind the technique is to create 3D images of symmetric objects from single-view 2D images without supervising the process. The method is based on an Autoencoder.

In this work, an Autoencoder factors each input image into **Depth, Albedo, Viewpoint, and Illumination**. While the depth is to identify the information related to the distance of surfaces of objects from a viewpoint, albedo is the reflectivity of a surface. Along with depth and albedo, viewpoint and illumination are crucial for creating 3D images as well; the variation in light and shadow is obtained from the illumination with the changing angle/viewpoint of the observer. All the aforementioned concepts play an important role in image processing to obtain 3D images. They then ensured that the model estimates a confidence score for each pixel in the input image that explains the probability of the pixel having a symmetric counterpart in the image.