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

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   - 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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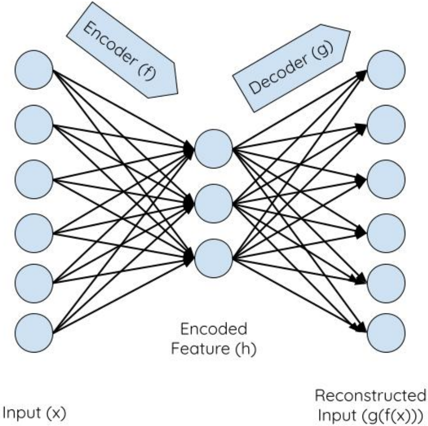
4. 

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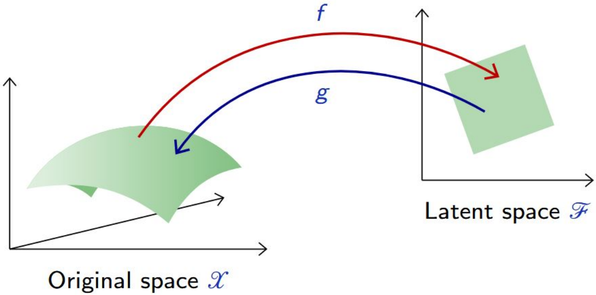

Figure credits: Francois Flueret

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

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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

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

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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)) ) )
```

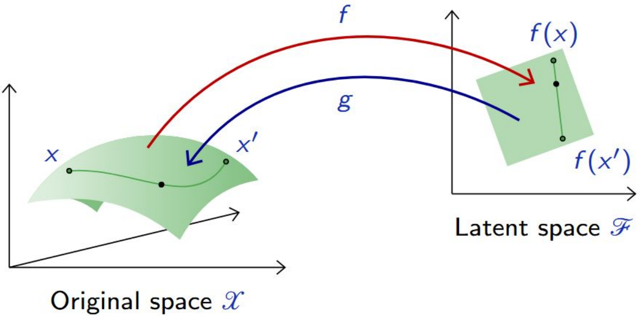
Deep Autoencoders

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

Figure credits:blog.keras.io

Latent Representations

1. Consider two samples in the latent space and reconstruct the samples along the line joining these



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Latent Representations

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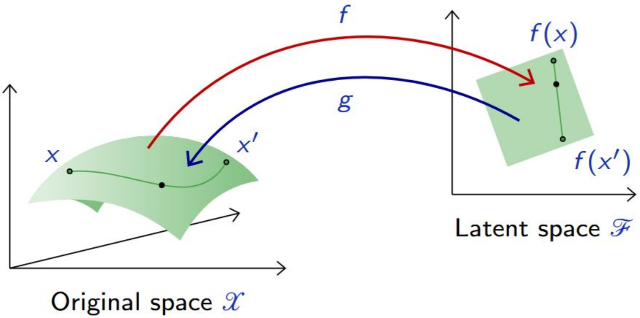
2. $g(\alpha x + (1-\alpha)x')$



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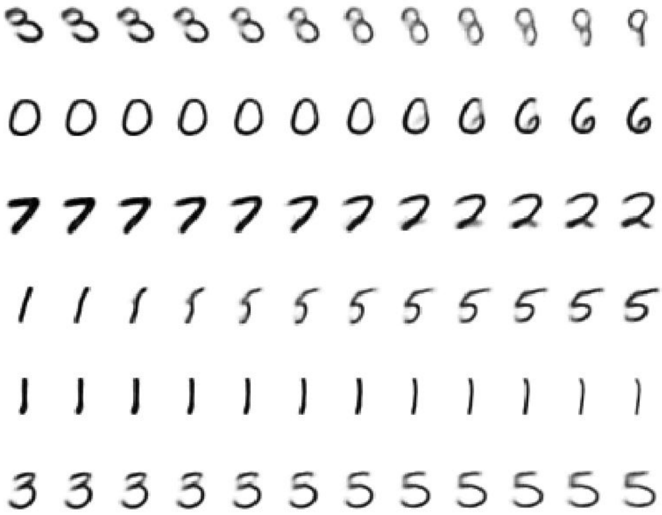
Latent Representations



Generative Modeling by Autoencoder

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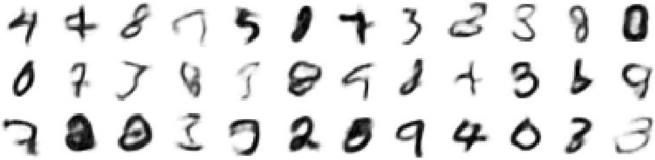
3. For instance, use a Gaussian density for modeling the latent space from the training data (estimate mean and a diagonal covariance matrix)

Generative Modeling by Autoencoder

Autoencoder sampling ($d = 8$)



Autoencoder sampling ($d = 16$)

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3. Good model still needs to capture the empirical distribution on the data although in a lower dimensional space