AutoEncoders

ML Instruction Team, Fall 2022

CE Department
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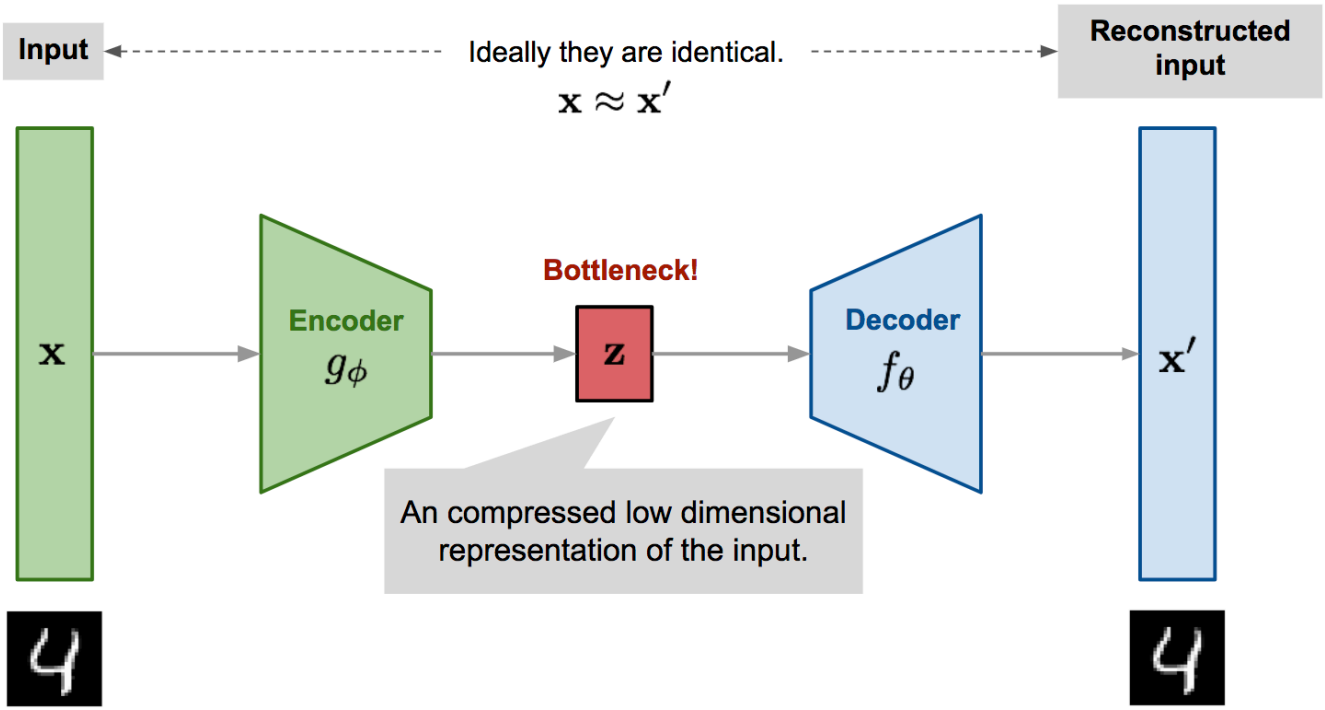
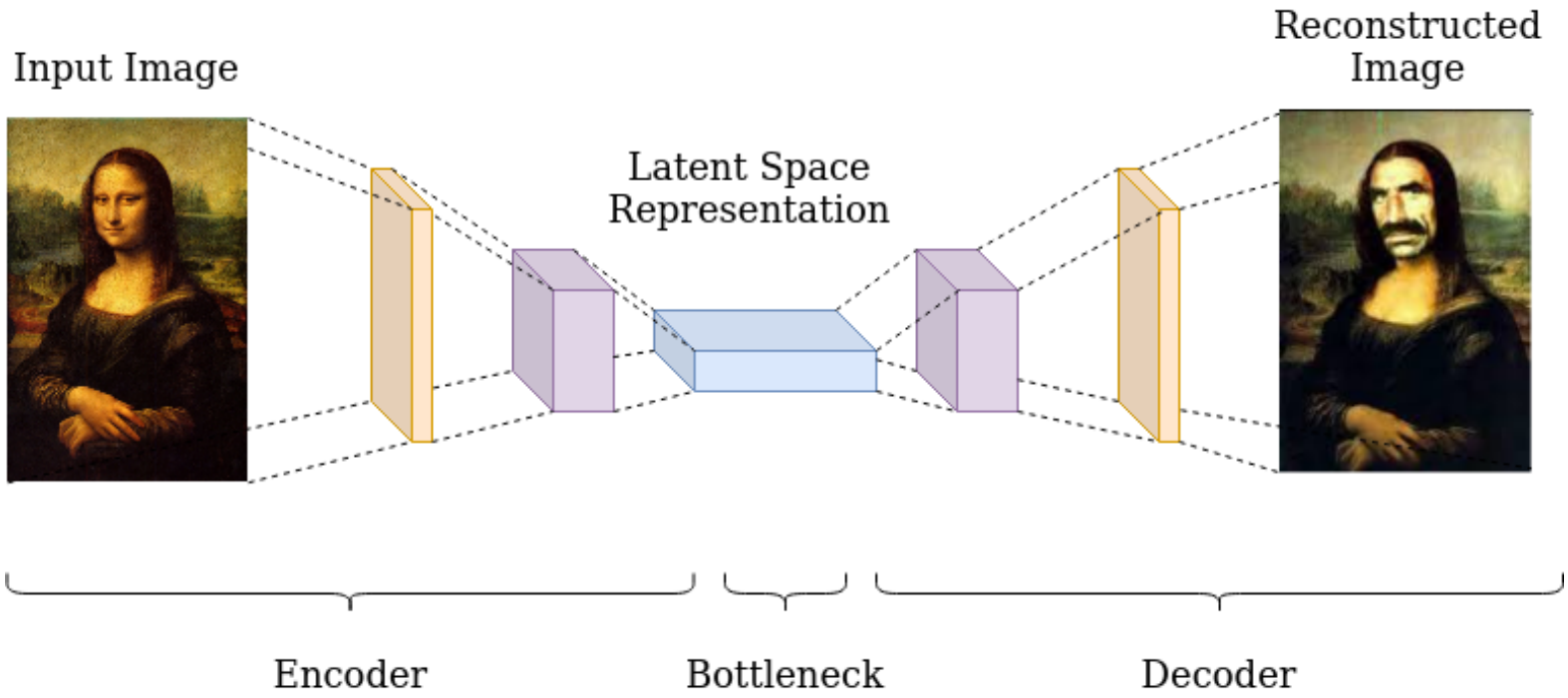
Autoencoders

- Autoencoders are artificial neural networks capable of learning dense representations of the input data, called *latent representations* or *codings*, without any supervision (i.e., the training set is unlabeled).
- Their job is to take an input X and predict X. To make this non-trivial, we need to add a bottleneck layer whose dimension is much smaller than the input.



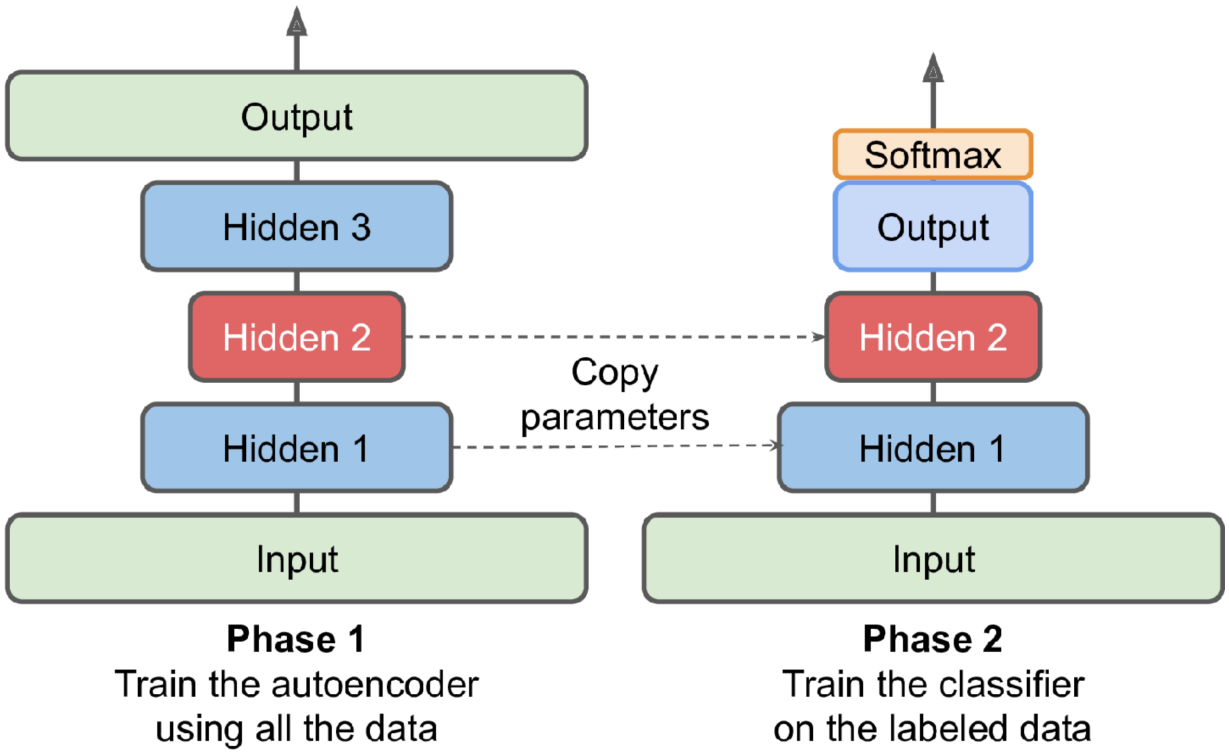
Autoencoders: Structure

- Encoder: compress input into a latent-space of usually smaller dimension. $h = f(x)$
- Decoder: reconstruct input from the latent space. $r = g(f(x))$ with r as close to x as possible



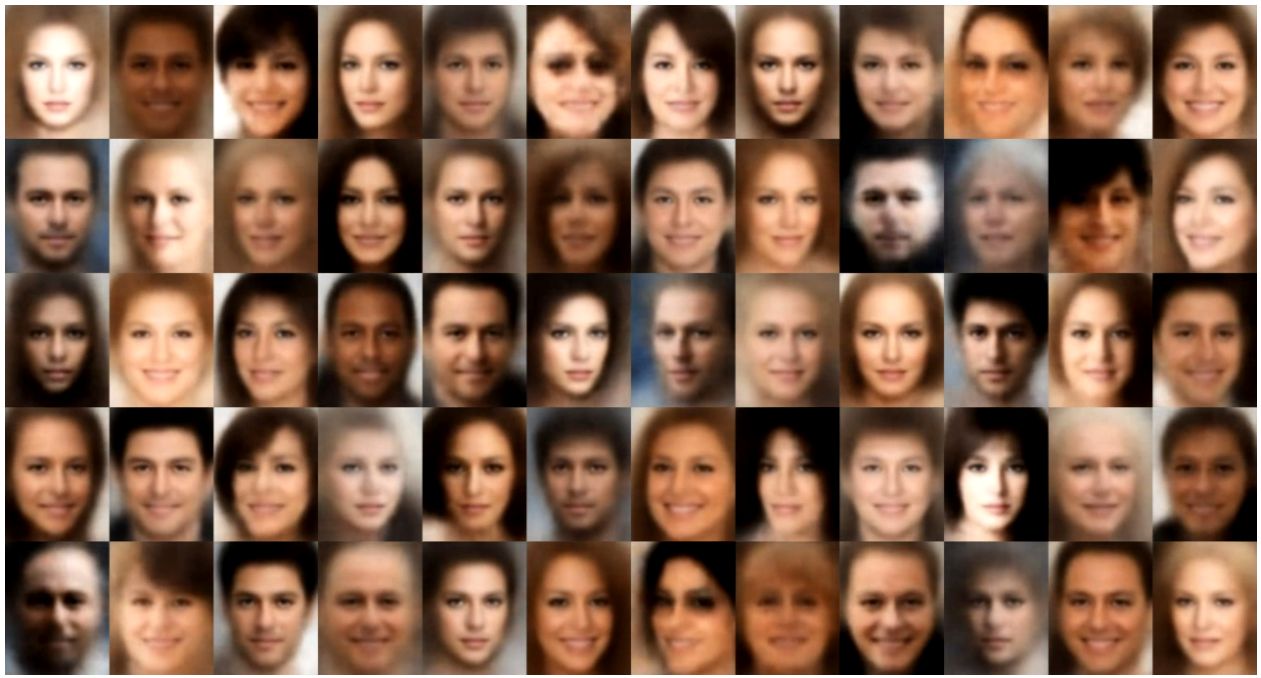
Autoencoders: Applications

- Autoencoders can
  - act as feature detectors
  - be used for unsupervised pretraining of deep neural networks



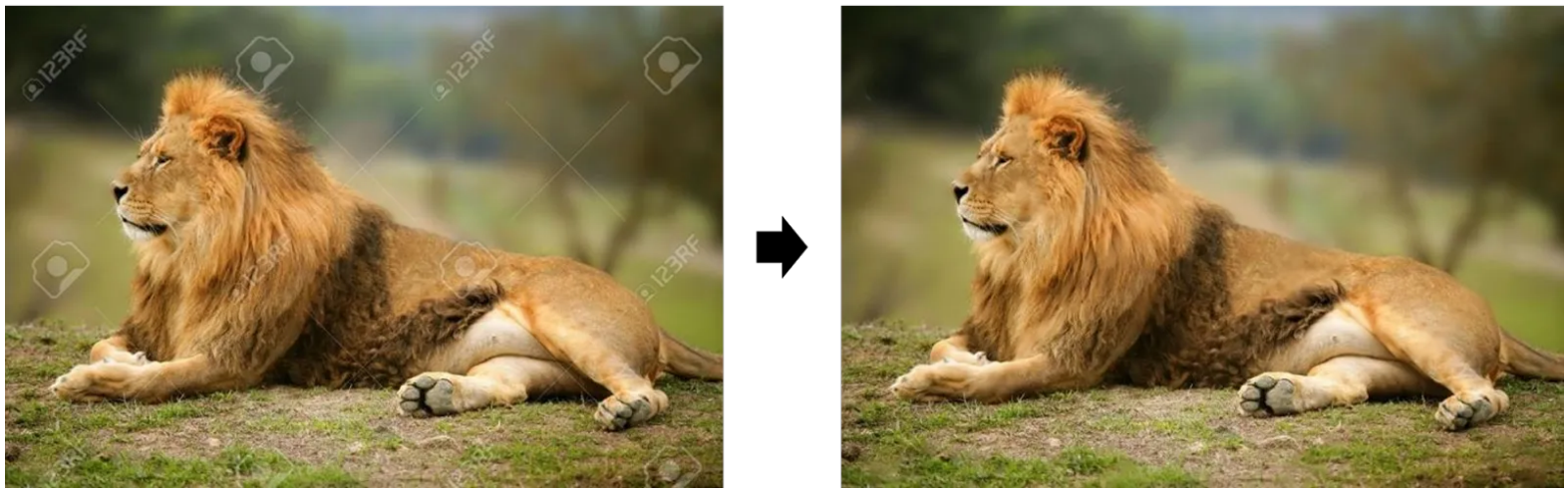
Autoencoders: Applications

- Autoencoders can be used as generative models. (will be discussed more later in this chapter.)



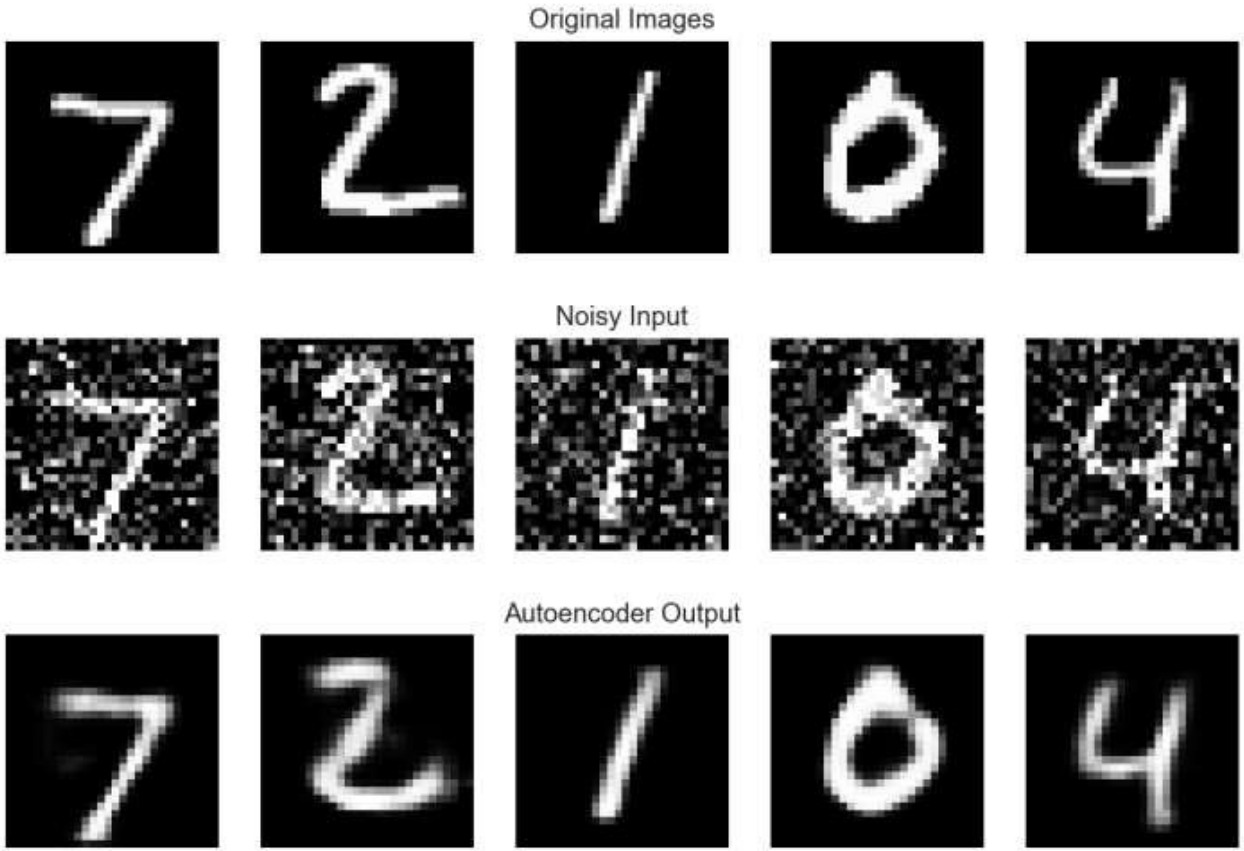
Autoencoders: Applications

- Watermark removal



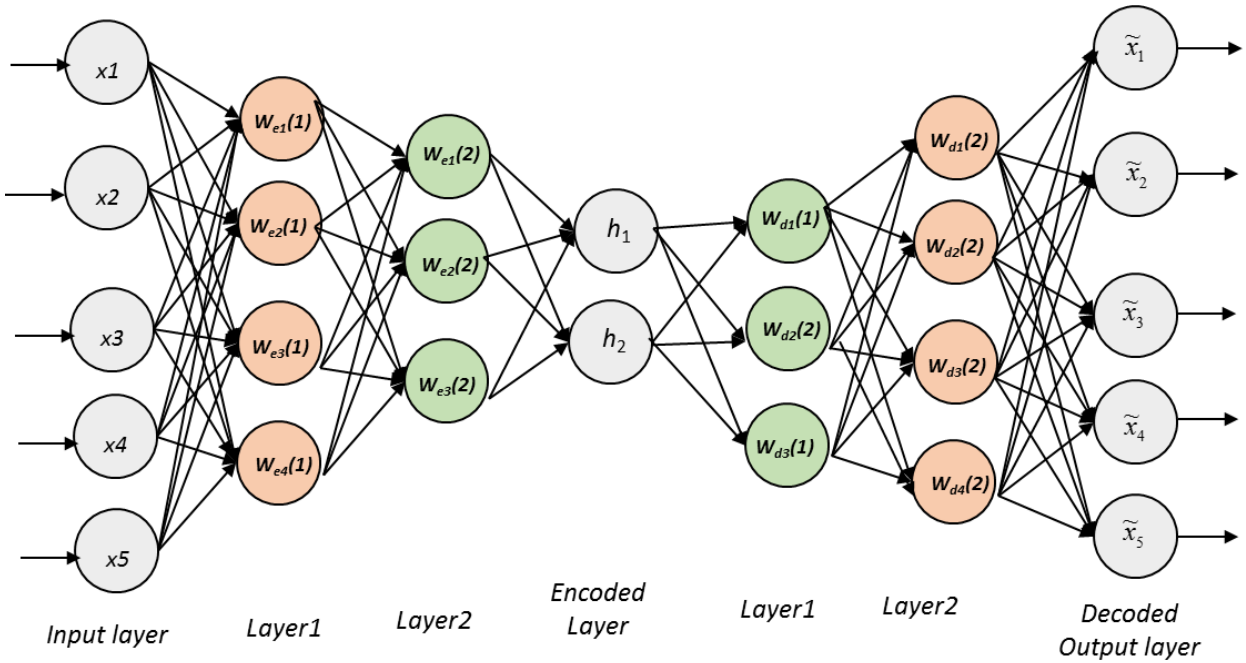
Autoencoders: Applications

- Noise reduction



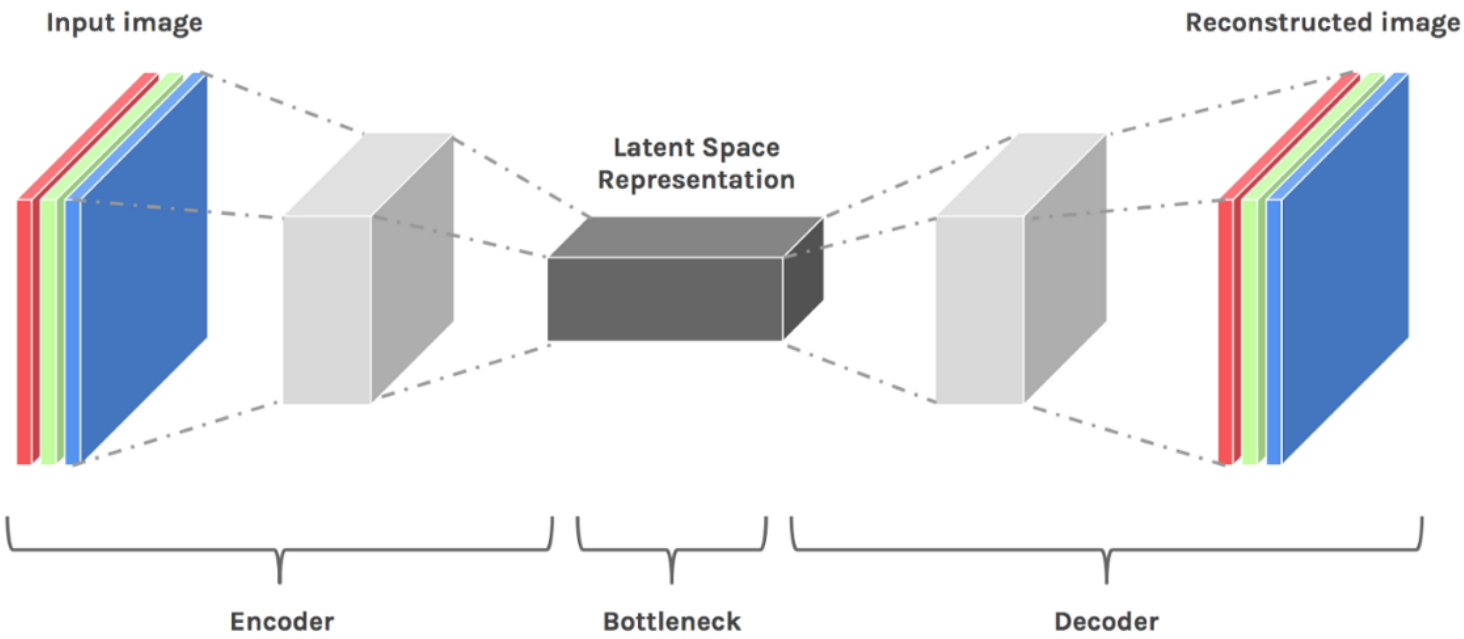
Stacked Autoencoders

- Autoencoders can have multiple hidden layers. In this case they are called *stacked autoencoders* (or *deep autoencoders*).
- Adding more layers helps the autoencoder learn more complex codings. but be careful about overfitting!



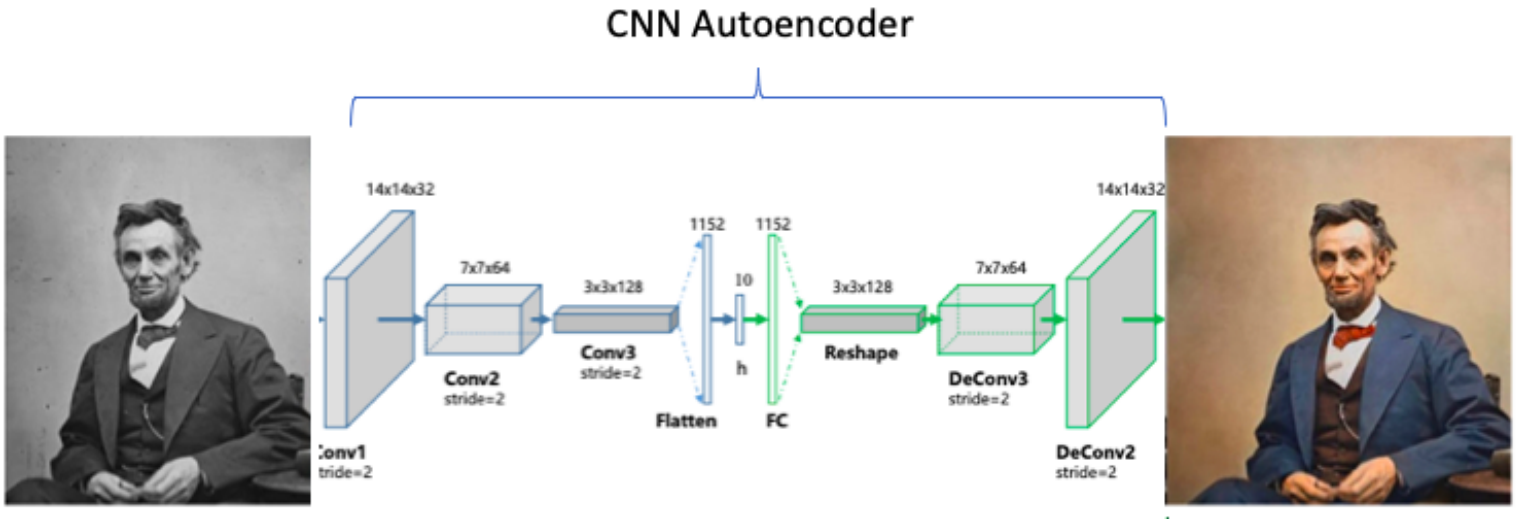
Autoencoders & Images

Are normal Autoencoders suitable for working with images?



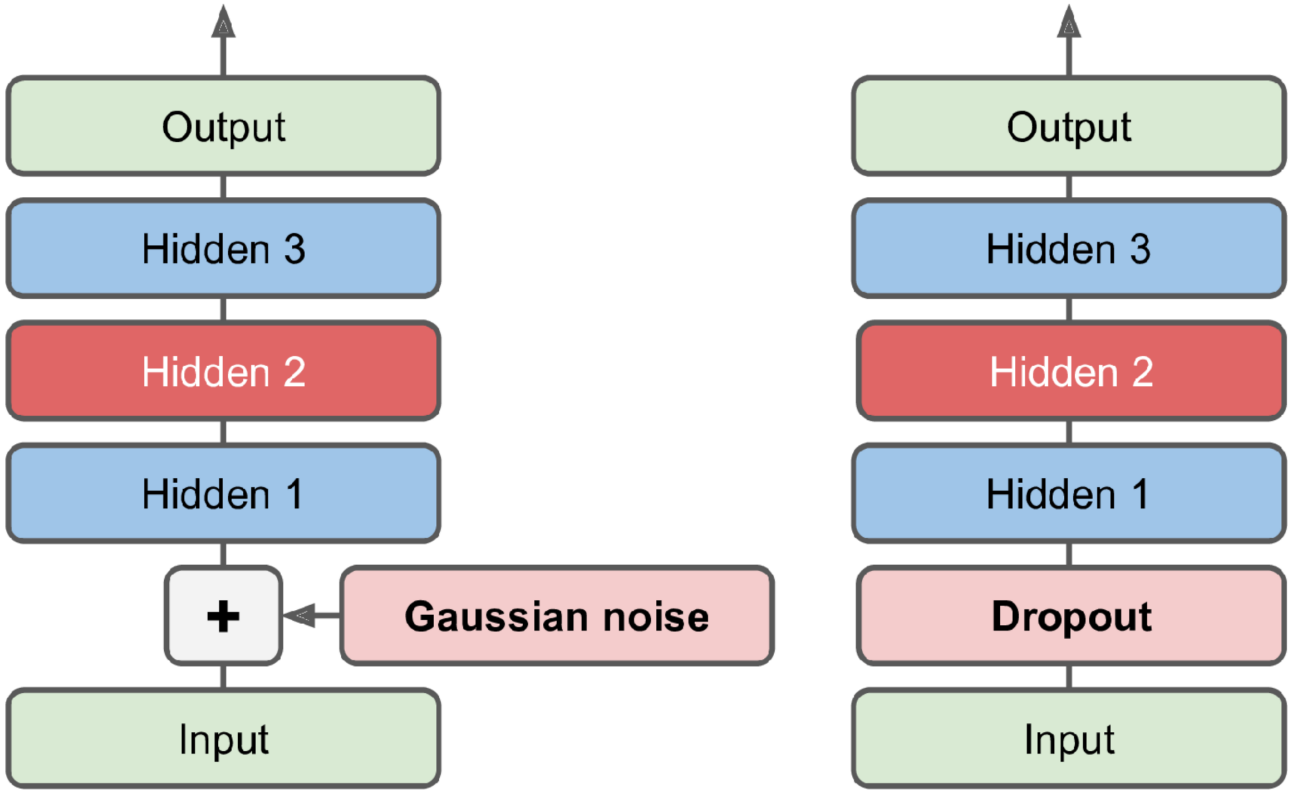
Autoencoders & Images

- Convolutional Autoencoders



Denoising Autoencoders

- Another way to force the autoencoder to learn useful features is to add noise to its inputs.
- Denoising autoencoders train to minimize the loss between x and $g(f(x + w))$, where w is random noise.
- Denoising autoencoders, with Gaussian noise (left) or dropout (right):

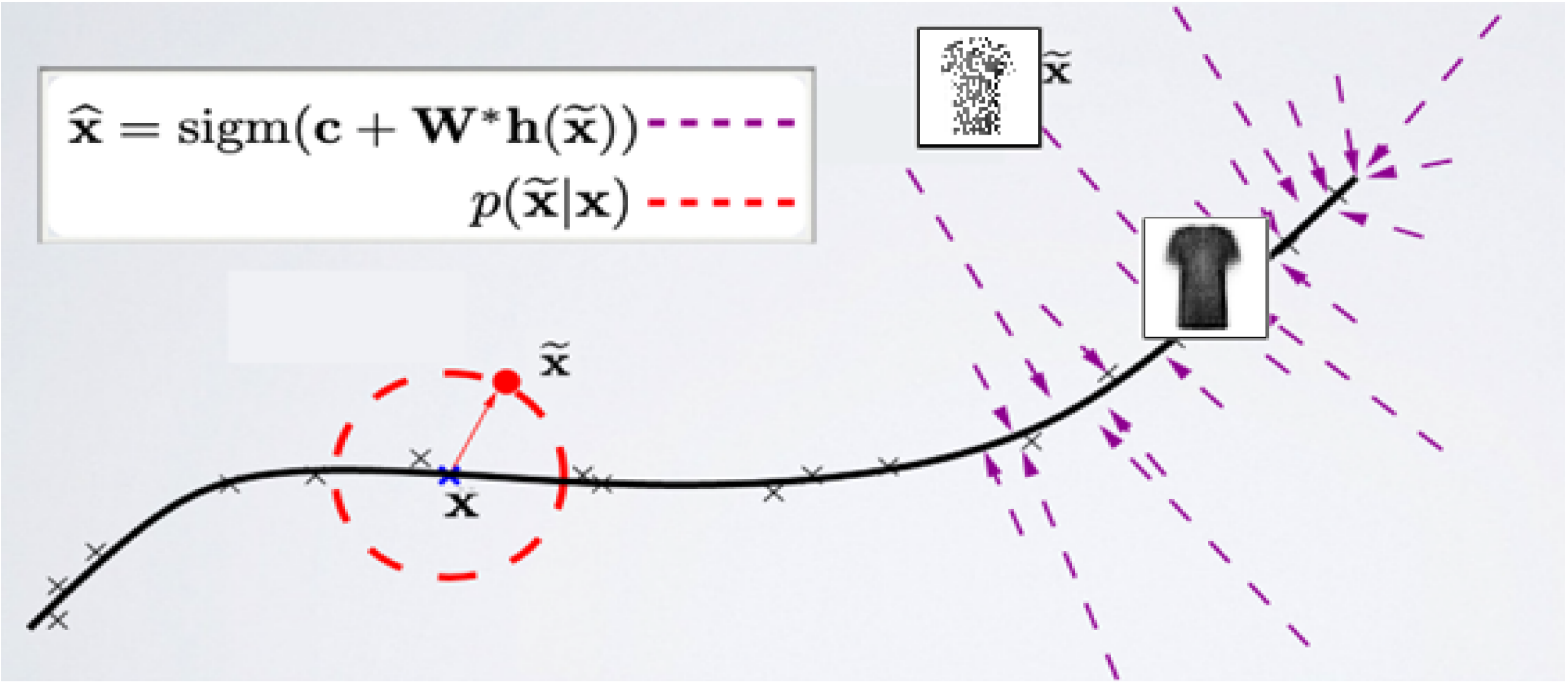


Denoising Autoencoders

- A few noisy images (with half the pixels turned off), and the images reconstructed by the dropout-based denoising autoencoder. Notice how the autoencoder guesses details that are actually not in the input, such as the top of the white shirt (bottom row, fourth image).

Denoising Autoencoders

- Intuitively, a denoising autoencoder learns a projection from a neighborhood of our training data back onto the training data.



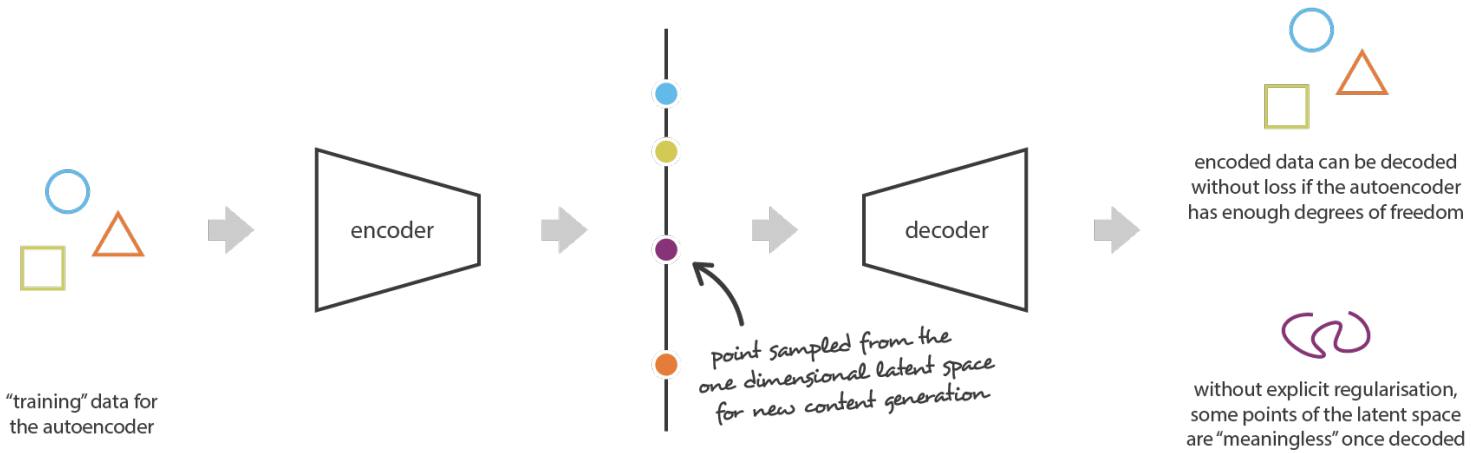
Autoencoder Generative Models

How can we generate NEW data with Autoencoders??

hint: Autoencoder learns the feature space!

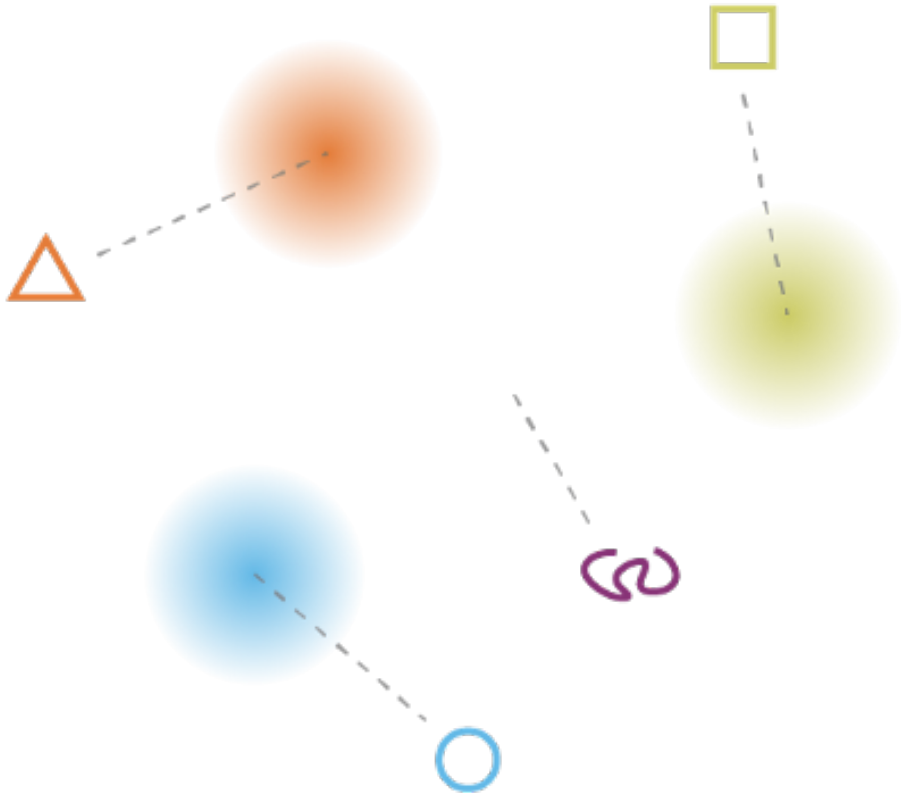
Walking through an example

- We want to reconstruct some shapes.



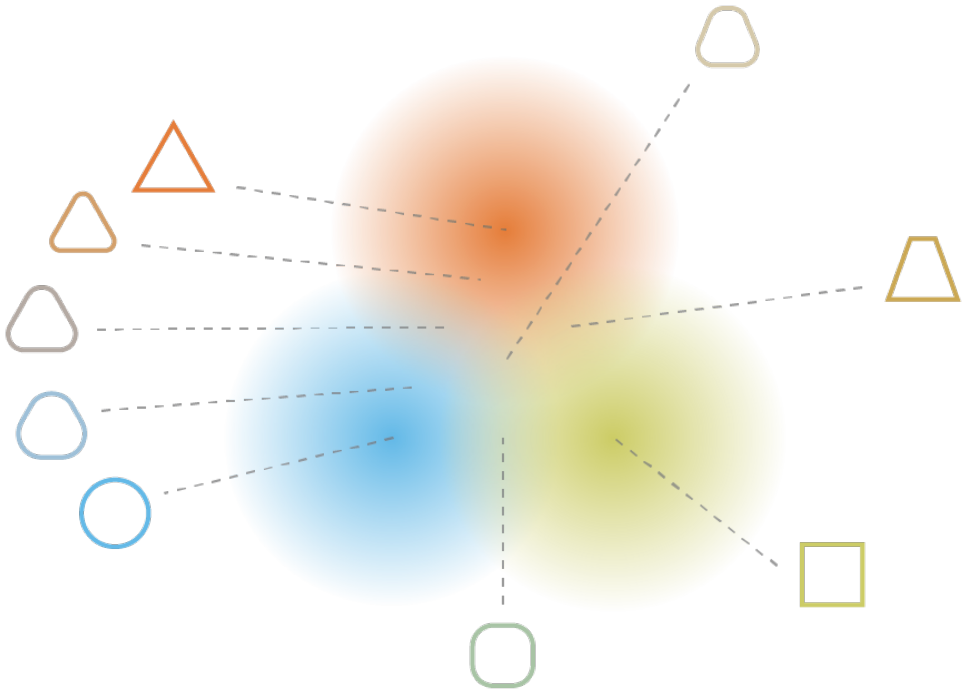
Walking through an example

- Not all of the points in latent space have meaningful reconstructions.



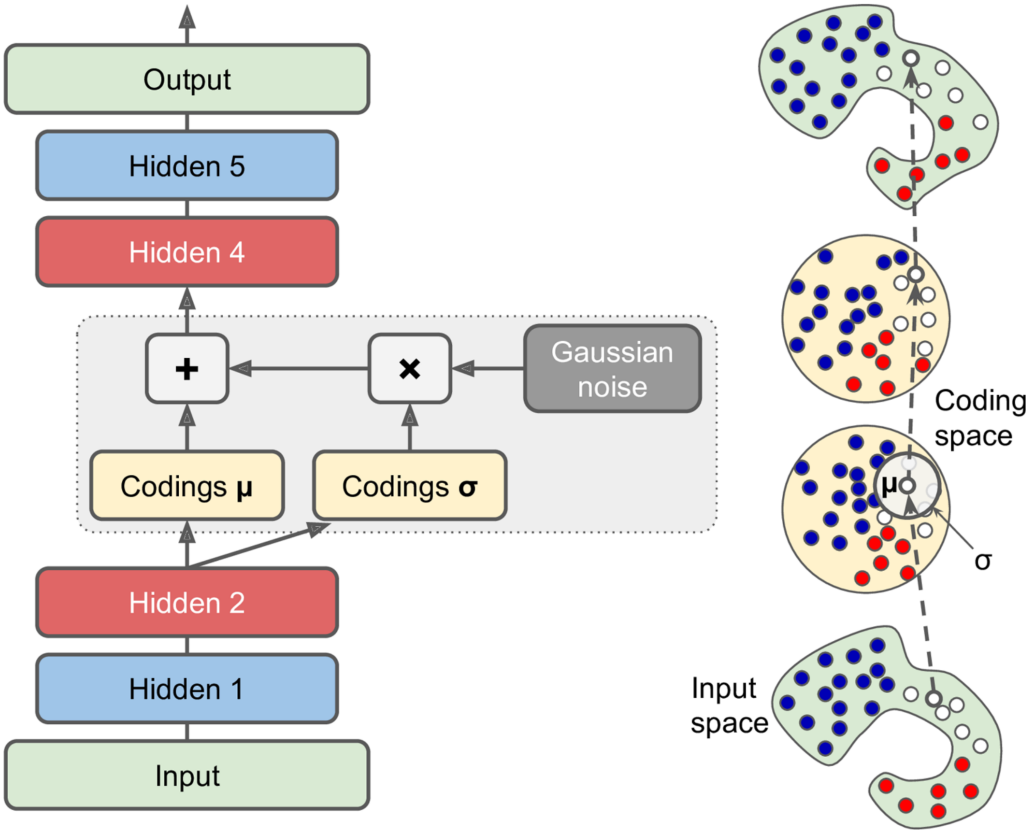
Walking through an example

- What we want is something like the following picture. So that with sampling from the latent space, we can generate new shapes.

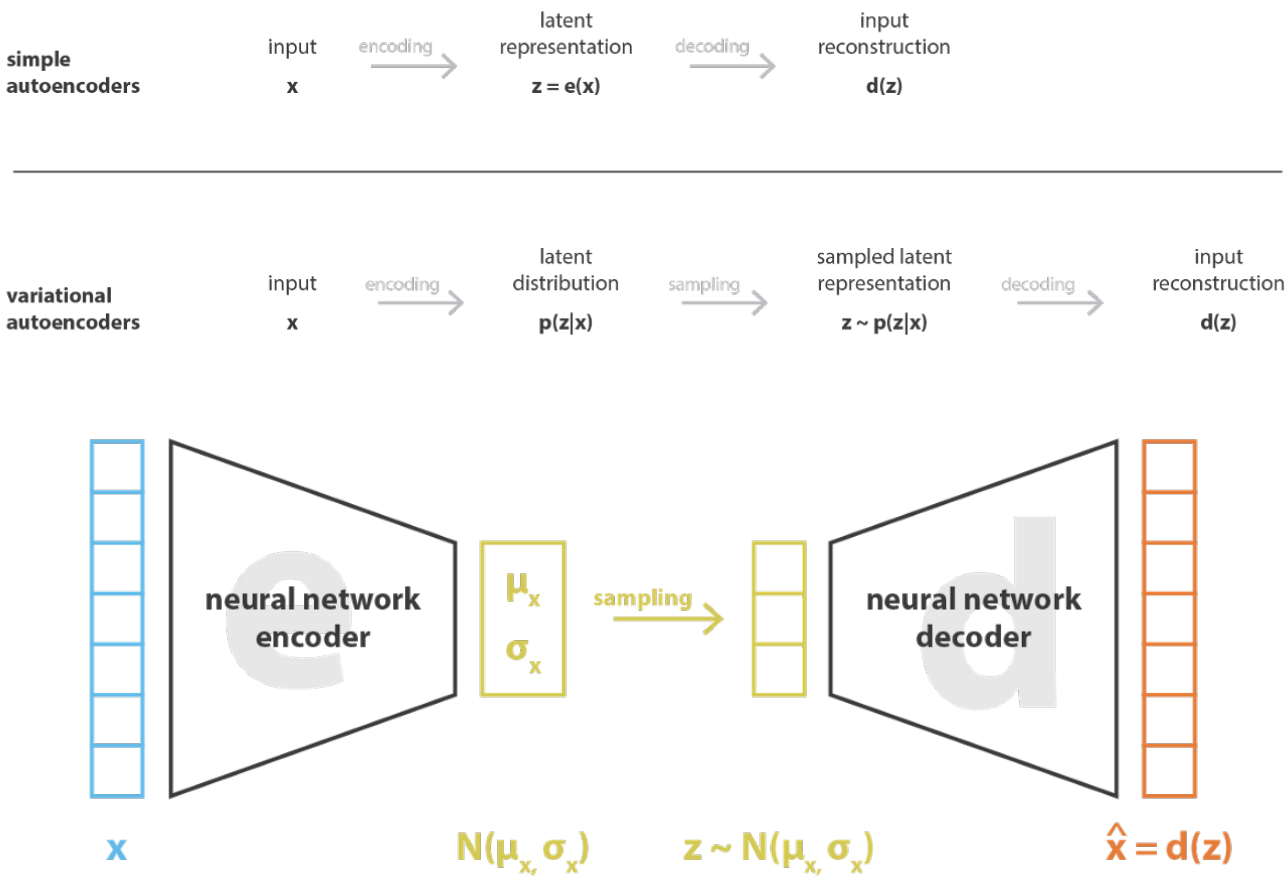


Variational Autoencoders

- instead of directly producing a coding for a given input, the encoder produces a mean coding μ and a standard deviation σ. The actual coding is then sampled randomly from a Gaussian distribution with mean μ and standard deviation σ



Variational Autoencoders



$$\text{loss} = ||x - \hat{x}||^2 + KL[N(\mu_x, \sigma_x), N(0, I)] = ||x - d(z)||^2 + KL[N(\mu_x, \sigma_x), N(0, I)]$$

Test

- One
  - One
  - Two
  - Three
- For two-dimensional tensors, we have a corresponding sum with indices (a, b) for f and $(i - a, j - b)$ for g, respectively:

$$(f * g)(i, j) = \sum_a \sum_b f(a, b) g(i - a, j - b)$$

- It is given by,

$$w_{t+1} = w_t - \left(\alpha_t / \sqrt{(v_t}\right) + e) * (\delta L / \delta w_t)$$

where,

$$v_t = \beta * v_t + (1 - \beta) * (\delta L / \delta w_t)^2$$

Image References

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Thank You!

Any Question?