Deep Learning

7.2 Autoencoders

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Beyond Classification and Regression

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2. These applications require to learn the meaningful degrees of freedom that constitute the signal
3. These degrees of freedom are of lesser dimensions than the signal

Example: Synthesizing Human faces

1. For generating new faces, it makes sense to capture a small number of degrees of freedom such as
   - skull size and shape
   - color of skin and eyes
   - features of nose and lips, etc.

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2. Even a comprehensive list of such things will be less than the number of pixels in the image (i.e. resolution)
3. If we can model these relatively small number of dimensions, we can synthesize a face with thousands of dimensions

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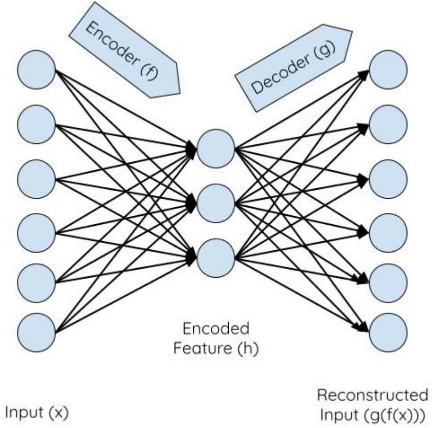

4.

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2. Dimension of the latent space is a hyper-parameter chosen from prior knowledge, or through heuristics

Autoencoder

1. Let p be the data distribution in the input space, autoencoder is characterized with the following loss

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1. Let p be the data distribution in the input space, autoencoder is characterized with the following loss

$$\mathbb{E}_{x \sim p} \left\| x - g \circ f(x) \right\|^2 \approx 0$$

2. Training the autoencoder consists of finding the parameters for the encoder $(f(\cdot; w_f))$ and decoder $(g(\cdot; w_g)$ optimizing the following empirical loss

$$\hat{w}_f, \hat{w}_g = \underset{w_f, w_g}{\operatorname{argmin}} \frac{1}{N} \sum_n \left\| x_n - g(f(x_n; w_f); w_g) \right\|^2$$

Autoencoder

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1. A simple example: f and g are linear functions $\rightarrow$ optimal solution is PCA
2. Better results can be made possible with sophisticated transformations such as deep neural networks $\rightarrow$ Deep Autoencoders

Deep Autoencoders

```
AutoEncoder (
(encoder): Sequential (
(0): Conv2d(1, 32, kernel_size=(5, 5), stride=(1, 1)) (1): ReLU (inplace)
(2): Conv2d(32, 32, kernel_size=(5, 5), stride=(1, 1)) (3): ReLU (inplace)
(4): Conv2d(32, 32, kernel_size=(4, 4), stride=(2, 2)) (5): ReLU (inplace)
(6): Conv2d(32, 32, kernel_size=(3, 3), stride=(2, 2)) (7): ReLU (inplace)
(8): Conv2d(32, 8, kernel_size=(4, 4), stride=(1, 1)) )
(decoder): Sequential (
(0): ConvTranspose2d(8, 32, kernel_size=(4, 4), stride=(1, 1)) (1): ReLU
(inplace)
(2): ConvTranspose2d(32, 32, kernel_size=(3, 3), stride=(2, 2)) (3): ReLU
(inplace)
(4): ConvTranspose2d(32, 32, kernel_size=(4, 4), stride=(2, 2)) (5): ReLU
(inplace)
(6): ConvTranspose2d(32, 32, kernel_size=(5, 5), stride=(1, 1)) (7): ReLU
(inplace)
(8): ConvTranspose2d(32, 1, kernel_size=(5, 5), stride=(1, 1)) ) )
```

Deep Autoencoders

Top row: original data samples
Bottom row: corresponding reconstructed samples (with linear layer of dimension 32)

Figure credits:blog.keras.io