# Applied Machine Learning

- Noise and Autoencoders
- Perceptual Loss
- Training a Denoising Autoencoder

#### Noise in Autoencoders

- Cost function sensitive to noise:  $\|\mathscr{D}(Z_i, \theta_d) I_i\|^2$
- Denoising autoencoders account for potential noise at the input: noise( $I_i$ )
  - Additive Gaussian Noise
    - per pixel: add independent samples of normal random variable
  - Salt and pepper noise
    - select at random a predefined number of pixels: replace with random selection of [0,1]
  - Masking Noise:
    - select at random a predefined number of pixels: set to 0
  - Masking Blocks
    - select predefined blocks of pixels: set to 0
    - selection of blocks to train the network to complete them in case they are blocked in source images

## Denoising Autoencoders - Loss

- Perceptual loss
  - Accounts for perceptual changes at the output
  - Input to network:  $I_k$
  - At layer i: Output:  $D_i(I_k)$  dimensions:  $W_i \times H_i \times F_i$ 
    - flattened:  $\mathbf{d}_i(I_k)$  number of components:  $W_iH_iF_i$
  - $_{\bullet}$  Feature reconstruction loss at layer i between images  $I_1$  and  $I_2$  :

$$\mathcal{L}_{\mathsf{fr},i}(I_1,I_2) = \frac{\|\mathbf{d}_i(I_1),\mathbf{d}_i(I_2)\|^2}{W_i H_i F_i}$$

Perceptual loss between images:

$$\mathcal{L}_{\mathsf{per}(I_1,I_2)} = \sum_{i} w_i \mathcal{L}_{\mathsf{fr},i}(I_1,I_2)$$

General Loss

$$\mathcal{L}_{gen}(\mathcal{D}(Z_i, \theta_d), I_i) = \lambda_1 \mathcal{L}_{per}(\mathcal{D}(Z_i, \theta_d), I_i) + \lambda_2 \|\mathcal{D}(Z_i, \theta_d) - I_i\|^2$$

## Denoising Autoencoder - Training

- Dataset of N images  $I_1, ... I_N$
- Apply model noise to each image  $I_i$ : noise( $I_i$ )
- Output at encoder:  $Z_i = \mathcal{E}(\text{noise}(I_i), \theta_e)$
- Output at decoder:  $\mathcal{D}(Z_i, \theta_d)$
- Loss:  $\mathcal{L}_{gen}(\mathcal{D}(Z_i, \theta_d), I_i)$
- Train through Stochastic Gradient Descent

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