

# Autoencoder Architectures

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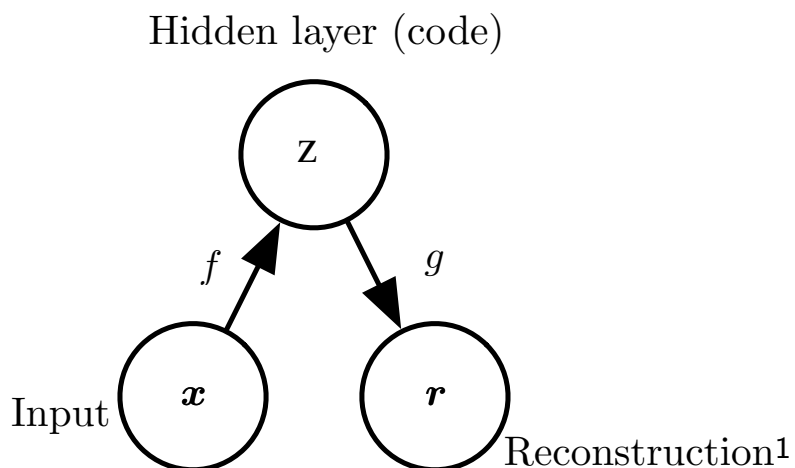
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## Autoencoder

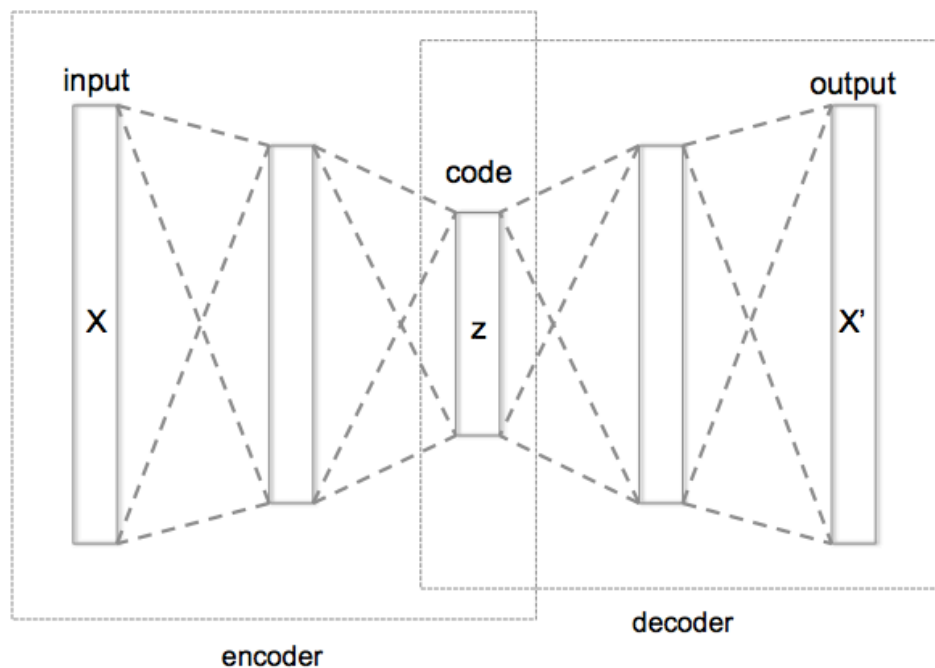
The aim of an autoencoder is to learn a representation (encoding) for a set of data, typically for dimensionality reduction, by training the network to ignore signal noise.



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<sup>1</sup>Image taken from Deep Learning book by Goodfellow et al.

# Deep Autoencoder



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<sup>2</sup>Image taken from wikipedia

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## Denoising Autoencoder

- ▶ Denoising autoencoders take a partially corrupted input and train to recover the original undistorted input.
- ▶ To train an autoencoder to denoise data, it is necessary to perform a preliminary stochastic mapping to corrupt the data ( $x \rightarrow \tilde{x}$ ).
- ▶ A normal autoencoder is used with  $\tilde{x}$  is used as input and  $x$  as output.
- ▶ In a denoising autoencoder, the loss should be computed on  $\mathcal{L}(x, \hat{x})$  as opposed to  $\mathcal{L}(\tilde{x}, \hat{x})$ .

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# Sparse Autoencoder

- ▶ In a sparse autoencoder, there are more hidden units than inputs, but only a small number of the hidden units are allowed to be active at the same time.

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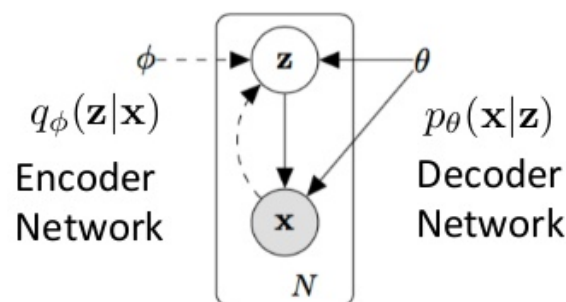
## Autoencoder Applications

- ▶ Any basic AE (or its variant) is used to learn a compact representation of data.
- ▶ You can learn automatic features from data. E.g. HAR with sensor data.
- ▶ Denoising can help generalise over the test set since the data is distorted by adding noise.
- ▶ Pretraining networks by learning your network weights using a stacked AE.

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# Variational Autoencoders (VAEs)

## Variational Autoencoder



Minimize:  $D_{KL}[q_\phi(\mathbf{z}|\mathbf{x})||p_\theta(\mathbf{z}|\mathbf{x})]$

$$\text{Intractable: } p_\theta(\mathbf{z}|\mathbf{x}) = \frac{p_\theta(\mathbf{x}|\mathbf{z})p_\theta(\mathbf{z})}{p_\theta(\mathbf{x})}$$

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<sup>3</sup>Slide taken from  
<https://www.slideshare.net/ckmarkohchang/variational-autoencoder>

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## Variational Autoencoder

- ▶ In VAEs, data is generated by a directed graphical model  $p(\mathbf{x}|\mathbf{z})$ .
- ▶ The encoder is learning an approximation  $q_\phi(\mathbf{z}|\mathbf{x})$  to the posterior distribution  $p_\theta(\mathbf{x}|\mathbf{z})$ , where  $\phi$  and  $\theta$  denote the parameters of the encoder and decoder, respectively.
- ▶ The objective of the VAE has the following form  
 $\mathcal{L} = D_{KL}(q_\phi(\mathbf{z}|\mathbf{x})||p_\theta(\mathbf{z})) - \mathbb{E}_{q_\phi}(\log p_\theta(\mathbf{x}|\mathbf{z}))$

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