TU-Delft Deep Learning course 2018-2019

08.Unsupervised

27 April 2019

Delft University of Technology

Lecturer: Jan van Gemert

Unsupervised learning

Book: Chapters 14, 20

- Q: What is unsupervised learning?

Unsupervised learning

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  A: No ground truth label.

- Q: Why is that good?

Unsupervised learning

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  A: Labels are often the most expensive to obtain
- Q: What is it good for?

Unsupervised learning

Book: Chapters 14, 20

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- Q: Why is that good?
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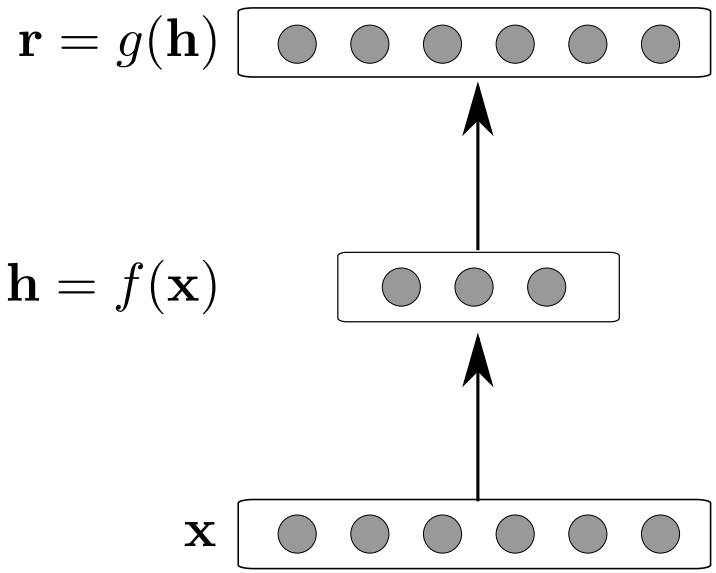
- Q: What is it good for?
  A: Learn compression to store large datasets, pre-training for feature learning, density estimation, generating new data samples.

Autoencoder

Book: Chapter 14

Feed forward network to reproduce its input at the output layer; $g(f(x)) = x$



Decoder:

$$\begin{aligned} r &= g(h) \\ &= \sigma(c + W^* h) \end{aligned}$$

Encoder:

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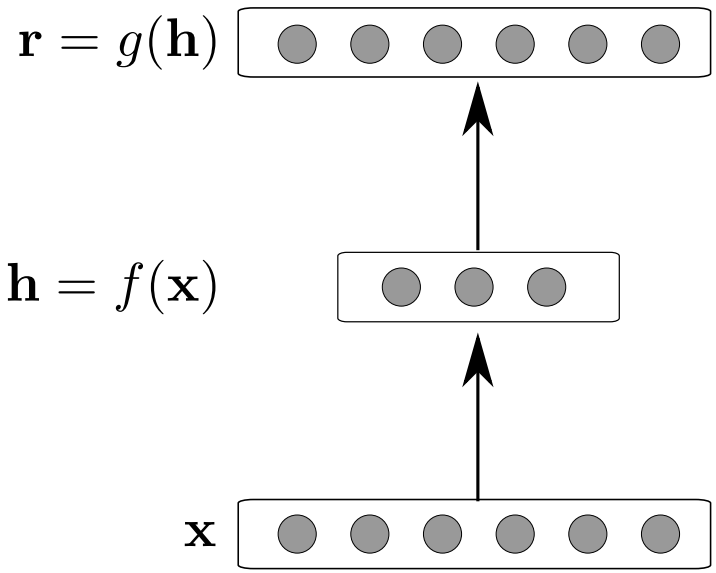

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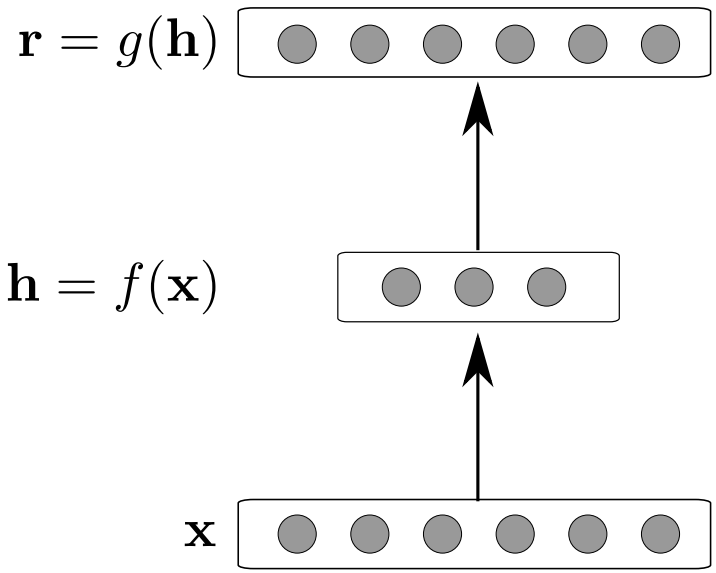

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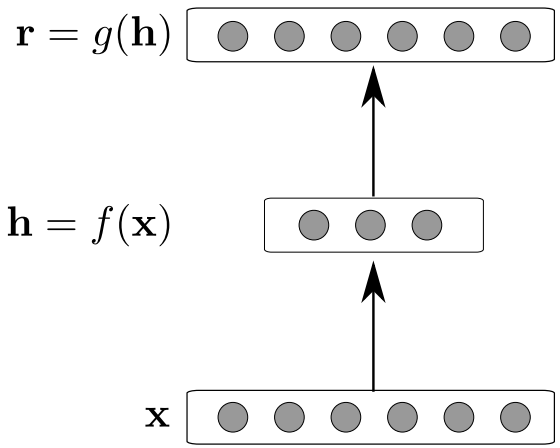
Q: What loss function would you minimize to train $g(f(x)) = x$?
A: $\sum_i \frac{1}{2}(g(f(x_i)) - x_i)^2$ (if x is continue)

Size of the hidden (bottleneck) layer

Book: Chapter 14



$h < x$, **Undercomplete** hidden layer:

- "Compress" the input
- Compresses well for training samples

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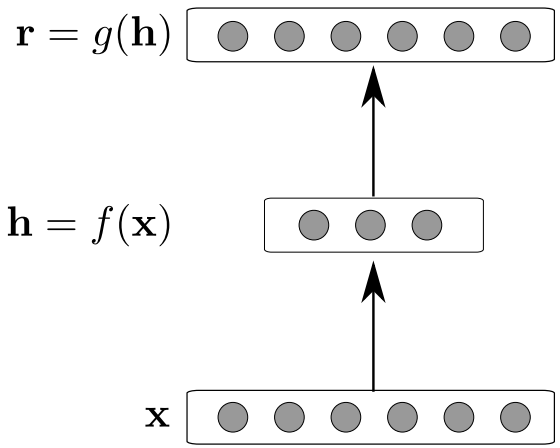

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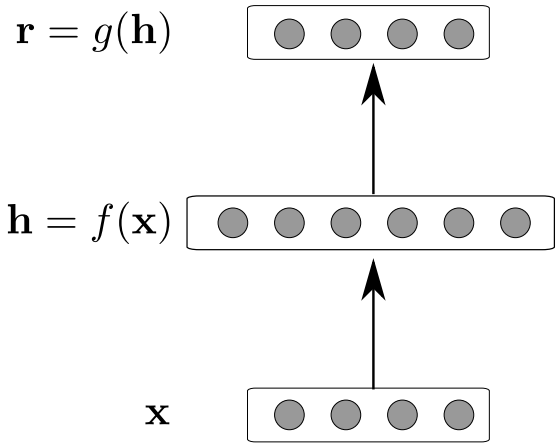

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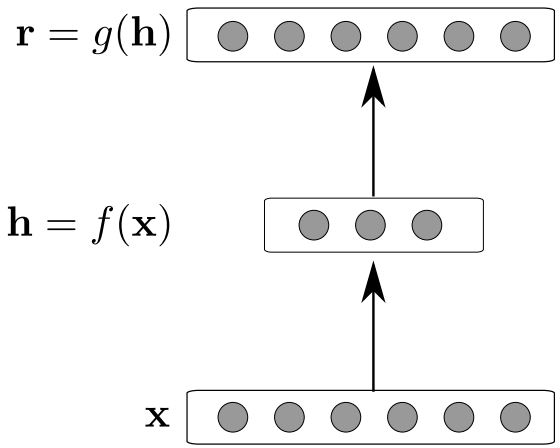

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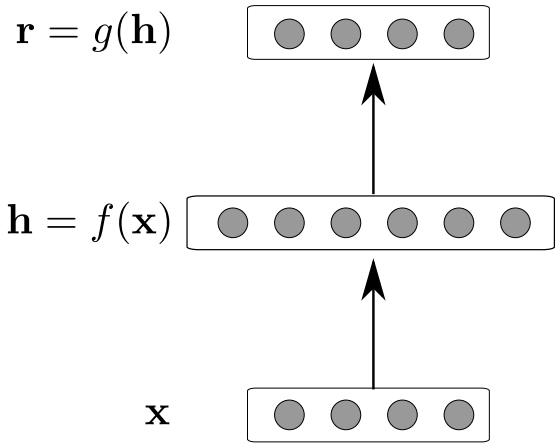

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Size of the hidden (bottleneck) layer

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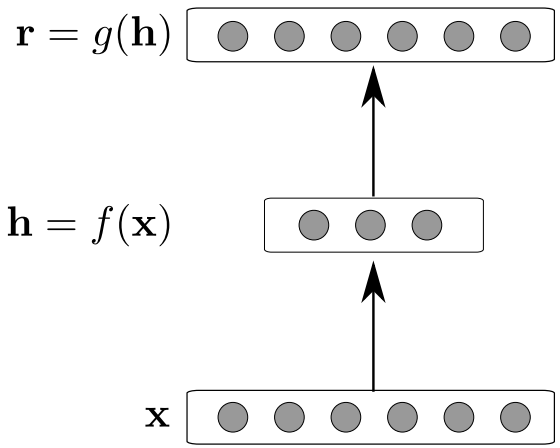

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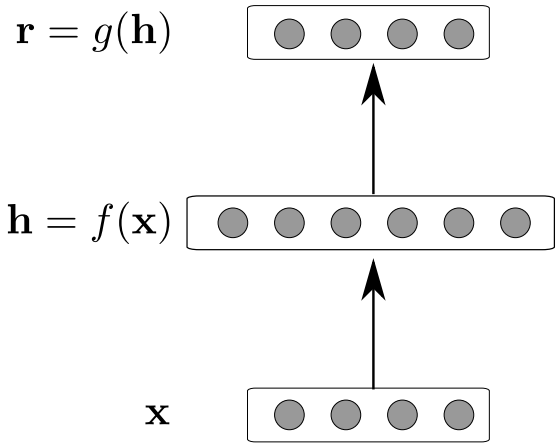

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- Useful for representation learning

  Q: What lecture topic could prevent copying the input?
  A: Regularization

Overcomplete: Denoising autoencoder

Book: 14.2.2, 14.5

Idea: Regularization by making reconstruction robust to noise.

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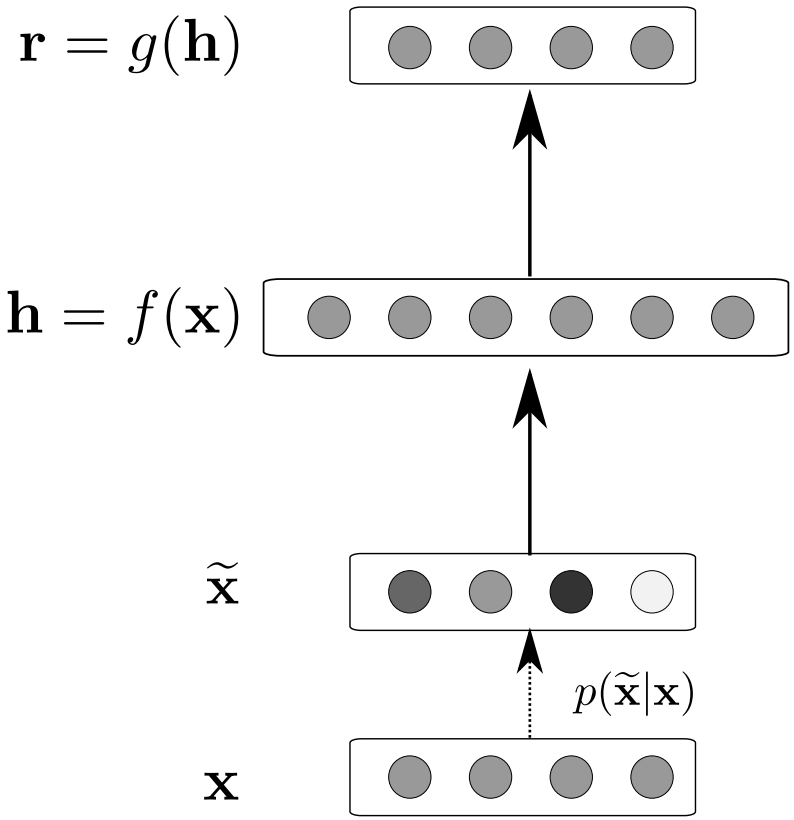
Book: 14.2.2, 14.5

Idea: Regularization by making reconstruction robust to noise.



Generate noisy $\widetilde{x}$ from a distribution $p(\widetilde{x}|x)$

Q: How to make robust to noise?

Overcomplete: Denoising autoencoder

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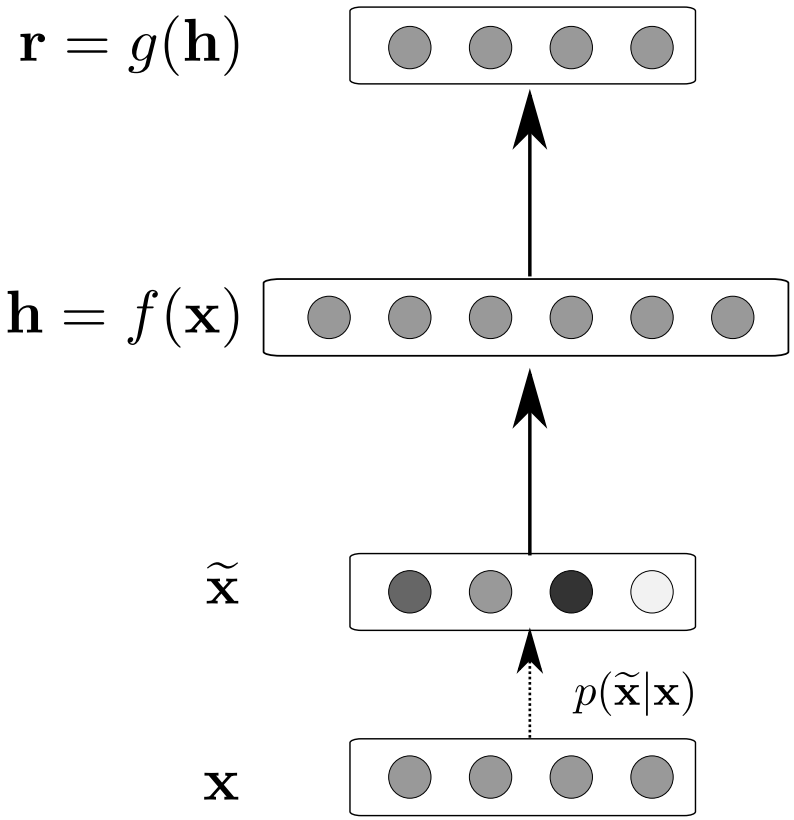
Idea: Regularization by making reconstruction robust to noise.



Generate noisy $\widetilde{x}$ from a distribution $p(\widetilde{x}|x)$

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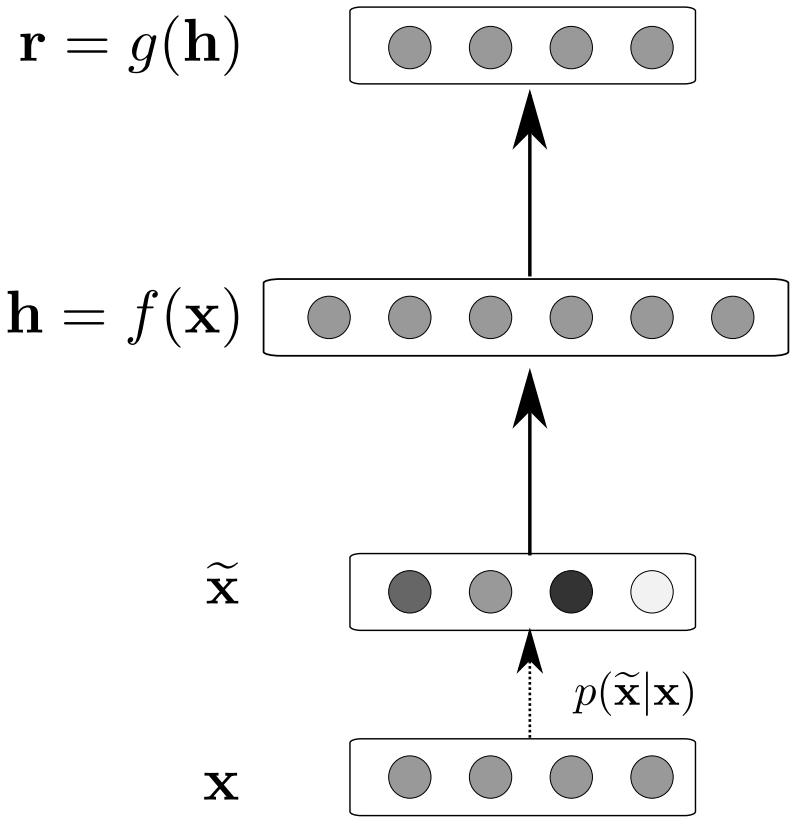

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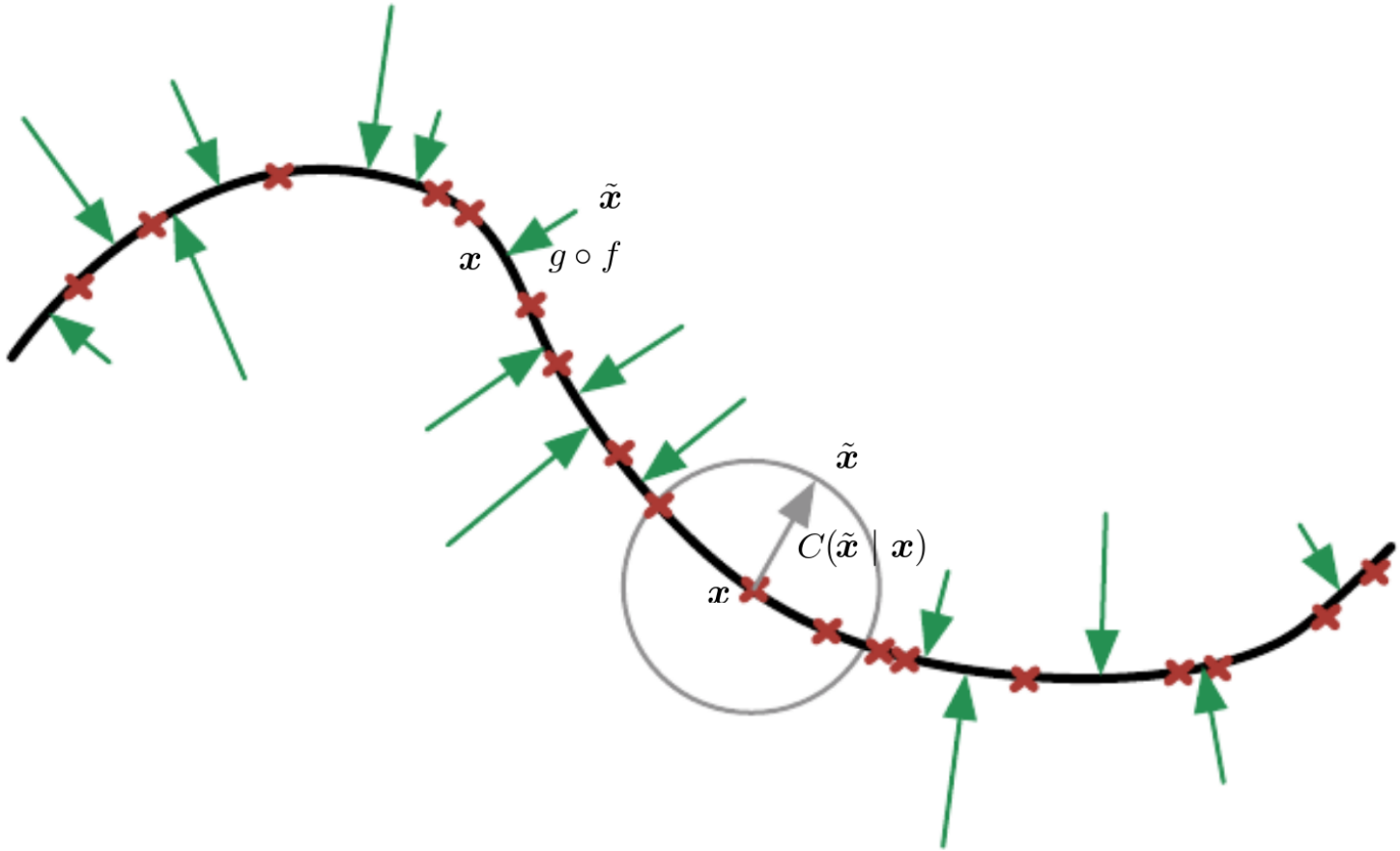
Q: How to make robust to noise?
A: Reconstruct the loss on $g(f(\widetilde{x})) = x$

Input a noisy sample $\widetilde{x}$ and optimize to reconstruct the noise-free x.

Denoising autoencoder

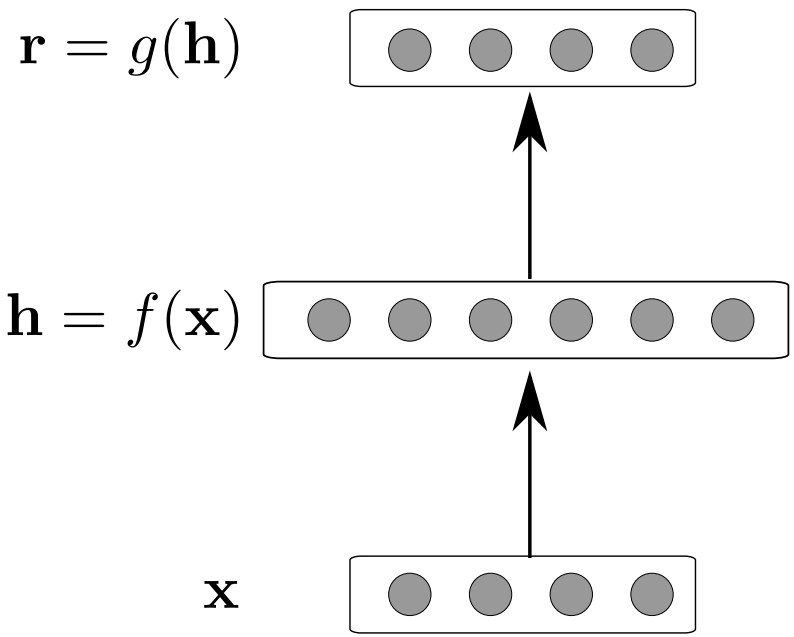
Fig 14.4 in book



True sample x, noisy sample $\widetilde{x}$, Noise process $C(\widetilde{x}|x)$, wrt $p(\widetilde{x}|x)$

Overcomplete: Contractive autoencoder

Book: 14.2.3, 14.7



Penalize "unwanted variations".

$$l(g(f(x)), x) + \lambda \left\| \frac{\partial f(x)}{\partial x} \right\|_F^2$$

$\Omega(h) = \left\| \frac{\partial f(x)}{\partial x} \right\|_F^2$ Frobenius norm of Jacobian

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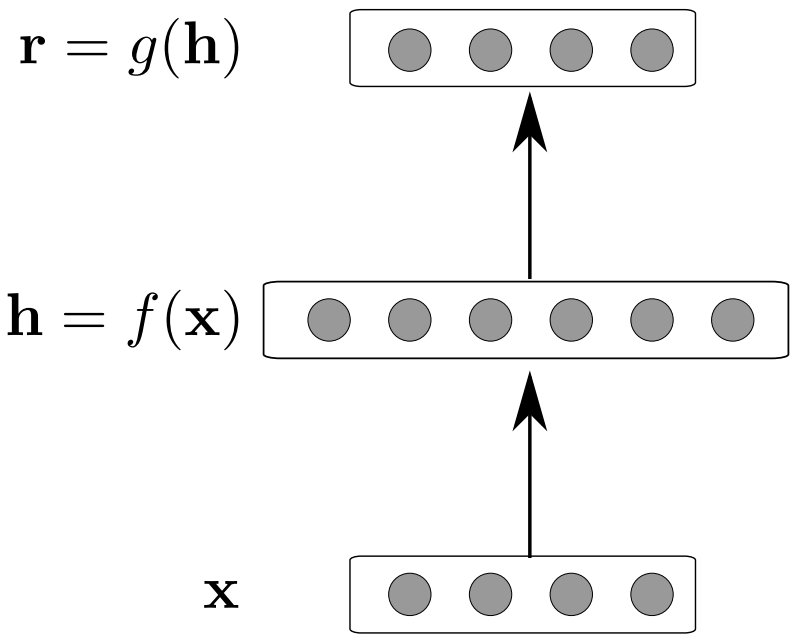

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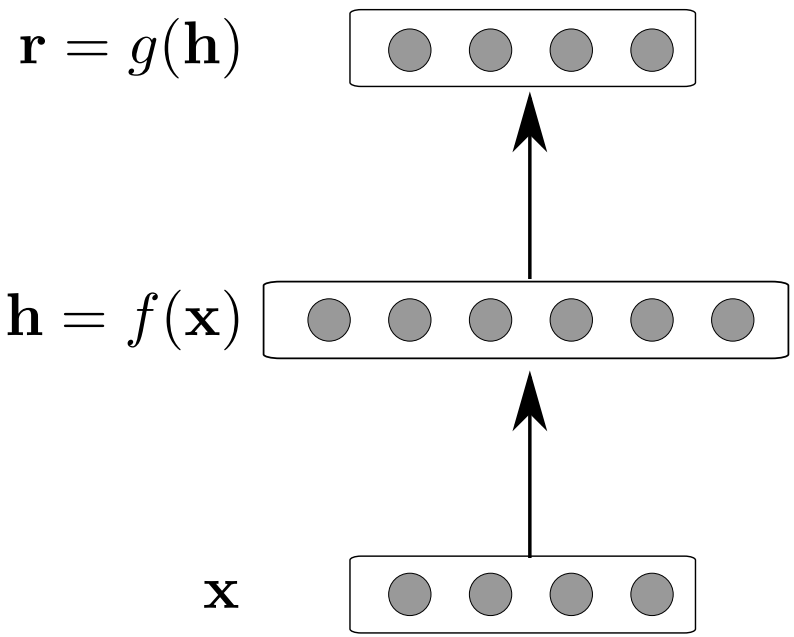

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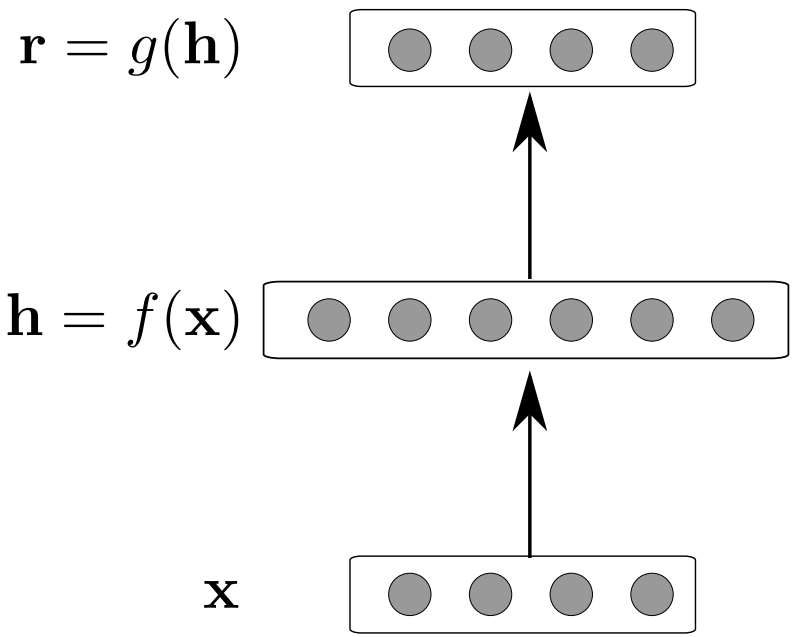

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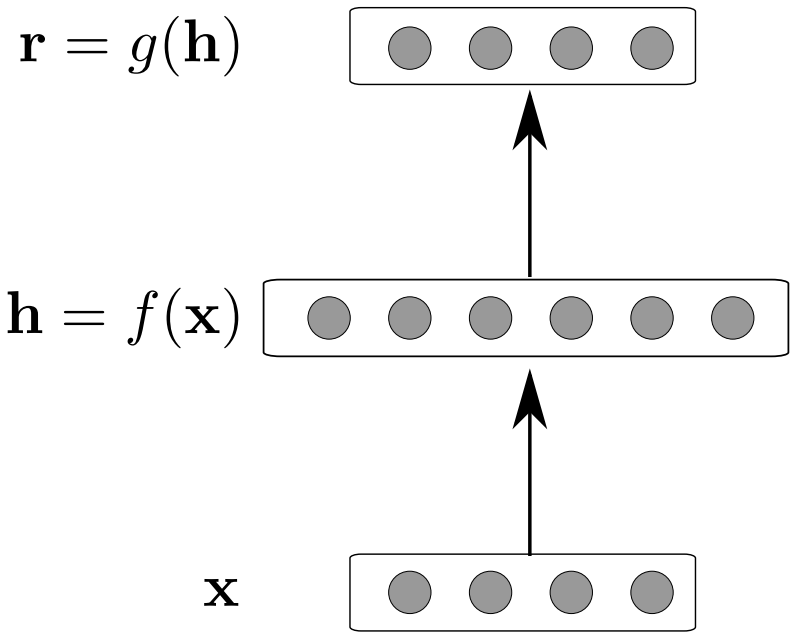

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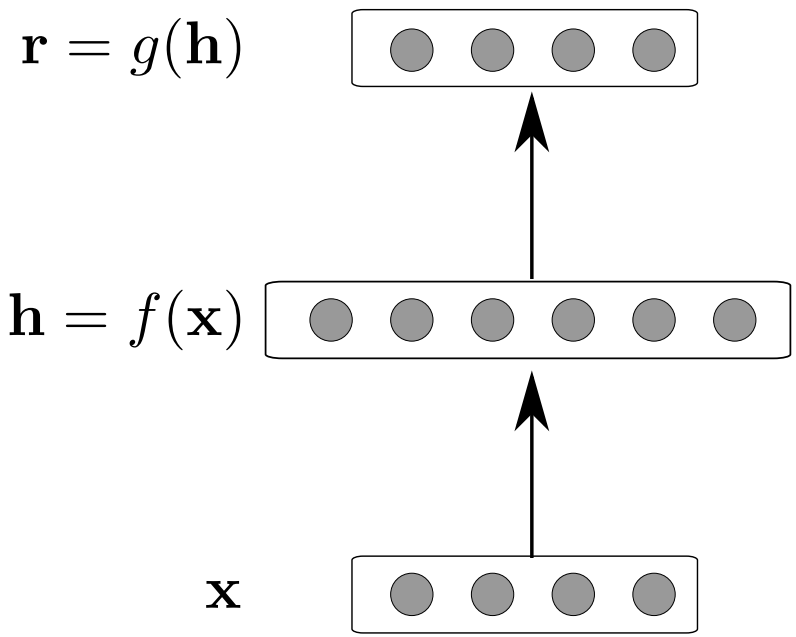

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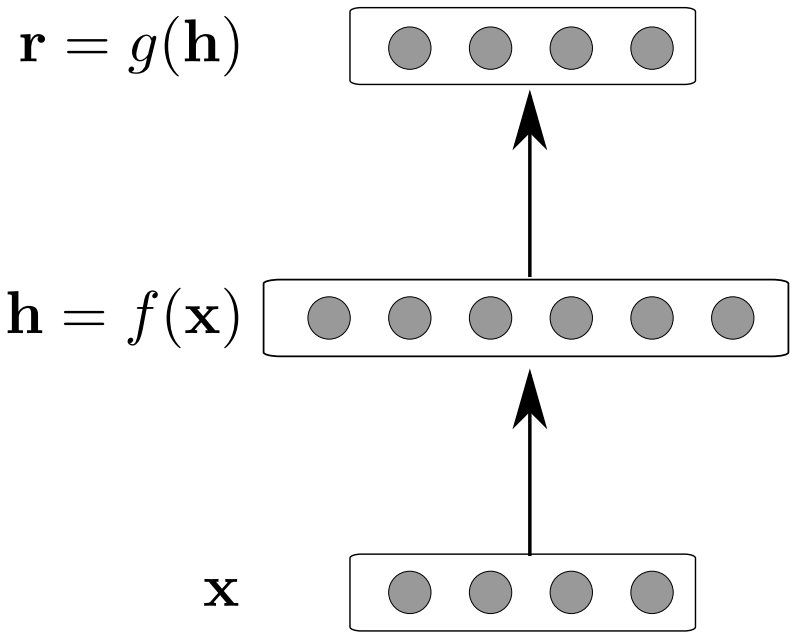

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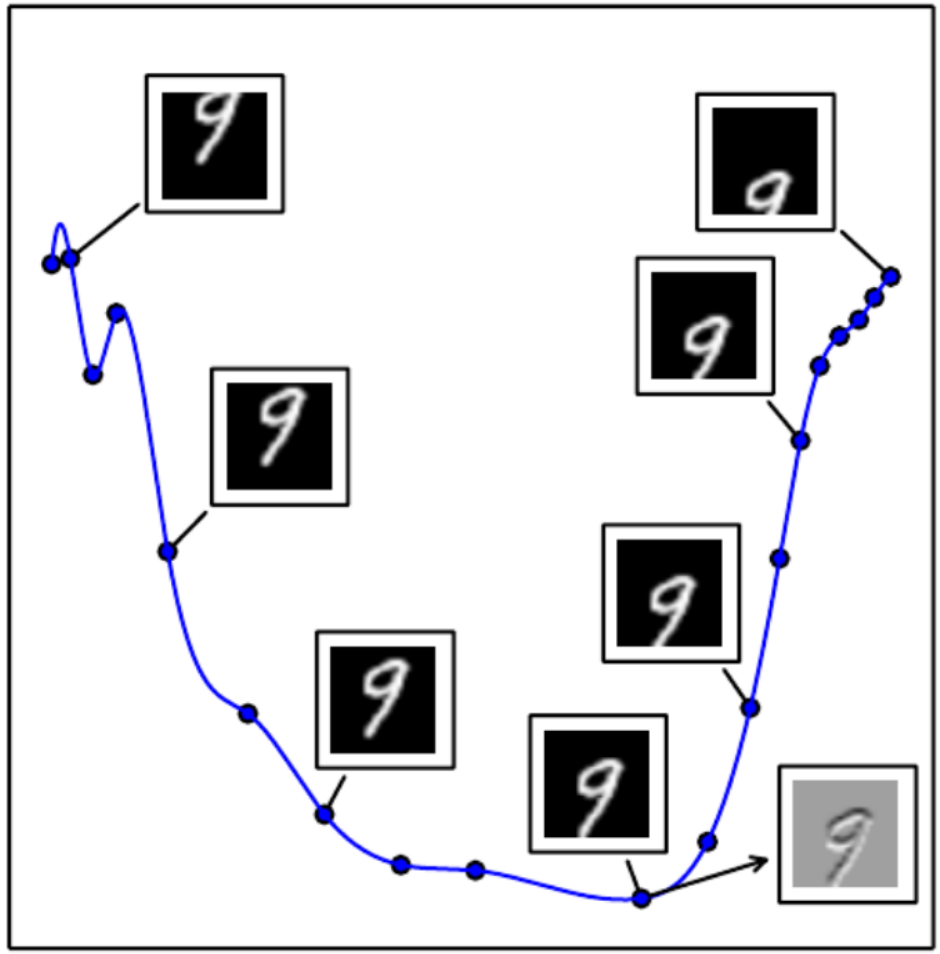
A: $O(x \times h)$

Contractive autoencoder

Fig 14.6 in book



Gray pixels: little change. White/Black pixels higher change.

Questions?

Variational Autoencoder

Book: 20.10.3, 20.9, Better: `https://www.jeremyjordan.me/variational-autoencoders/`

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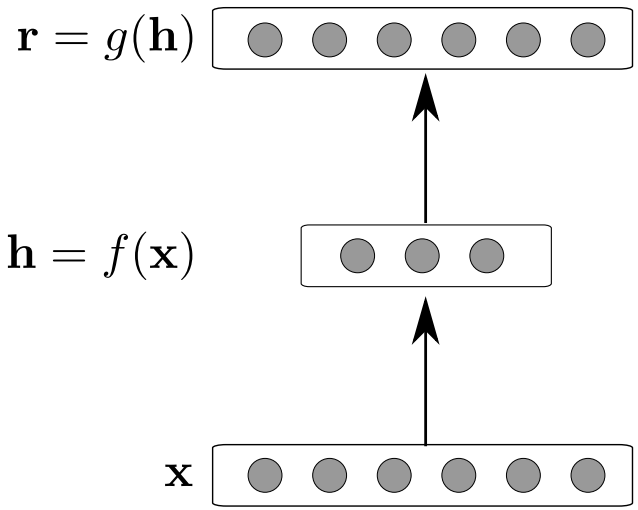

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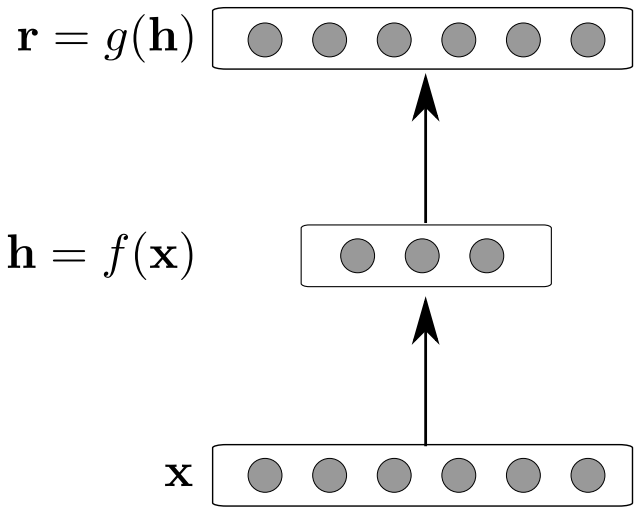

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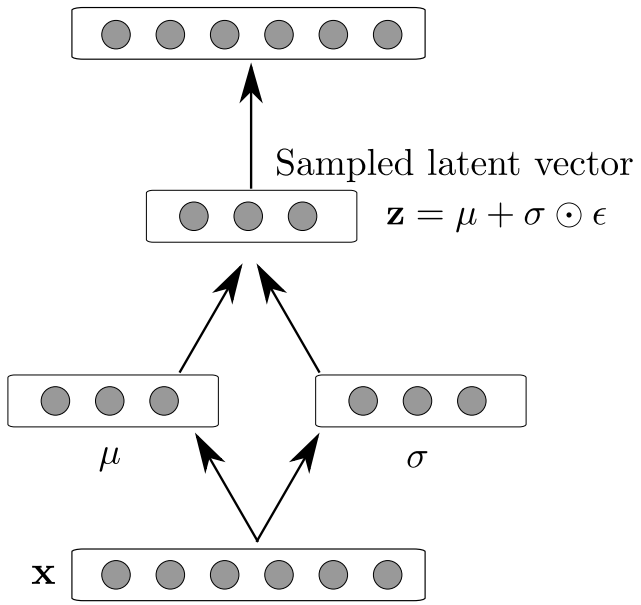

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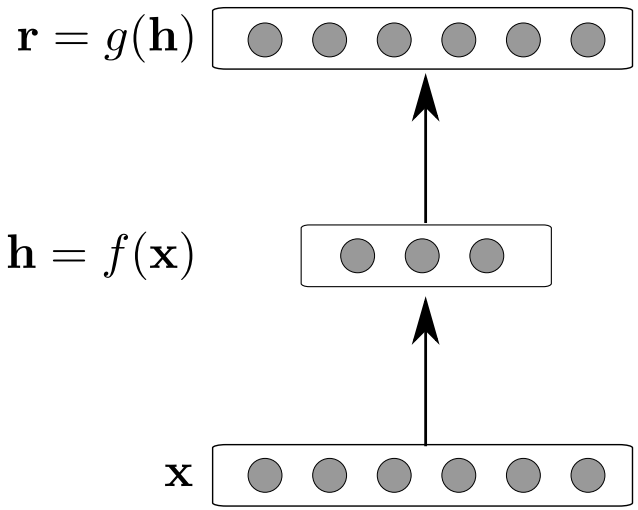

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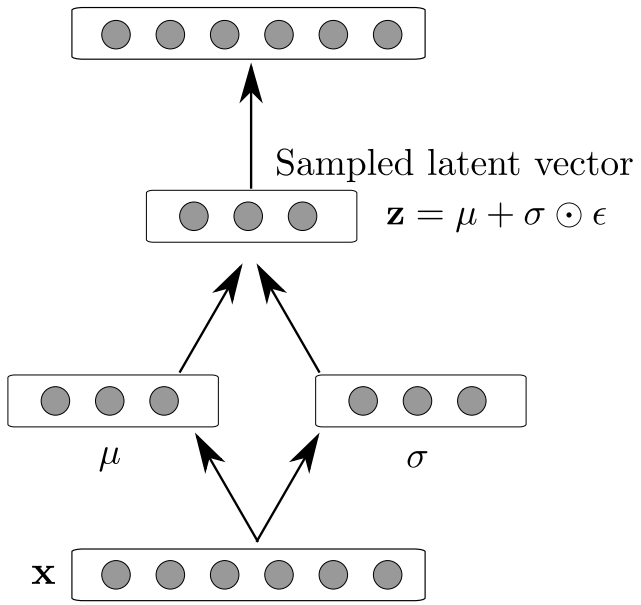

Reparameterization trick: Compute sampler gradients, draw $\epsilon \sim \mathcal{N}(0, 1)$. (Book: 20.9).

Variational autoencoder: Examples in 2D

Faces:

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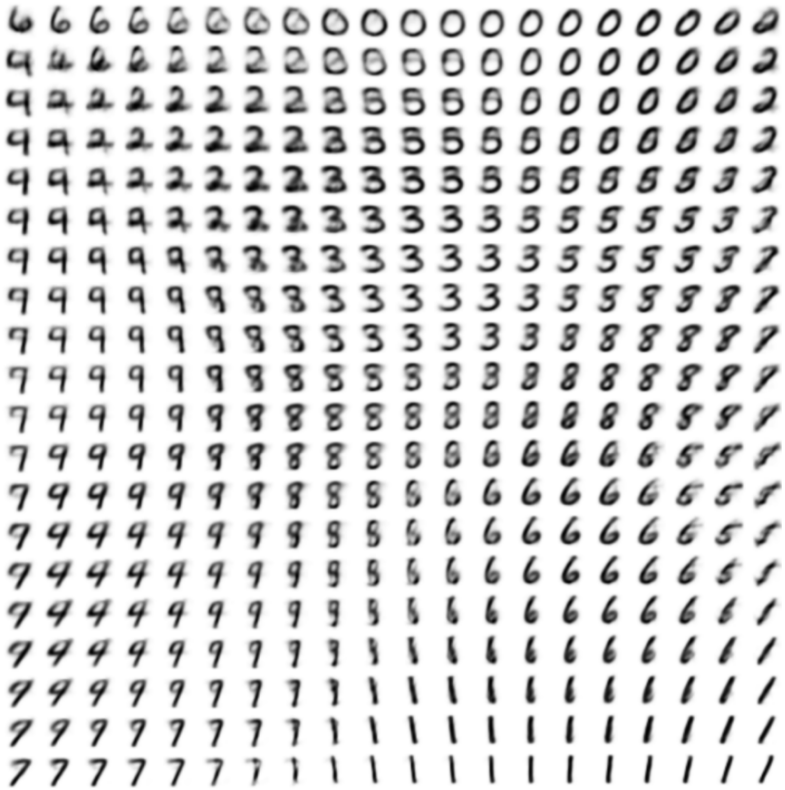
Faces:

MNIST:



Generative Adversarial Networks

Book: Chapter 20.10.4

Problem: No direct way to sample from high dimensional training distribution.

Solution: Sample from simple distribution, such as random noise, and learn transformation from noise to training distribution.

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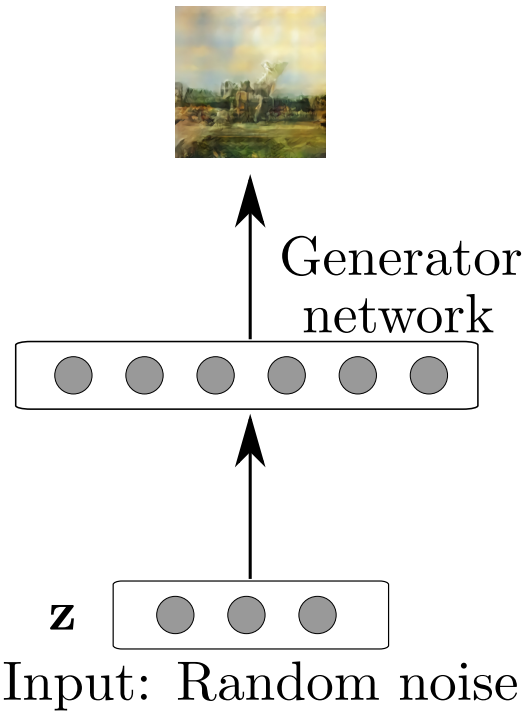

Training GANS: Two player game

Generator network:
Try to fool the discriminator by generating real looking images.

Discriminator network:
Try to discriminate between real and fake images.

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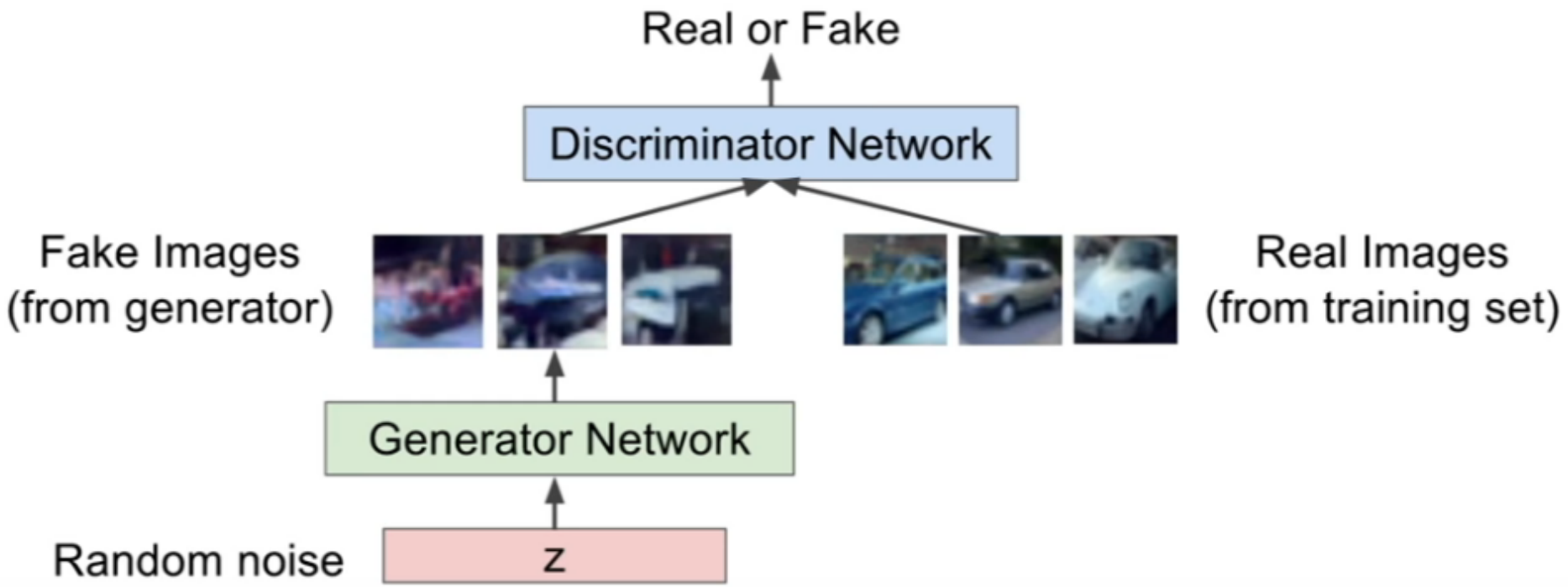

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Objective:

$$\arg\min_{\theta_G}\max_{\theta_D}\mathbb{E}_{x\sim p_{\text{data}}}\log D_{\theta_D}(x)+\mathbb{E}_{x\sim p(z)}\log(1-D_{\theta_D}(G_{\theta_G}(z)))$$

Q: What values for which terms does each network aim to obtain?

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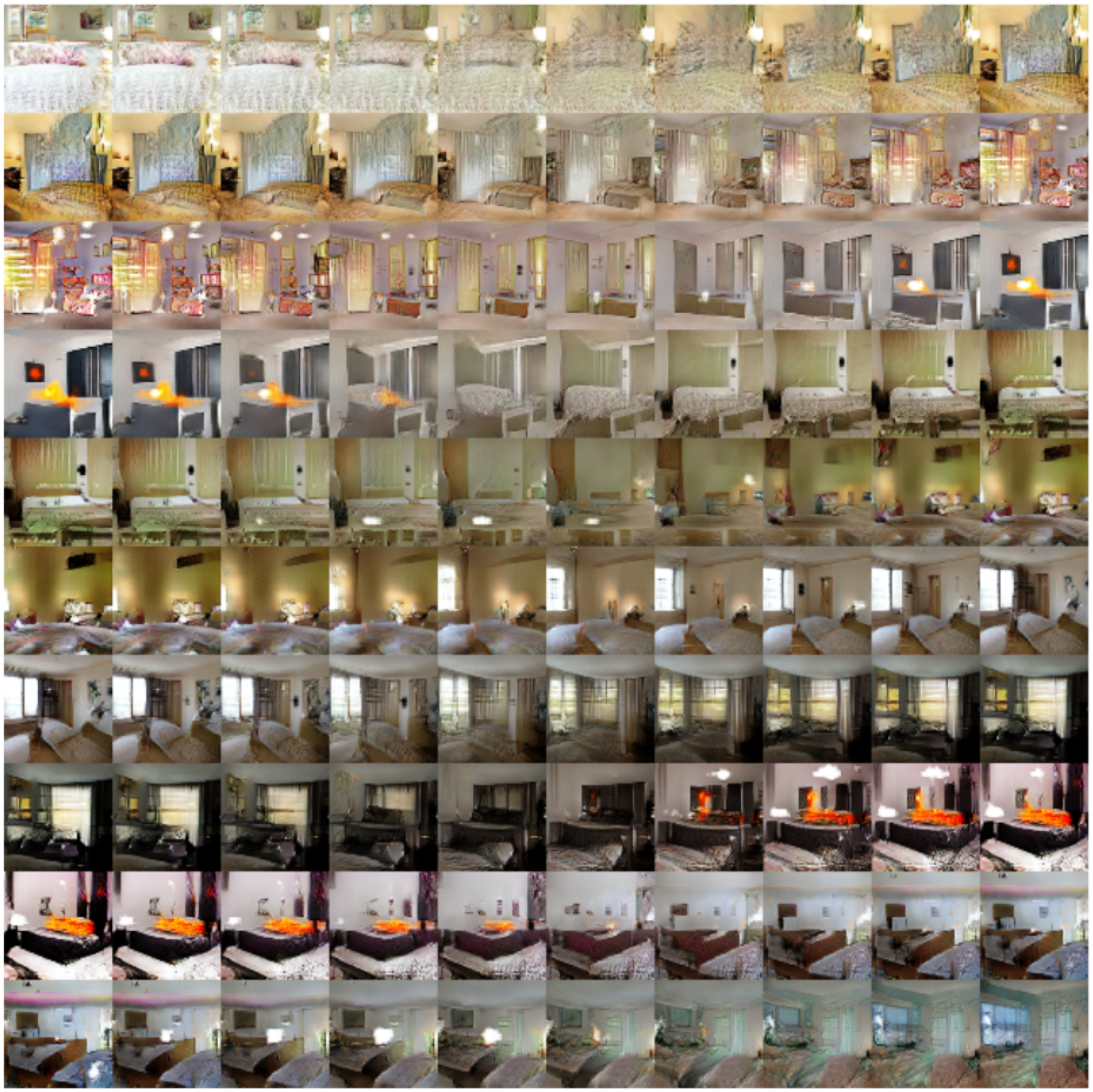
Q: What values for which terms does each network aim to obtain?
Discriminator D_{θ_D} aims to **maximize** so that $D_{\theta_D}(x)$ is close to 1 for real data and $D_{\theta_D}(G_{\theta_G}(x))$ is 0 for fakes.

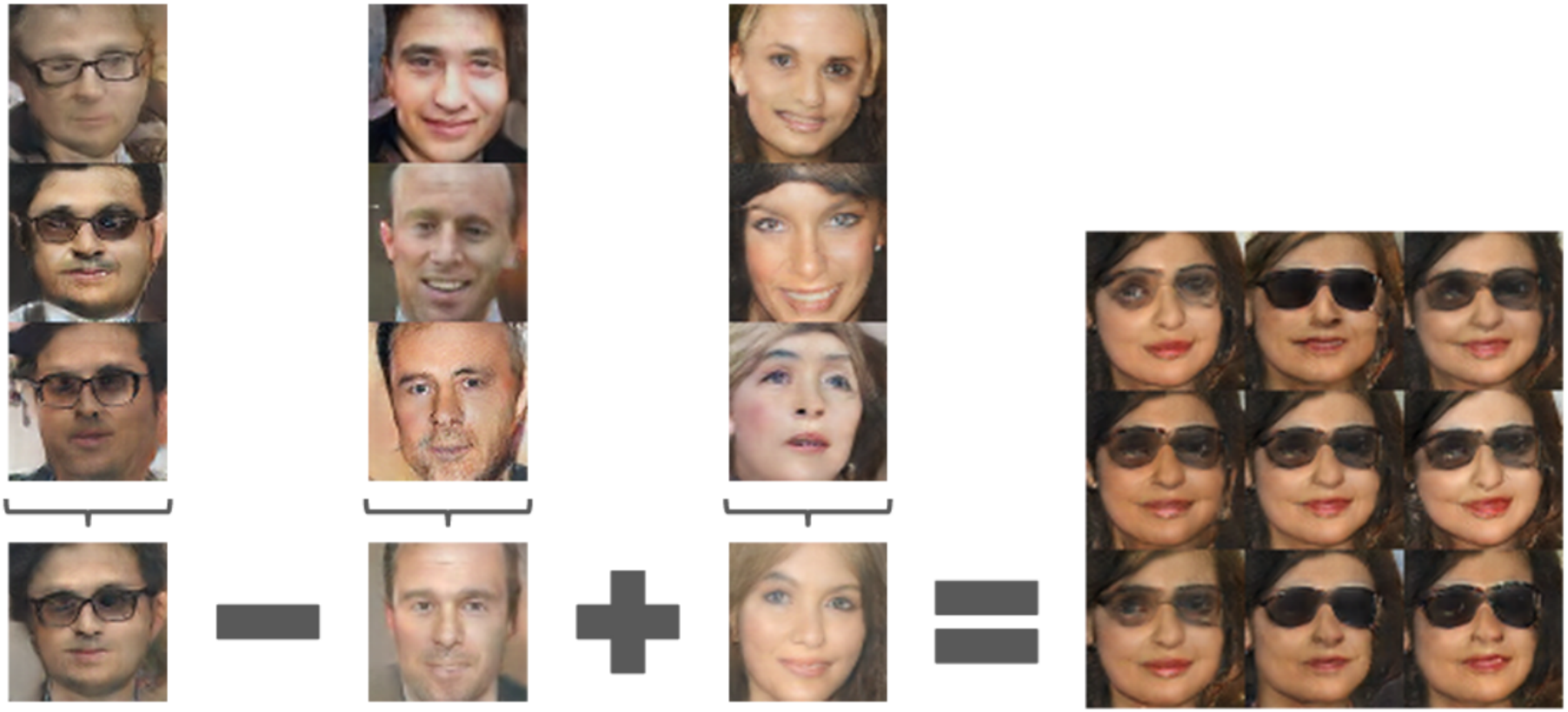
Generator G_{θ_G} aims to **minimize** so that $D_{\theta_D}(G_{\theta_G}(x))$ is close to 1 (fooling the discriminator)

Interpolation in latent space



Vector arithmetics

Vector arithmetics



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Book: Chapter 20.14

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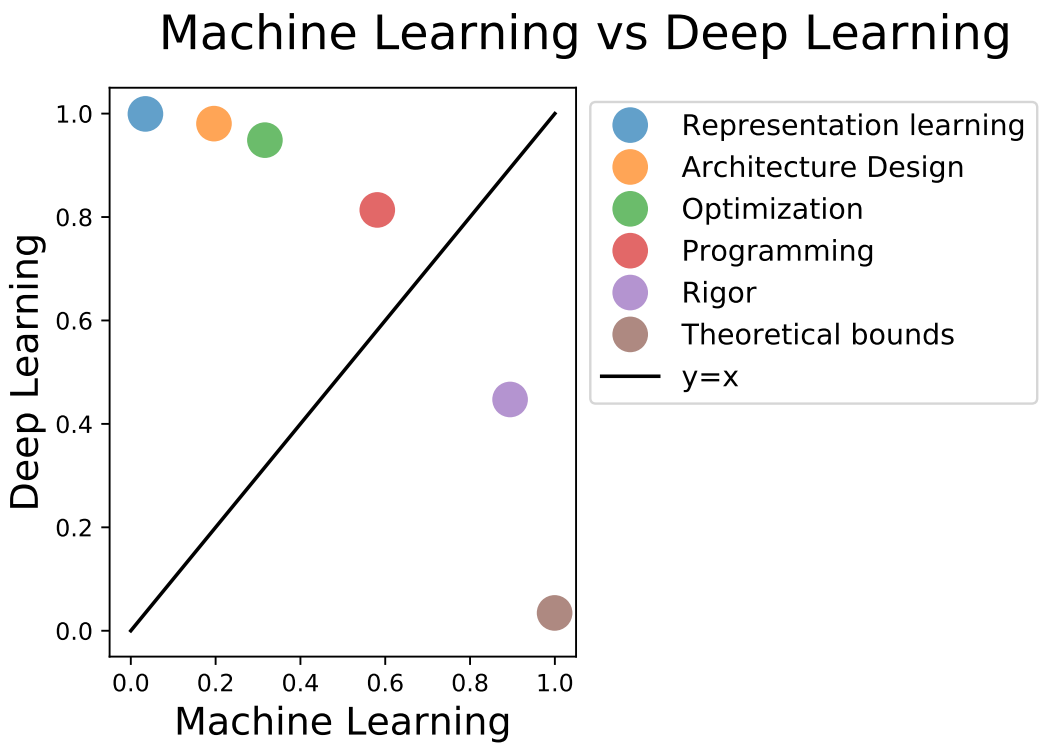
  A: Just copying the training set will do very well
- Q: Can't we use the unsupervised features to evaluate another task (e.g., classification accuracy)?
  A: Yes, but that does limit the use of generative models

How to evaluate generative models is still a research topic.

Questions?

Deep learning and Machine learning

Difference between
machine learning and deep learning



- Deep learning: coupled to the application
- Machine learning: application independent
- Lets discuss this slide again after the course