Introduction to the basics of AI - S10

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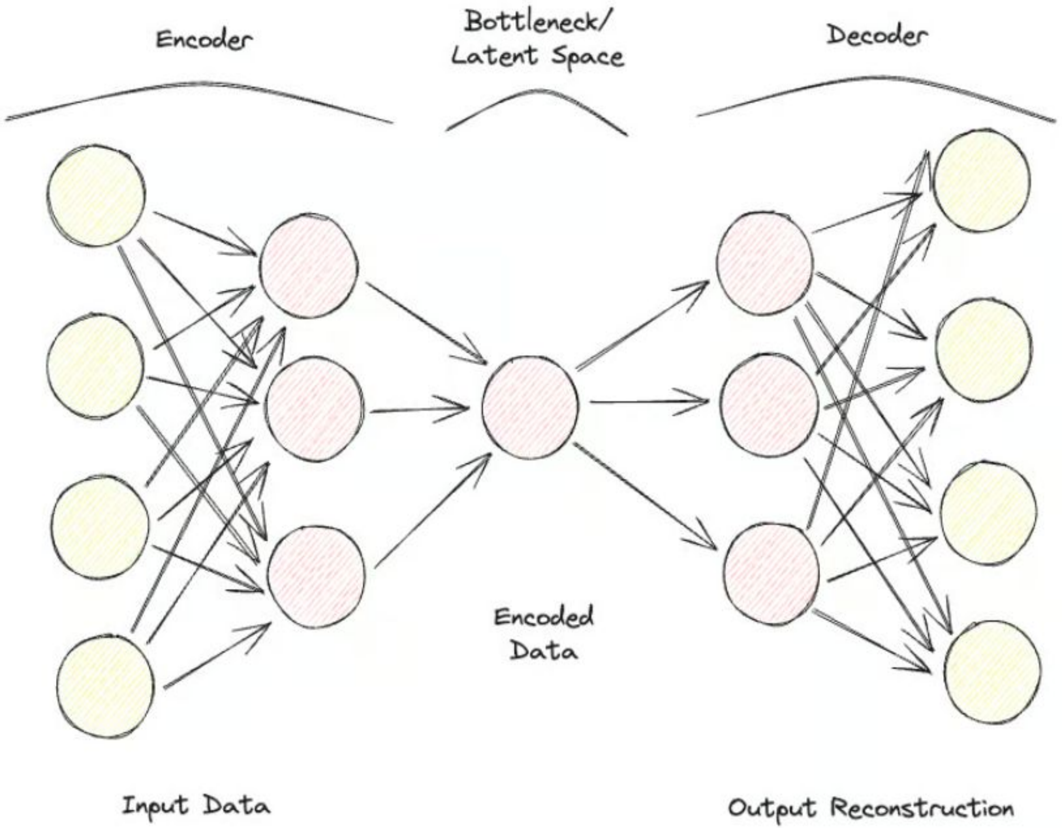
Outline for today’s course

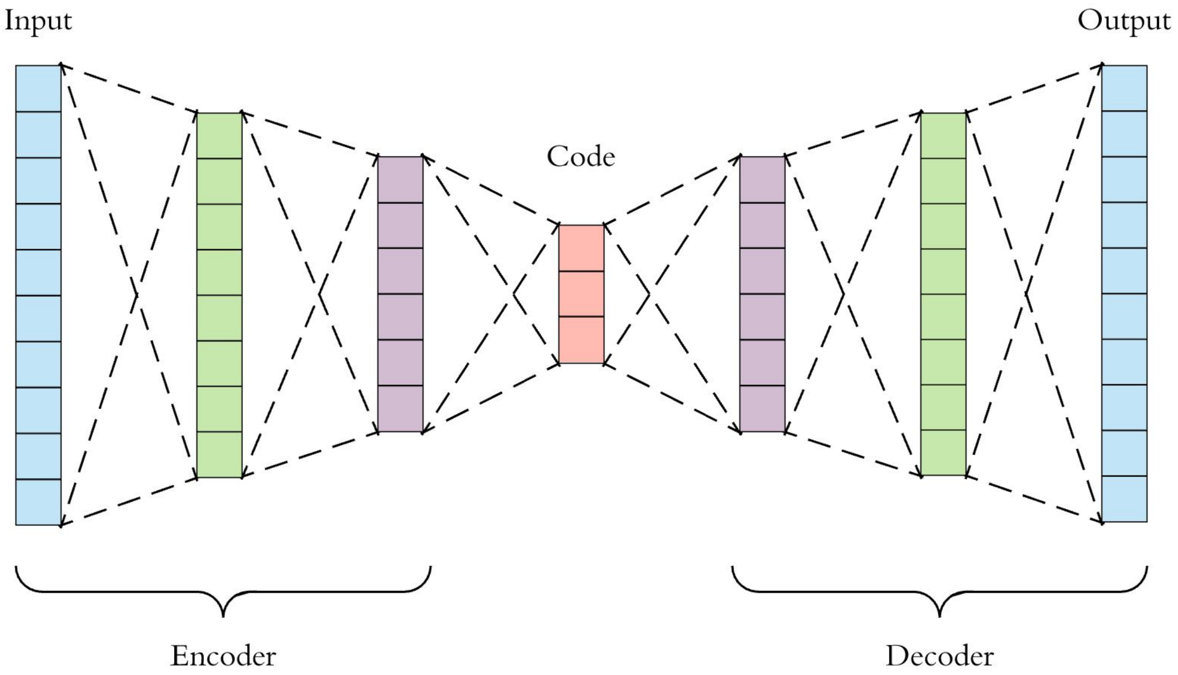
- Auto-Encoders
- CNN-Based Encoder-Decoder
- RNN-Based Encoder-Decoder
- Implementation

Auto-Encoders



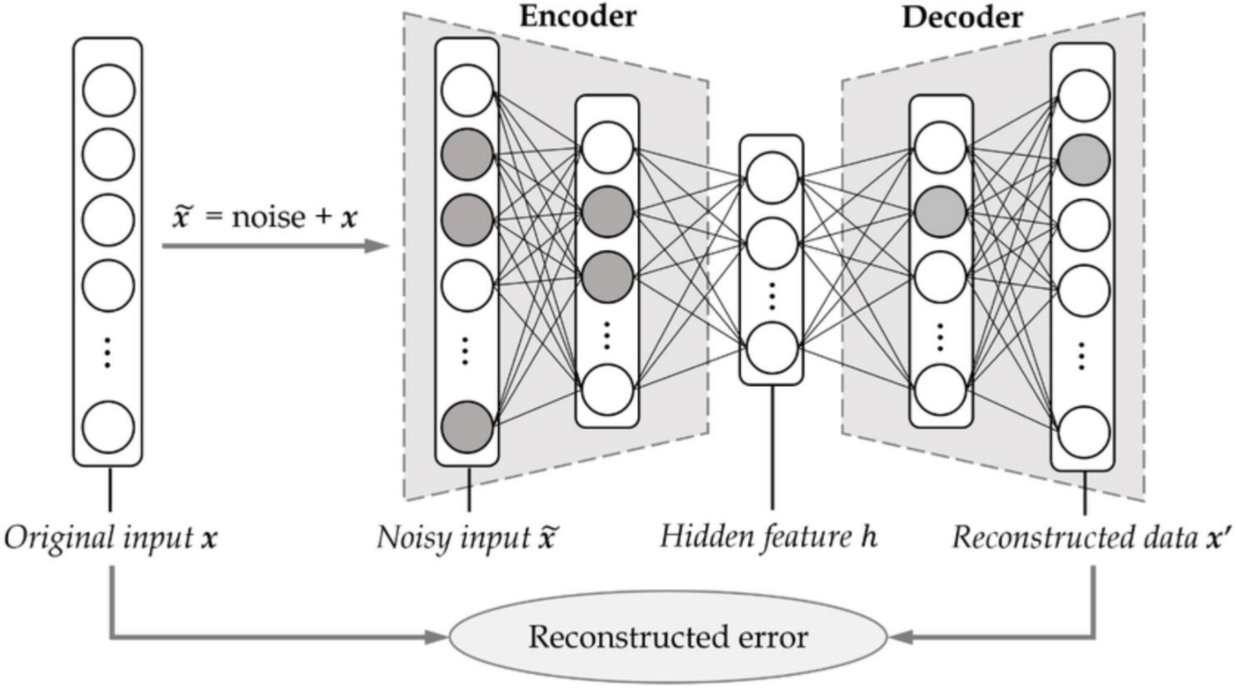
Auto-Encoders Types

- Vanilla Auto-Encoders



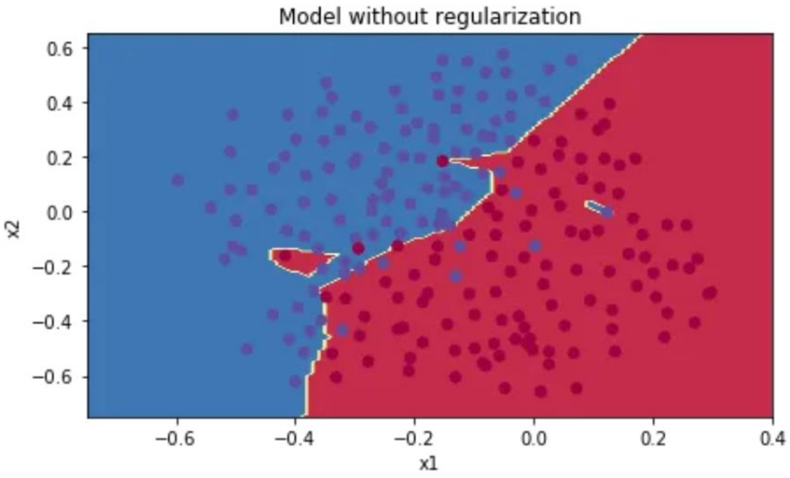
Auto-Encoders Types

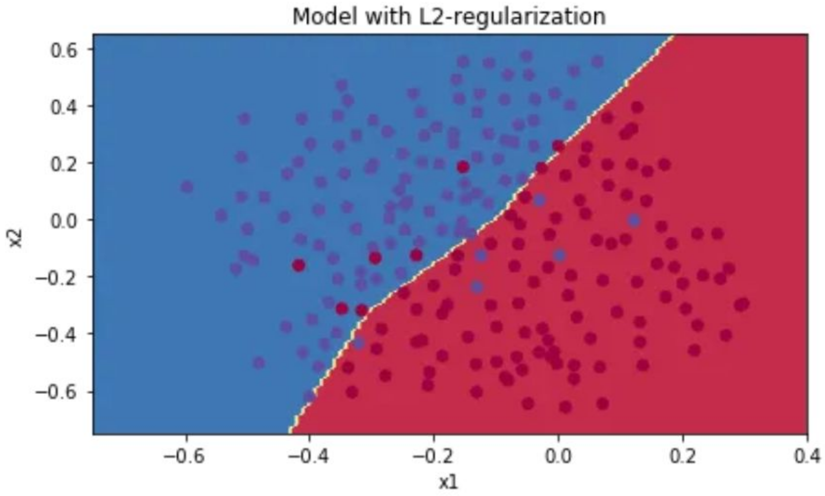
- Denoising Auto-Encoders



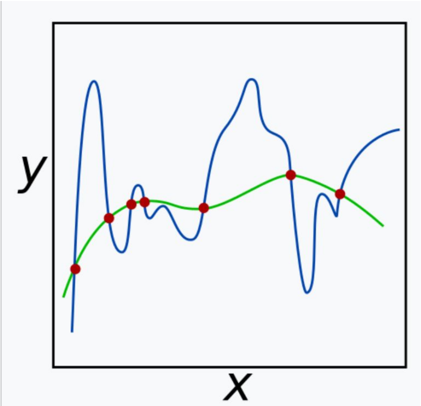
Auto-Encoders Types

- Sparse Auto-Encoders → Reminder of Regularization





Auto-Encoders Types

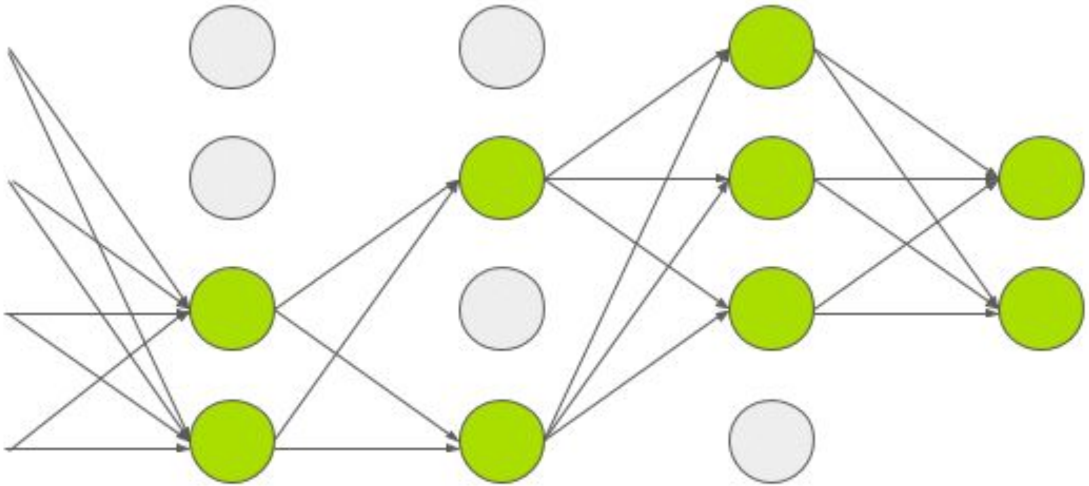


- Sparse Auto-Encoders → Reminder of Regularization

Types of Regularization

- Implicit
  - Dropout
  - Early Stop
- Explicit
  - Tikhonov
  - L_k Regularizers

Implicit Regularization: Dropout



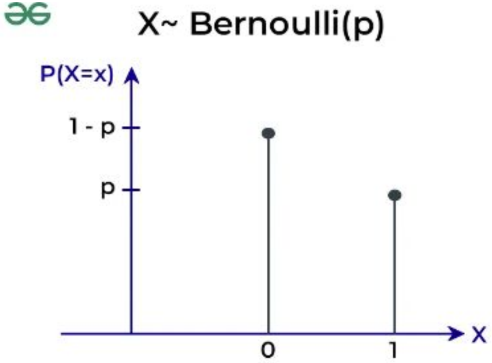
Explicit Regularization Terms

- L_2/Tikhonov $$J(W; X, y) + \lambda \cdot ||W||^2$$ $$w_i = w_i - \eta \left(\frac{\partial \text{Loss}}{\partial w_i} + 2\lambda w_i \right)$$

- LASSO/L1 $$J(W; X, y) + \lambda \cdot ||W||$$ $$w_i = w_i - \eta \left(\frac{\partial \text{Loss}}{\partial w_i} + \lambda \text{sign}(w_i) \right)$$

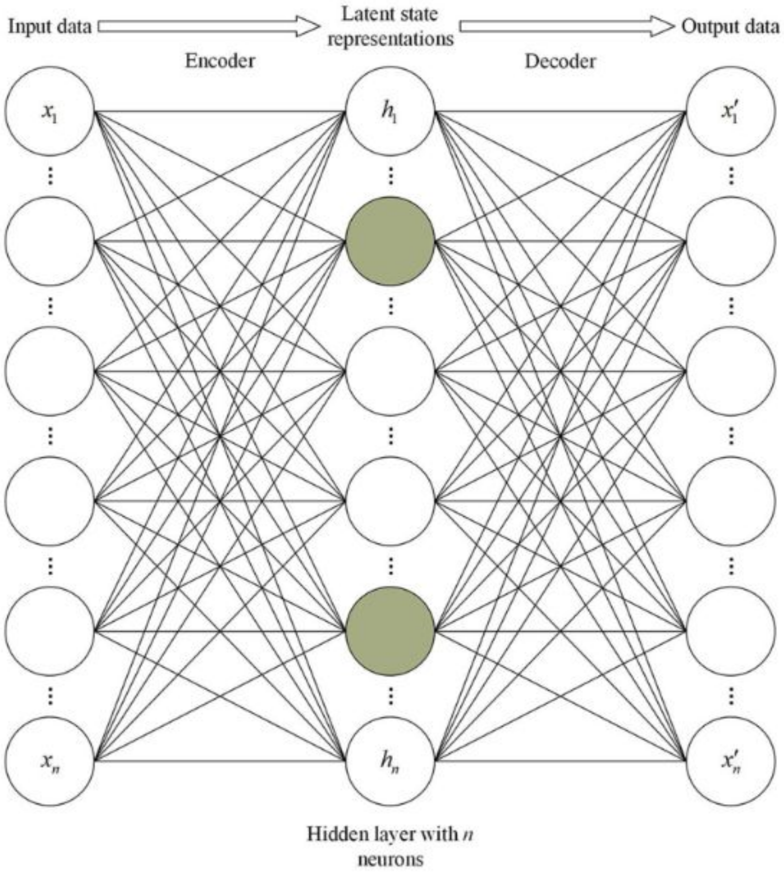
- Kullback-Leiber Divergence Regularization

$$J_{\text{sparse}}(W, b) = J(W, b) + \beta \sum_{j=1}^{s_2} \text{KL}(\rho || \hat{\rho}_j)$$

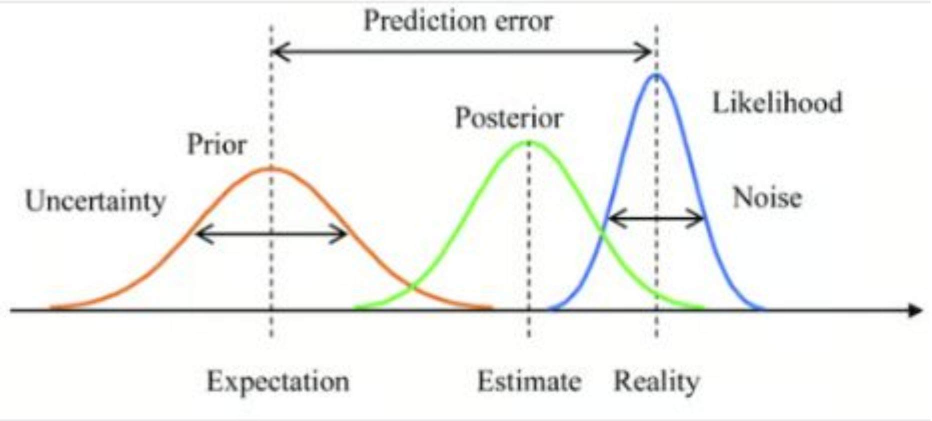


$$D_{\text{KL}}(P \parallel Q) = \sum_{x \in \mathcal{X}} P(x) \log \left(\frac{P(x)}{Q(x)} \right)$$

Sparse Auto-Encoders



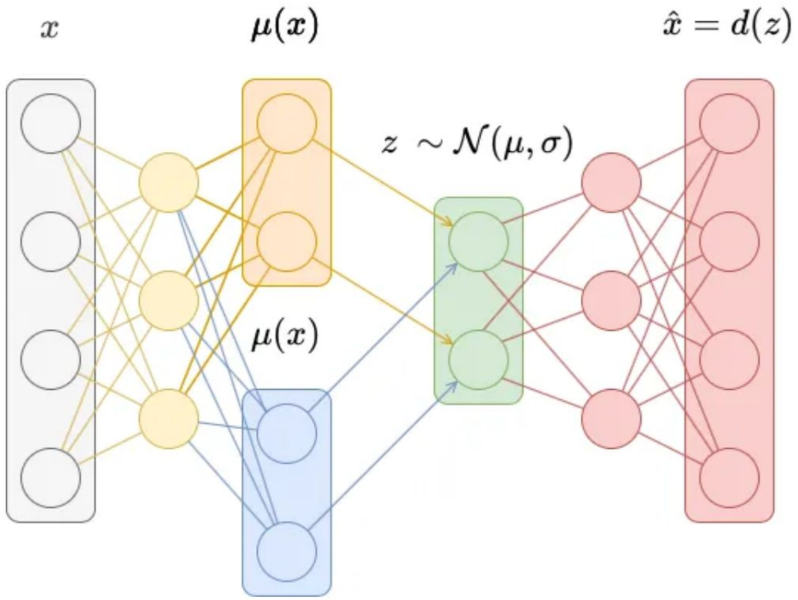
Variational Auto-Encoders



Here is how the process flow looks:

1. The input data x is fed into the encoder, which outputs the parameters of the latent space distribution $q(z/x)$ (mean μ and variance σ^2).
2. Latent variables z are sampled from the distribution $q(z/x)$ using techniques like the reparameterization trick.
3. The sampled z is passed through the decoder to produce the reconstructed data $\hat{x}$, which should be similar to the original input x.

Variational Auto-Encoders

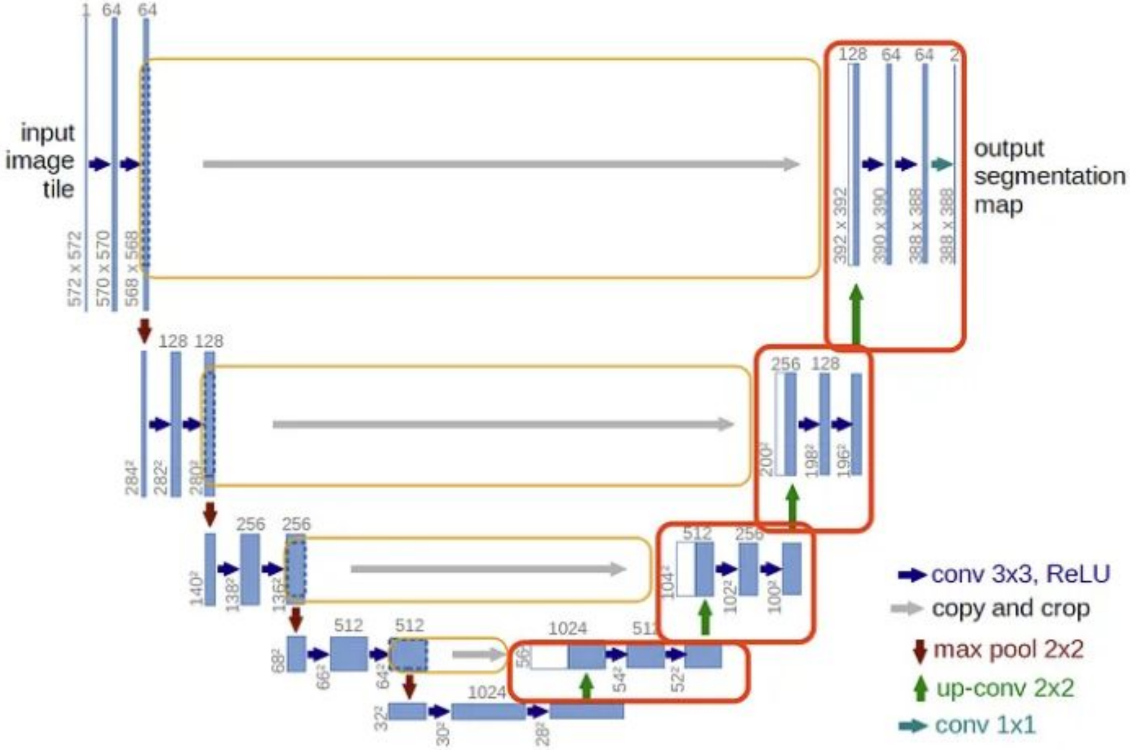


Variational Auto-Encoders

1. **The Distribution Trick:** Instead of a point in the latent space, the encoder of a VAE outputs the parameters that define a probability distribution (usually mean and variance). During training, we sample a point from this distribution to feed into the decoder.
2. **The Reparameterization Trick:** This is the clever part. Directly backpropagating gradients through random sampling is tricky. The reparameterization trick lets us express the sampled point in the latent space as a deterministic function of the distribution parameters and an external random variable. This allows for proper training.
3. **Loss Function: Beyond Reconstruction:** The VAE's loss function has two parts:

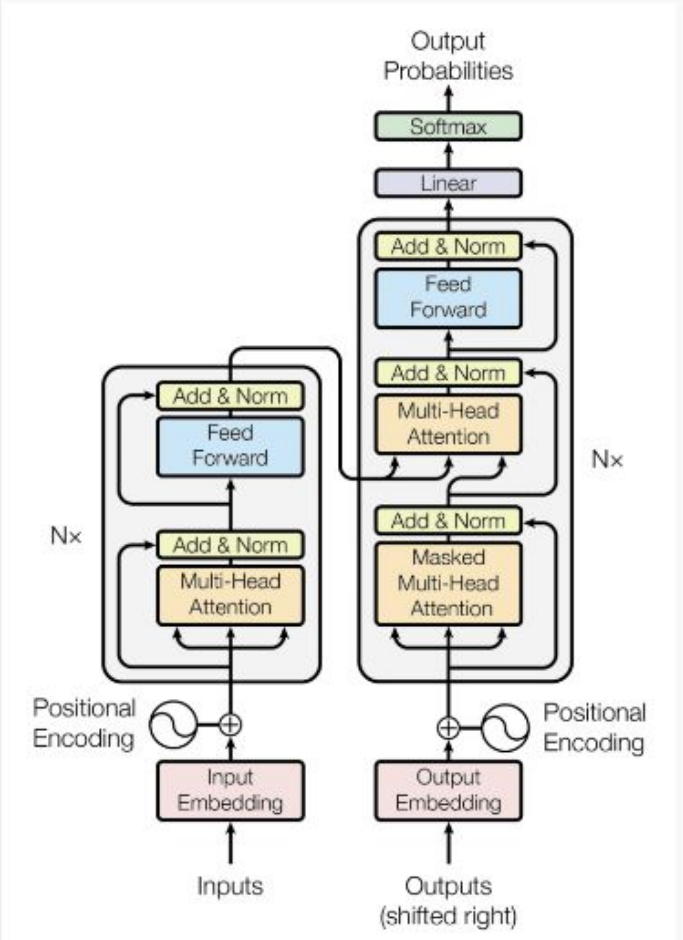
- **Reconstruction Loss:** Just like in an autoencoder, this part ensures that the decoder accurately reconstructs the input.
- **KL Divergence:** This is where the probabilistic twist comes in. The Kullback-Leibler (KL) divergence measures how much the encoder's learned distribution diverges from a standard prior distribution (often a standard Gaussian). This encourages a well-structured, regular latent space.

U-Net



input image tile
output segmentation map
conv 3x3, ReLU
copy and crop
max pool 2x2
up-conv 2x2
conv 1x1

Transformer



Tutorials

https://www.geeksforgeeks.org/sparse-autoencoders-in-deep-learning/

https://github.com/Jackson-Kang/Pytorch-VAE-tutorial/tree/master

Resources

https://www.datacamp.com/tutorial/introduction-to-autoencoders

https://medium.com/towards-data-science/understanding-autoencoders-with-an-example-a-step-by-step-tutorial-693c3a4e9836

https://medium.com/@tallaswapna9/types-of-autoencoders-in-deep-learning-383cfecc4d0e

https://www.researchgate.net/figure/The-overall-structure-of-a-denoising-autoencoder_fig2_331620099

https://en.wikipedia.org/wiki/Regularization_(mathematics)

https://medium.com/towards-data-science/understanding-the-scaling-of-l%C2%B2-regularization-in-the-context-of-neural-networks-e3d25f8b50db

https://web.stanford.edu/class/cs294a/sparseAutoencoder.pdf

https://www.researchgate.net/figure/Architecture-of-the-sparse-auto-encoder_fig3_344423909

https://arxiv.org/pdf/1906.02691

https://medium.com/@weidagang/demystifying-neural-networks-variational-autoencoders-6a44e75d0271