



# Lecture 9: Autoencoders

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CIS 6217 – Computer Vision for Data Representation

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# Outline

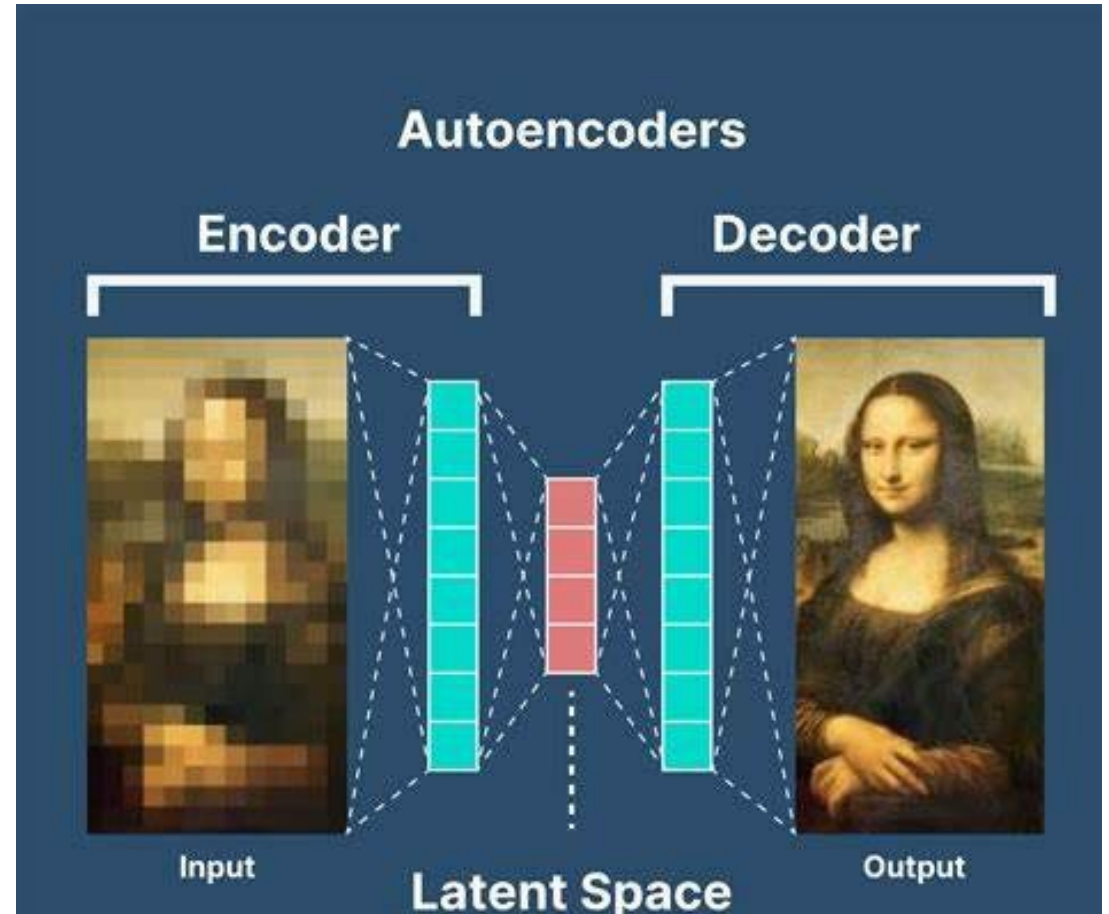
1. Autoencoders
2. Stochastic Encoders and Decoders
3. Denoising Autoencoders
4. Contractive Autoencoders

# ● Learning Outcomes

1. Explain generative modeling concept and purpose in vision
2. Describe architecture and working of GANs
3. Differentiate **generator** and **discriminator** networks
4. Discuss GAN training and evaluation methods
5. Explore generative models in visual creativity and AI applications

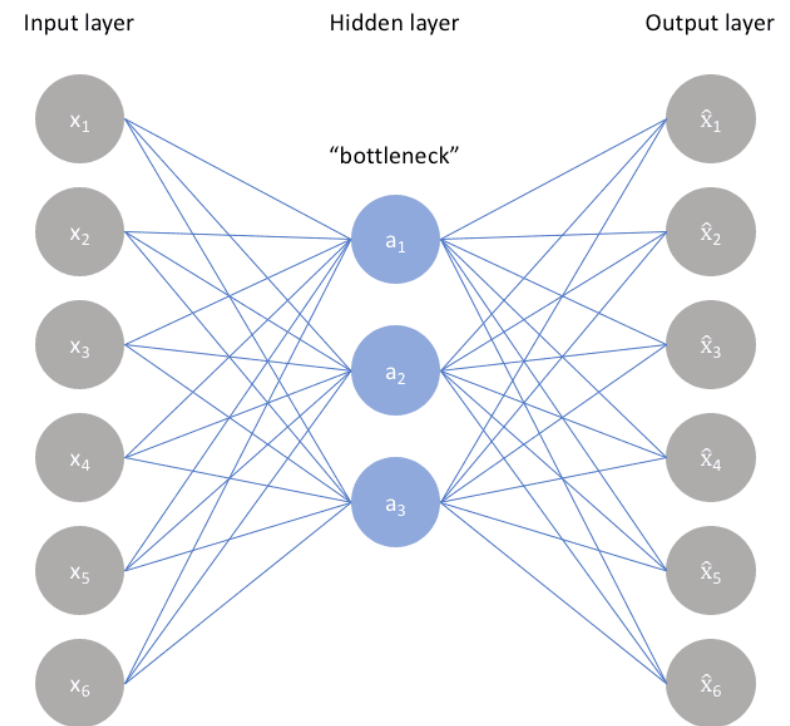
# What is Autoencoder?

- An **autoencoder** is a neural network trained to **reconstruct its input**, learning a compressed representation called the **latent code**.



# Autoencoder Architecture

- Encoder
- Bottleneck
- Decoder



*Autoencoders in Deep learning: Tutorial & use cases [2024]. V7. (n.d.).*  
<https://www.v7labs.com/blog/autoencoders-guide>

# Training Autoencoders

Four Hyperparameter

- Code Size
- Number of Layers
- Number of nodes per layer
- Reconstruction Loss

# ● Loss Functions in Autoencoders

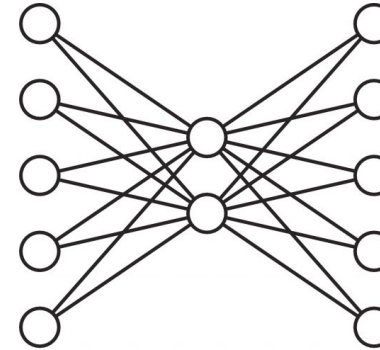
- Measures the difference between the original input and reconstructed output.
  - Mean Squared Error (MSE) – continuous data
  - Binary Cross-Entropy (BCE) – binary-probability-based data
  - Kullback-Leibler divergence - quantifies the difference between two probability distributions

# Types of Autoencoders

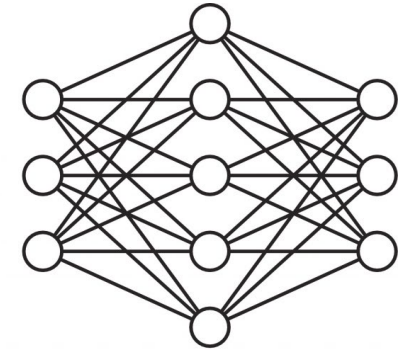


# Undercomplete Vs Overcomplete Autoencoders

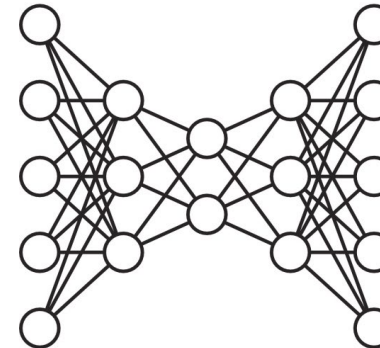
- Undercomplete:
  - Latent dimension smaller than input dimension
- Overcomplete
  - Latent dimension equal or larger than input dimension



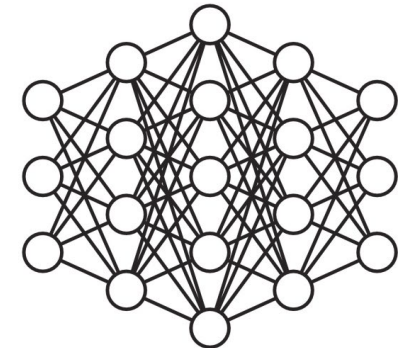
(a) Shallow undercomplete



(b) Shallow overcomplete



(c) Deep undercomplete



(d) Deep overcomplete

# ● Stochastic Encoder and Decoders

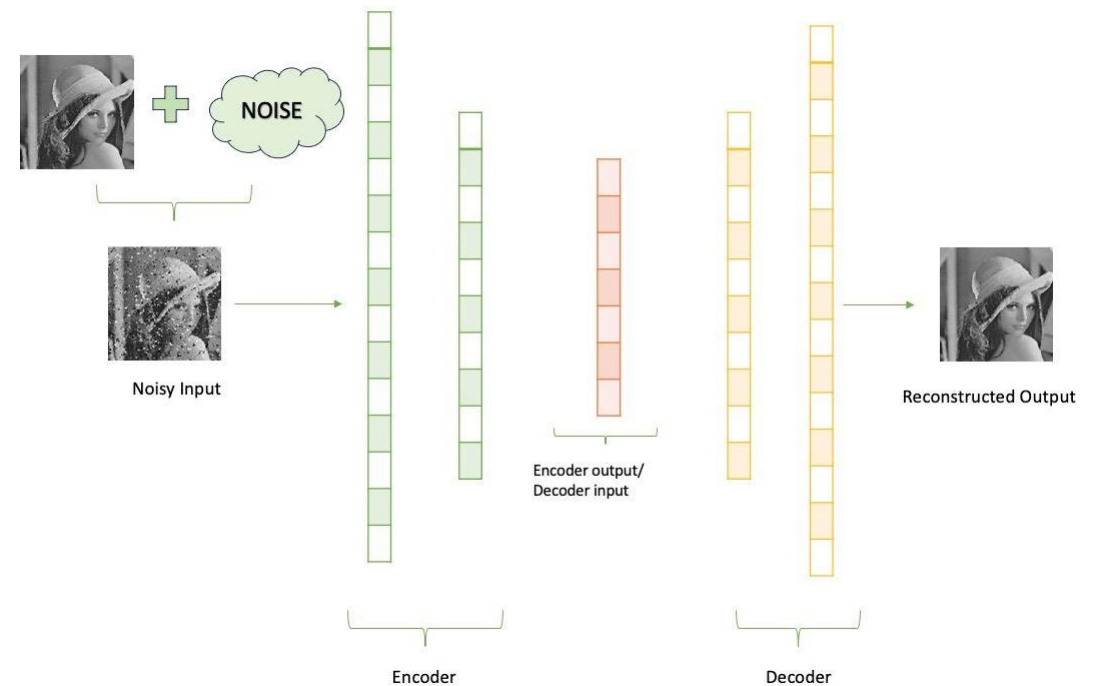
- The encoder maps to a distribution
- Introduces uncertainty
- Enables smooth generative latent spaces
- Prevents overfitting by injecting randomness
- Basis for Variational Autoencoders (VAEs)

# ● Architecture of Stochastic Autoencoder

- Stochastic Encoder: Instead of learning a single, fixed-size latent vector, a stochastic encoder learns the parameters of a probability distribution that represents the input data.
- Stochastic Decoder: The decoder receives a latent vector ( $z$ ) sampled from the encoder's distribution and reconstructs the original input data probabilistically.

# ● Denoising Autoencoders

- Force the network to reconstruct the **clean** input from a **corrupted** version.
- **Types of noise:**
  - Gaussian noise
  - Salt-and-pepper noise
  - Masking noise (randomly zero-out pixels)



# ● Contractive Autoencoders

- The idea behind that is to make the autoencoders robust to small changes in the training dataset.
- This is achieved by modifying the loss function as follows:
  - The first term is the reconstruction loss
  - The second term is the regularization term, which measures the sensitivity of the encoded representations to the input. By penalizing the sensitivity, the CAE learns to produce encodings that do not change much when the input is perturbed slightly.

# ● Comparison

Variant	Main Idea	Goal	Strength
<b>Basic Autoencoder</b>	Reconstruct input	Compression	Simple, fast
<b>Stochastic Encoder/Decoder</b>	Output distributions	Uncertainty modeling	Foundation for VAEs
<b>Denoising Autoencoder</b>	Reconstruct clean input from noise	Robustness	Learns essential features
<b>Contractive Autoencoder</b>	Penalize encoder sensitivity	Smooth latent space	Strong regularization



# ● Applications

- Image compression
- Feature extraction
- Image denoising
- Anomaly/outlier detection

# ● References

- Guide to CNNs for CV – Khan et al. (2018)
- Deep Learning with Python – Chollet (2018)
- Deep Learning in Computer Vision – Awad & Hassaballah (2020)
- Deep Learning for Vision Systems by Mohamed Elgendy (2020)