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Artificial Neural Networks - Auto-Encoders

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Autoencoders

- **Artificial Neural Networks**
  - Trained to reconstruct it’s input in an unsupervised manner
  - Learns efficient data encodings
  - Generalization of Principal Component Analysis:
    - Learns a non-linear manifold

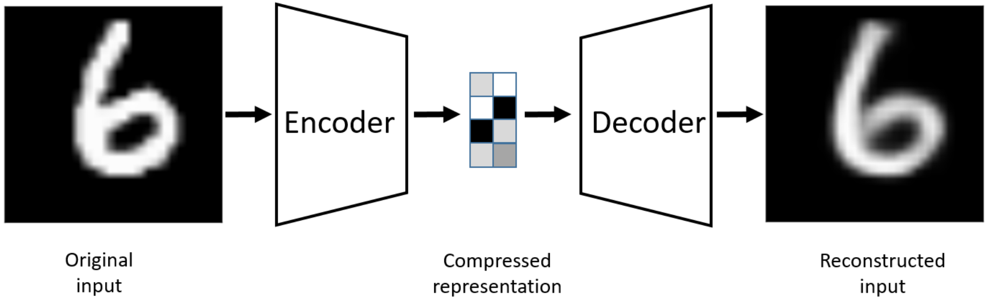


*Fig: Autoencoder example **

- **Tasks undertaken:**
  - A reduction network, that encodes the data
  - A reconstruction network, that generates the original information from the encoding

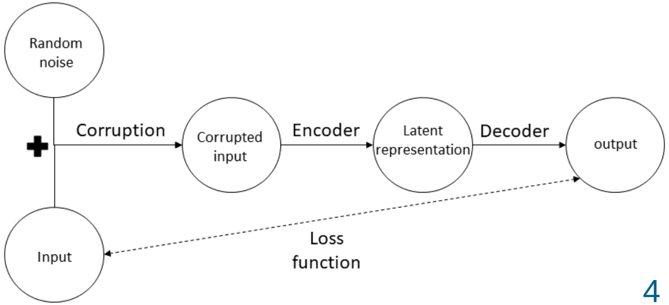
Types of Autoencoders

- **Regularized Autoencoders**
  - Encoders can simply learn the identity function
    - Given enough capacity of the encoder and the decoder, overfitting can occur (to the point where the network encodes input to an index)
  - Hence, the overfitting issue needs to be tackled
    - Traditionally, a ***bottleneck*** is imposed, which also provides low dimensional representation of the data. However, it can still cause overfitting.
  - Tackles the bias-variance tradeoff:
    - Reducing the reconstruction error vs. Generalizing the lower dimensional representation
- **Variational Autoencoders**
  - Generative models
    - Describes the generation of the data using probabilistic distributions.
    - Reflects the underlying causal relations, that have the potential for good generalization
  - Directed probabilistic graphical models (DPGM)
    - Whose posterior is approximated by a neural network, forming an autoencoder-like architecture

Regularized Autoencoders

- **Sparse Autoencoders**
  - Enforces sparsity on the hidden activation layers to deal with overfitting
    - Can be combined with bottleneck enforcement as well, of required
  - Similar to ordinary regularization, where they are applied on the activations instead of the weights
  - Two primary strategies:
    - *L1 Regularization*, which induces sparseness
    - *KL-Divergence,* which is a measure of the distance between two probability distributions

- **Denoising Autoencoders**
  - Can be either a regularization option, or a robust autoencoders for error correction
    - Input is disrupted by some noise
      - Using additive white Gaussian noise or Dropouts
    - Autoencoder is trained to reconstruct the clean version of the input



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Regularized Autoencoders

- **Contractive Autoencoders**
  - Maps a neighborhood of input points to a smaller neighborhood of output points
  - Conditions the encoder be resistant to perturbations of the input
    - Emphasis on making the feature extraction less sensitive to small perturbations
    - Forces the encoder to disregard perturbations that are not important for reconstruction by the decoder
  - The regularizer corresponds to the L2-norm minimization of the Jacobian matrix of the network's activations with respect to the input
    - Penalty imposed on the Jacobian of the network, forces the model to learn useful information about the training distribution
    - The latent representations of the input tend to be similar, thus making reconstruction difficult
    - Variations in the latent representation not important for reconstruction would be diminished by the regularization, while important variations would remain due to their impact on reconstruction error

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Variational Autoencoders

- VAEs are generative models that follow Variational Bayes (VB) Inference
  - Describe data generation through a probabilistic distribution
  - Equivalent to a probabilistic decoder
- A ***Reparameterization Trick*** is applied to estimate the variational lower bound
  - Results in an additional loss component and the Stochastic Gradient Variational Bayes (SGVB) estimator for the training algorithm

Advanced autoencoder techniques

- Autoencoders can suffer from low reconstruction quality (For e.g., blurry reconstructed images)
  - Based on the loss function
    - Does not account for realism of the result
    - For e.g., does not use the prior knowledge of the input images’ sharpness resulting in blurry output.
  - Hence, advanced techniques have been developed for the

- **Adversarially learned inference**
  - Generative Adversarial Networks (GANs)
    - The generator generates new samples
    - The discriminator distinguishes between real and generated samples
  - Suffers from mode collapse
    - Latent space represents only a part of the data, and drops modes from the distributions

Advanced autoencoder techniques

- **Deep feature consistent variational autoencoder**
  - Instead of measuring norm, a measure is used that also considers correlation
    - Instead of measuring the difference between the input/output directly, difference between their representation in the network layers is measured
    - Measuring difference at different layers imposes a more realistic difference measure for the autoencoder

- **Conditional image generation with PixelCNN decoders**
  - Another alternative proposes a composition between autoencoders and PixelCNN
    - Considers the local spatial statistics of the image
      - Using additive white Gaussian noise or Dropouts
    - Local statistics are replaced by the usage of an RNN, with the same concept in later developments

Applications of autoencoder

- **Generative Modelling**
  - VAEs are generative models that describe data generation through a probabilistic distribution
- **Classification**
  - Can be used in the semi-supervised setting for improving classification results
- **Clustering**
  - The latent representation serves as the input for any given clustering algorithm
- **Anomaly detection**
  - Follows the assumption that a trained autoencoder would learn the latent subspace of normal samples
  - Would result in a low reconstruction error for normal samples, and high reconstruction error for anomalies
- **Recommender Systems**
  - The latent representation serves as the input for Collaborative Filtering approaches
- **Dimensionality Reduction**
  - Learn a lower dimensional manifold based on the latent space structure