Autoencoders

ML Instruction Team, Fall 2022

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The Power Of Unsupervised Learning

- Huge datasets compared to supervised learning (No need for labeling)
- Can find previously unknown patterns in data that are impossible with supervised learning

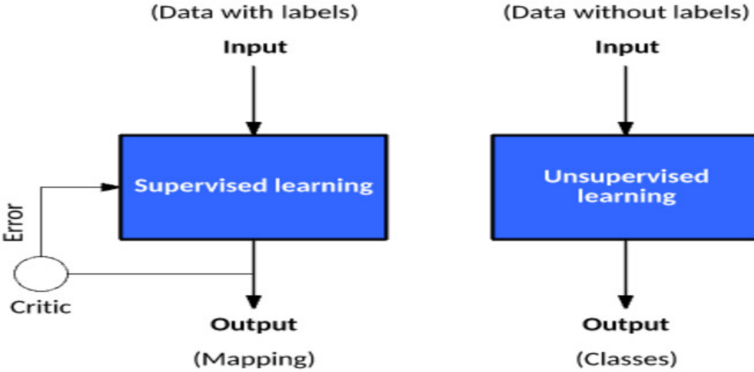
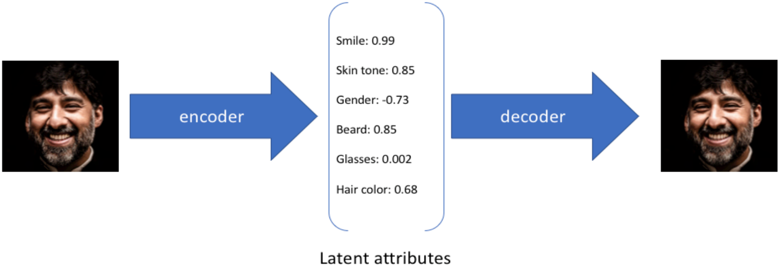


Figure: Types of Machine learning: Deep learning (supervised and unsupervised learning)(Jones [2017]), Source

Applications of Autoencoders

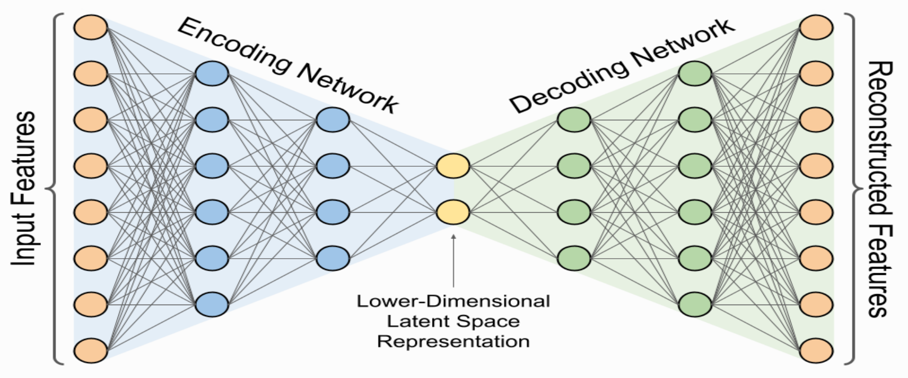
- Compression:
  - AEs can compress our input into a lower dimensional vector and try to reconstruct the original input from that vector



Source

Applications of Autoencoders

- Dimensionality Reduction:
  - AEs can perform dimensionality reduction



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Applications of Autoencoders

- Image coloring and noise reduction

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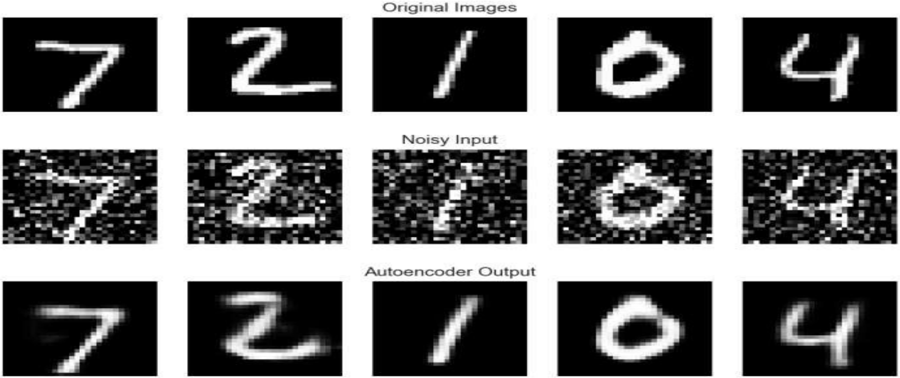
Applications of Autoencoders

- Noise reduction



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Applications of Autoencoders

- Watermark removal

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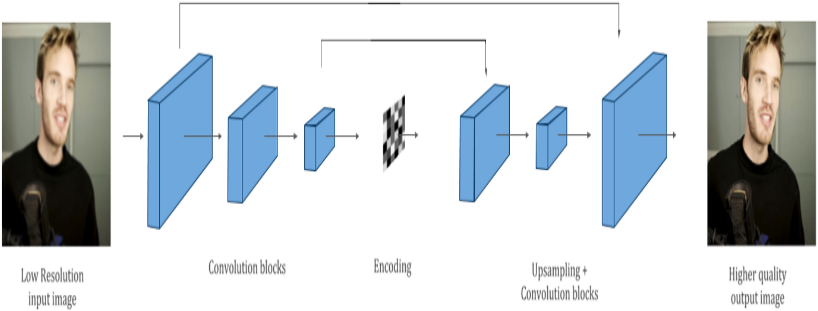
Applications of Autoencoders

- Super-Resolution



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What is an Autoencoder?

- An autoencoder is a type of artificial neural network, capable of learning a low dimensional representation of the input data (codings), without supervision (unlabeled training data - unsupervised learning)
- Autoencoders take an input X and try to predict X. We use a bottleneck layer with a smaller dimension compared to the input, to use as the coding.

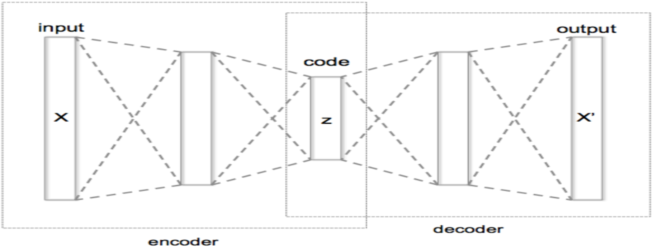


Figure: Schematic structure of an autoencoder with 3 fully connected hidden layers. The code (z - bottleneck) is the most internal layer, Source

Autoencoders: Architecture

- Autoencoders consist of 3 parts:
  1. Encoder : Function $f(x)$ that transforms input x to the latent variable z
  2. Bottleneck : Single layer of neurons that represent the encoding of our input, therefore the most important part of our model
  3. Decoder : Function $h(z)$ that tries to reconstruct input x from encoded latent variable $z \rightarrow h(z) = h(f(x)) = x'$

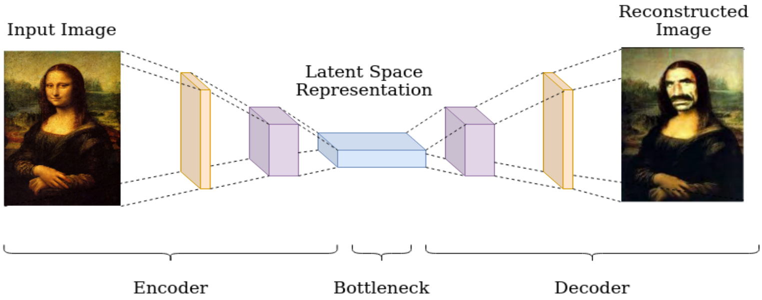


Figure: Autoencoder Architecture (with a little joke :)), Source

Linear vs. Non-Linear

- If your AE uses only linear activations and MSE loss function:
  - It will be performing PCA (Principal Component Analysis)
  - So we need non-linearity to get the most out of autoencoders

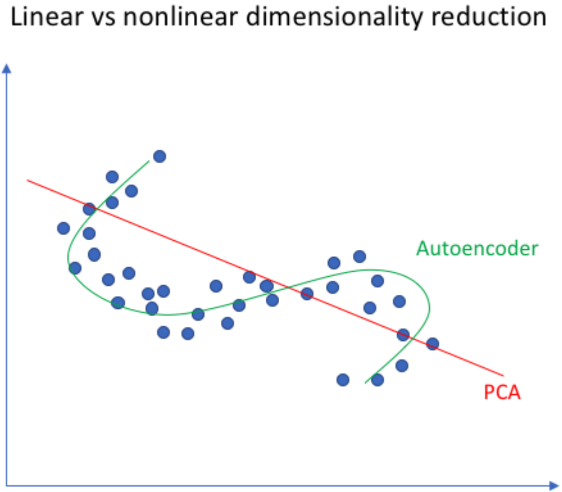
```
encoder = tf.keras.models.Sequential([tf.keras.layers.Dense(2,
    input_shape=input_shape)])

decoder = tf.keras.models.Sequential([tf.keras.layers.Dense(
    input_shape, input_shape=[2])])

pca_autoencoder = tf.keras.models.Sequential([encoder, decoder
    ])

pca_autoencoder.compile(loss="mse", optimizer=tf.keras.
    optimizers.SGD())
```

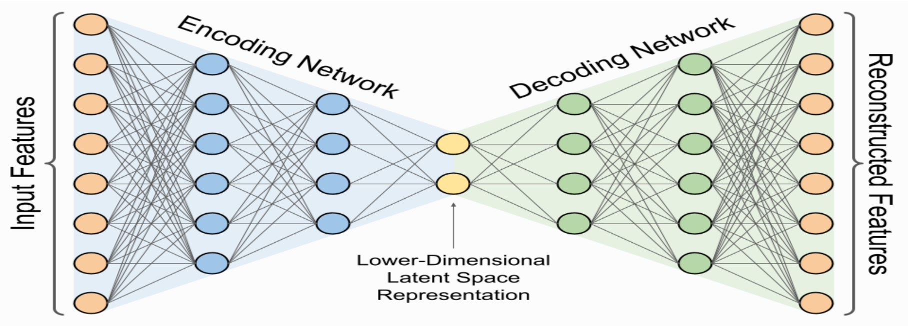
Linear vs. Non-Linear



Source

Stacked Autoencoders

- Autoencoders can have multiple hidden layers to learn more complex encoding/decoding functions - deep autoencoders
- Although, using too deep networks, can cause overfitting
  - Your model will just memorize points in the coding space for each training data, instead of learning a good latent representation of them



Source

Loss and Training

- We're trying to reconstruct our input
- Common loss functions for training autoencoders are:
  - L2: $loss(x, x') = \sum_{i=1}^{m}(x^{(i)} - x'^{(i)})^2$
  - Cross-Entropy

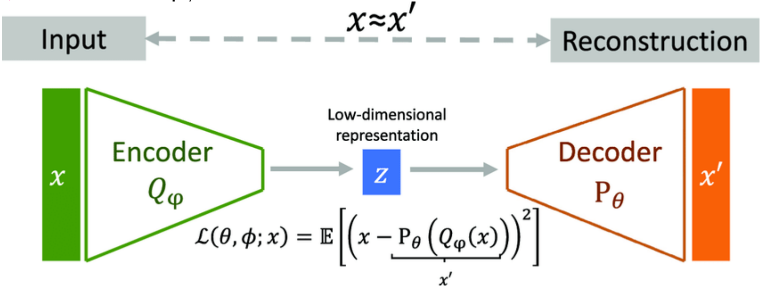


Figure: Schematic of an autoencoder architecture with mean-squared error reconstruction loss.[1]

Pretraining

- You can use an autoencoder for pretraining on supervised problems with few labeled data

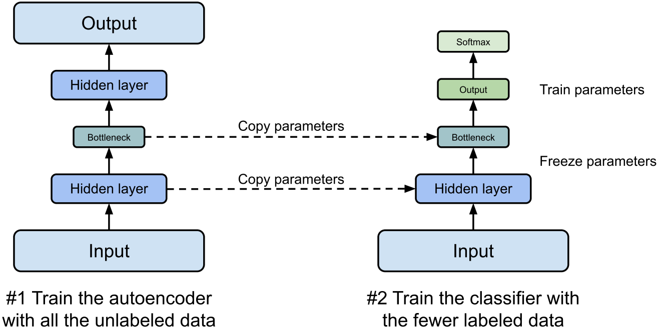
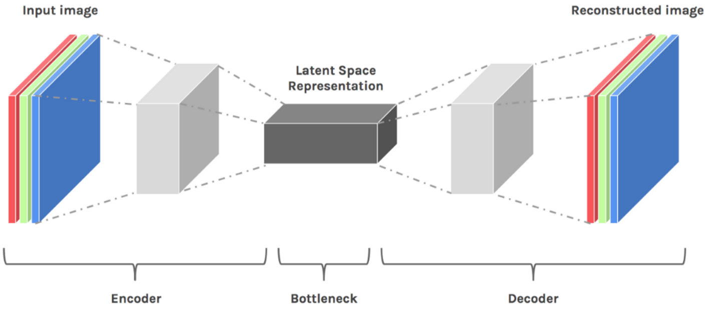


Figure: Using unsupervised learning for pretraining with autoencoders

Autoencoders & Images

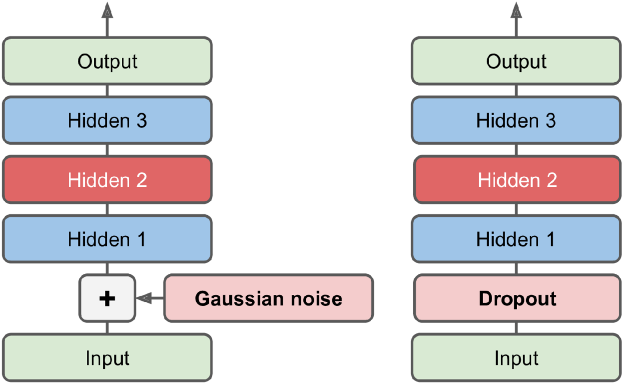
Are normal Autoencoders suitable for working with images?



Convolutional Encoder-Decoder architecture

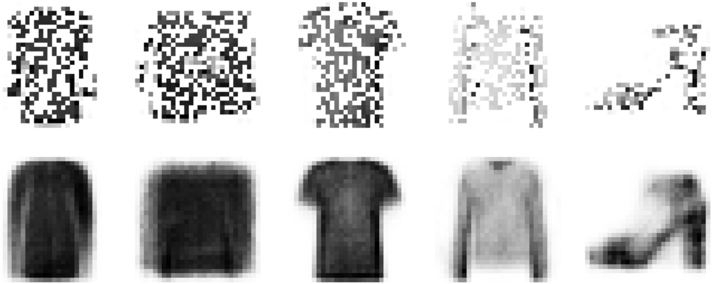
Denoising Autoencoders

- 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):



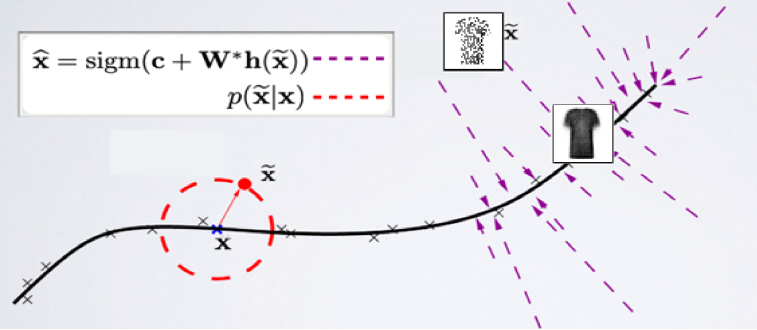
Denoising Autoencoders

- 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.



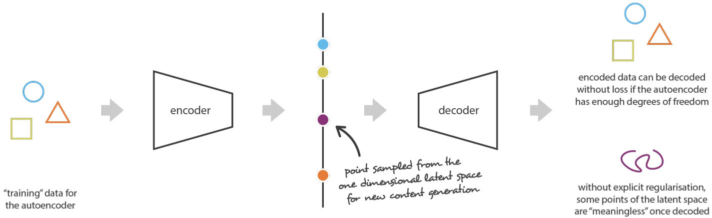
Autoencoder Generative Models

How can we generate NEW data with Autoencoders??

hint: Autoencoder learns the feature space!

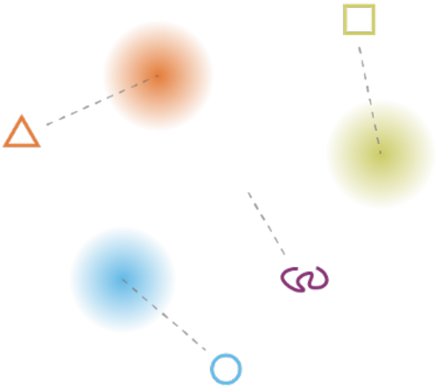
Walking through an example

- We want to reconstruct some shapes.



Walking through an example

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

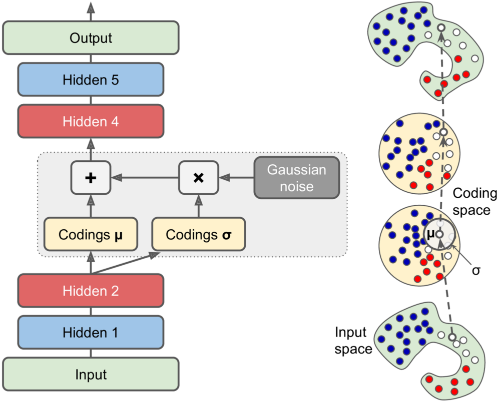


Walking through an example

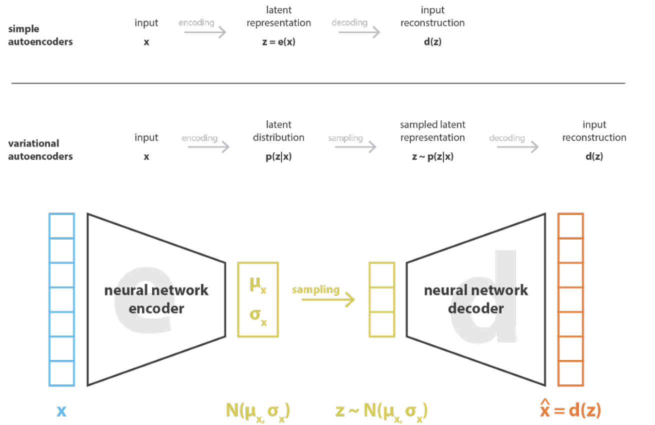
- What we want is something like the following picture. So that with sampling from the latent space, we can generate new shapes.

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



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

Image References

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Refrences

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Thank You!

Any Question?