

CAP5415 Computer Vision

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HEC-241



Features — II Autoencoder

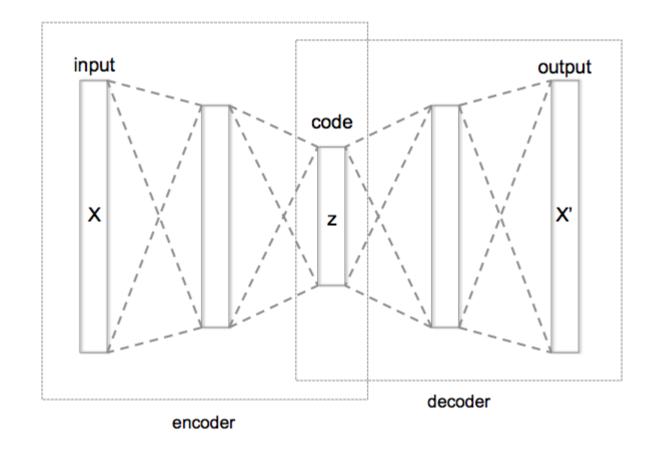
Lecture 10



- Reproduce the input
 - Via learning features
- Unsupervised learning
 - No labels required
 - Efficient way to learn features
 - Still need a loss function implicit supervision
- Supervised learning
 - Need labels/annotations



- Encoder decoder
- Encoding
 - Key idea

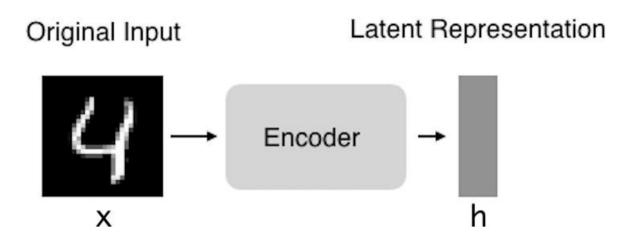




- Compare PCA/SVD
 - PCA produce smaller set of vectors
 - Very efficient for certain applications.
- Autoencoder
 - Can learn nonlinear dependencies
 - Can use convolutional layers
 - Can use transfer learning

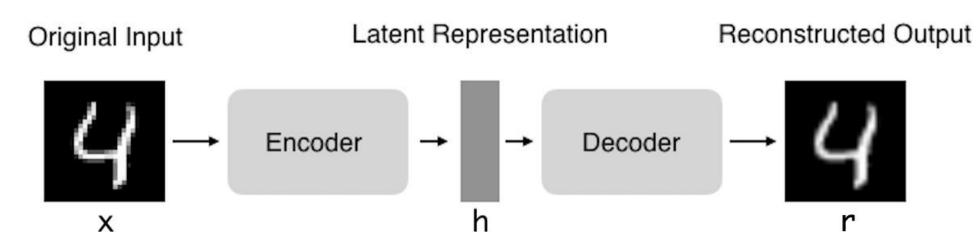


- Encoder: h = f(x)
 - Compress input into a latent-space
 - Usually smaller dimension
- Decoder: r = g(f(x))
 - Reconstruct input from the latent space



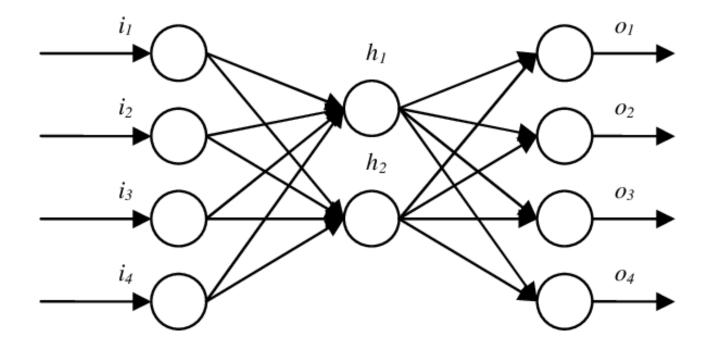


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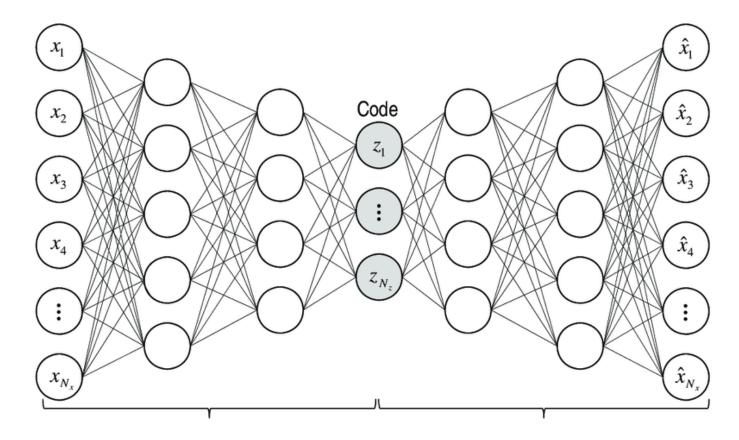


Shallow



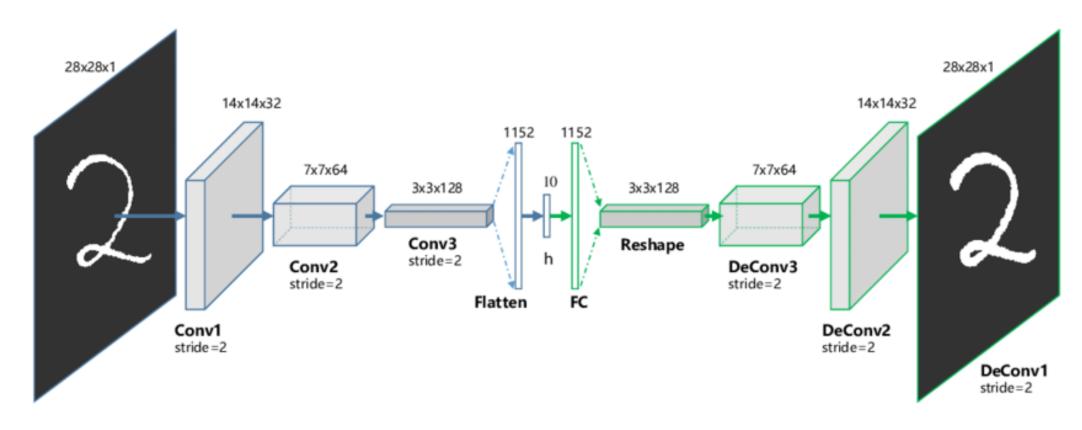


Deep



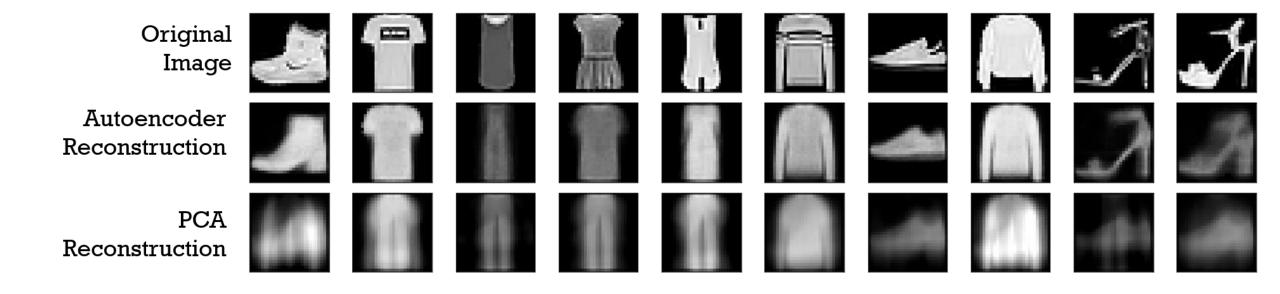


• CNN





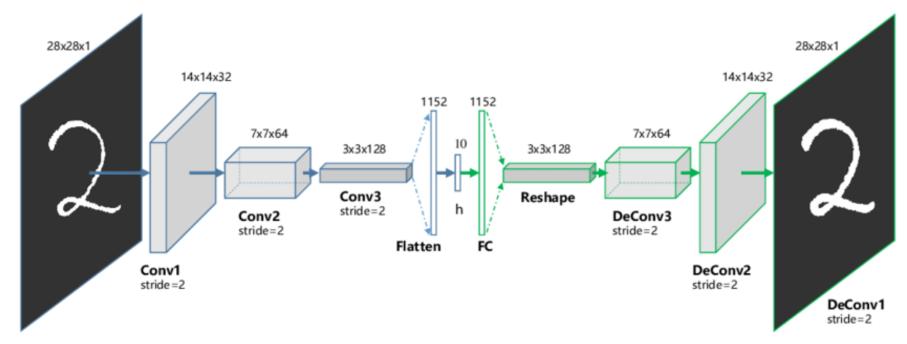
- Reconstruction
 - Latent vector of size 2
 - Compression from 28x28





Feature learning

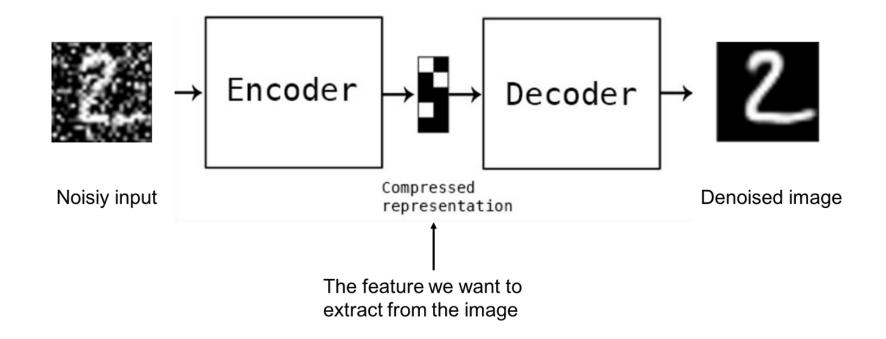
- Define a loss function
 - e.g., MSE.
- Optimize





Autoencoder – application

Denoising





Autoencoder – application

• Image colorization







Autoencoder – application

Anomaly detection

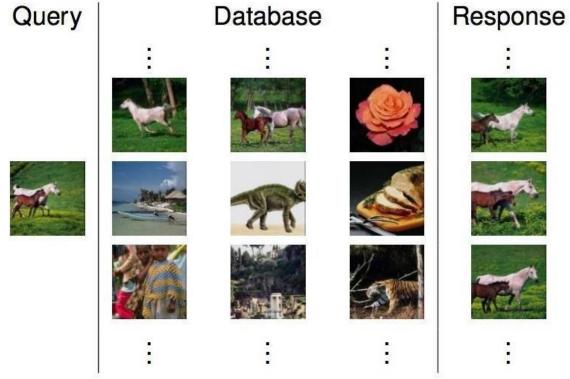






Feature learning

- Image retrieval
 - Dimensionality reduction helps





Properties of autoencoder

- Data-specific (similar data)
 - Compress data similar to what they have been trained on
 - Auto encoder deals outdoor and indoor data differently
- Lossy (loss fine details of image)
 - Outputs will be degraded compared to the original inputs
 - It is not matter in case of just extracting features
- Learned automatically from examples
 - It is easy to train
 - It will perform well on data similar to training samples
- Compare with hand-crafted features
 - Easy to understand



Questions?