University of Antwerp

Artificial Neural Networks

[2500WETANN]

José Oramas

Deep Generative Networks

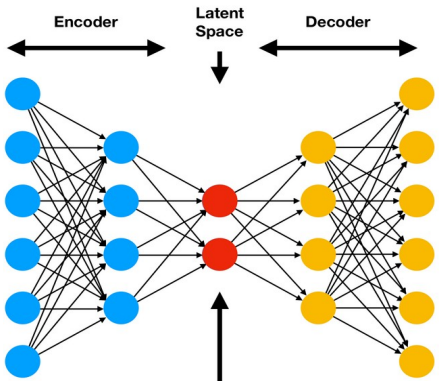
[Learning how to generate data]

José Oramas

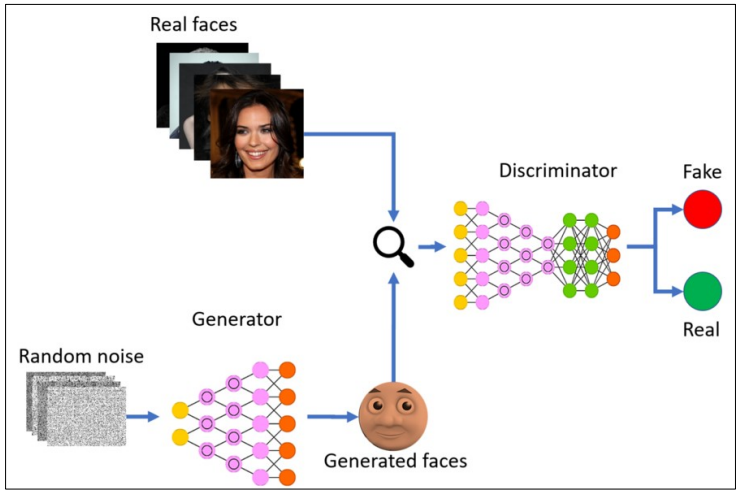
University of Antwerp

Today's Lecture : Deep Generative Networks

- [Variational] Autoencoders



- Generative Adversarial Networks (GANs)



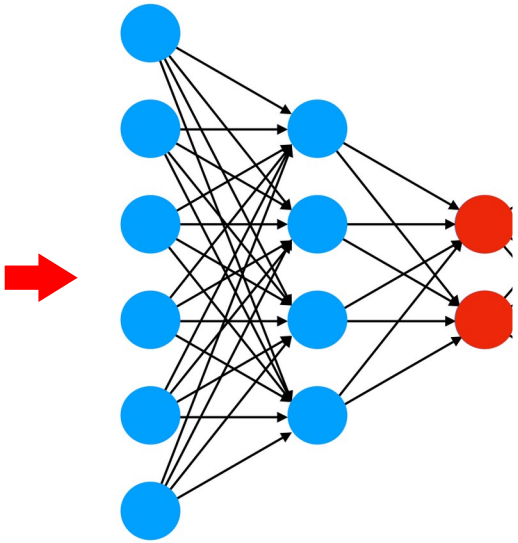
Autoencoders

[Reconstructing Inputs]

DNN Classifiers

Learn to classify the input – Discriminative Model

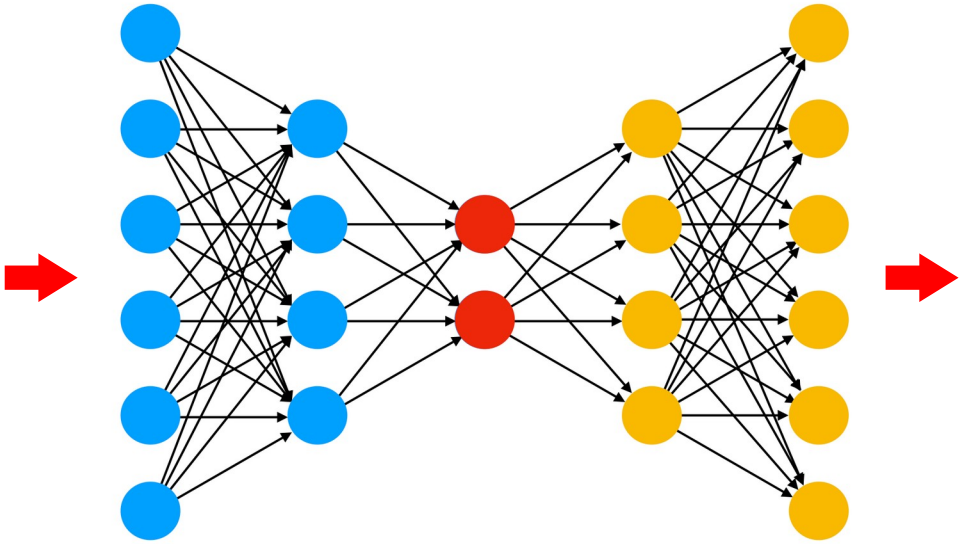
Original Input



Autoencoders

Learn to reconstruct the input

Original Input



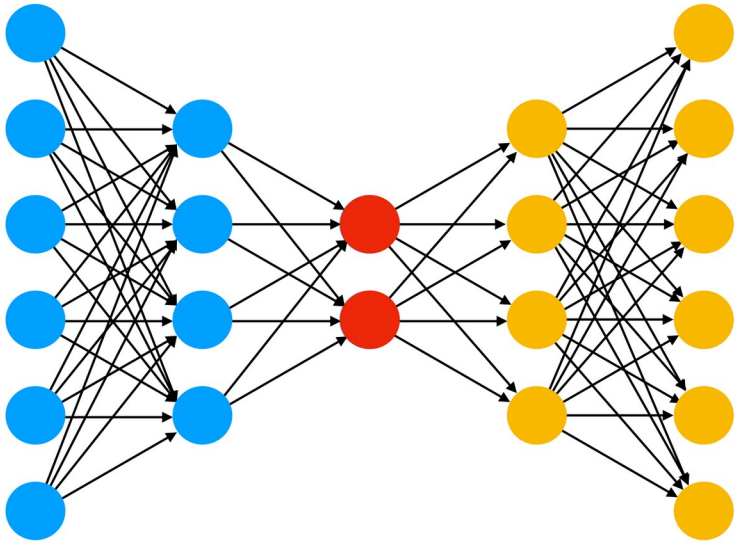
Reconstructed Input

Autoencoders

Learn to reconstruct the input

Original Input

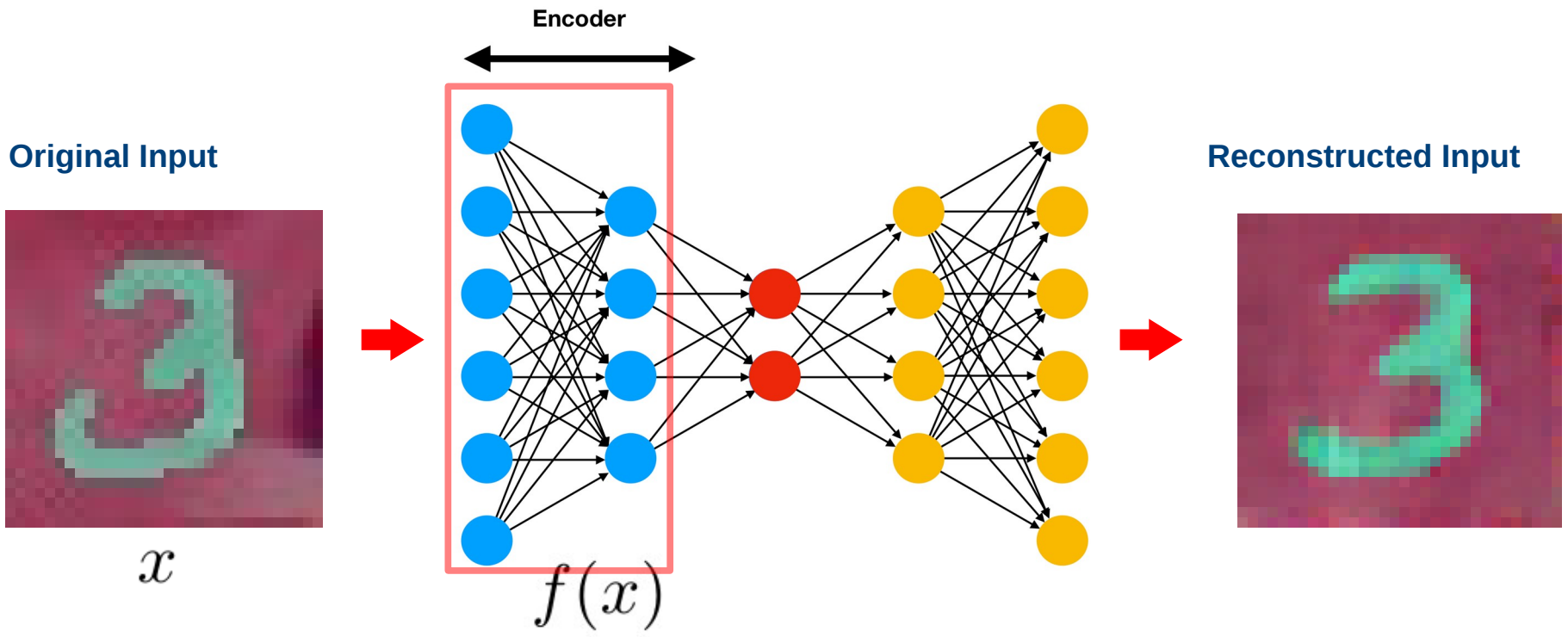
x



Reconstructed Input

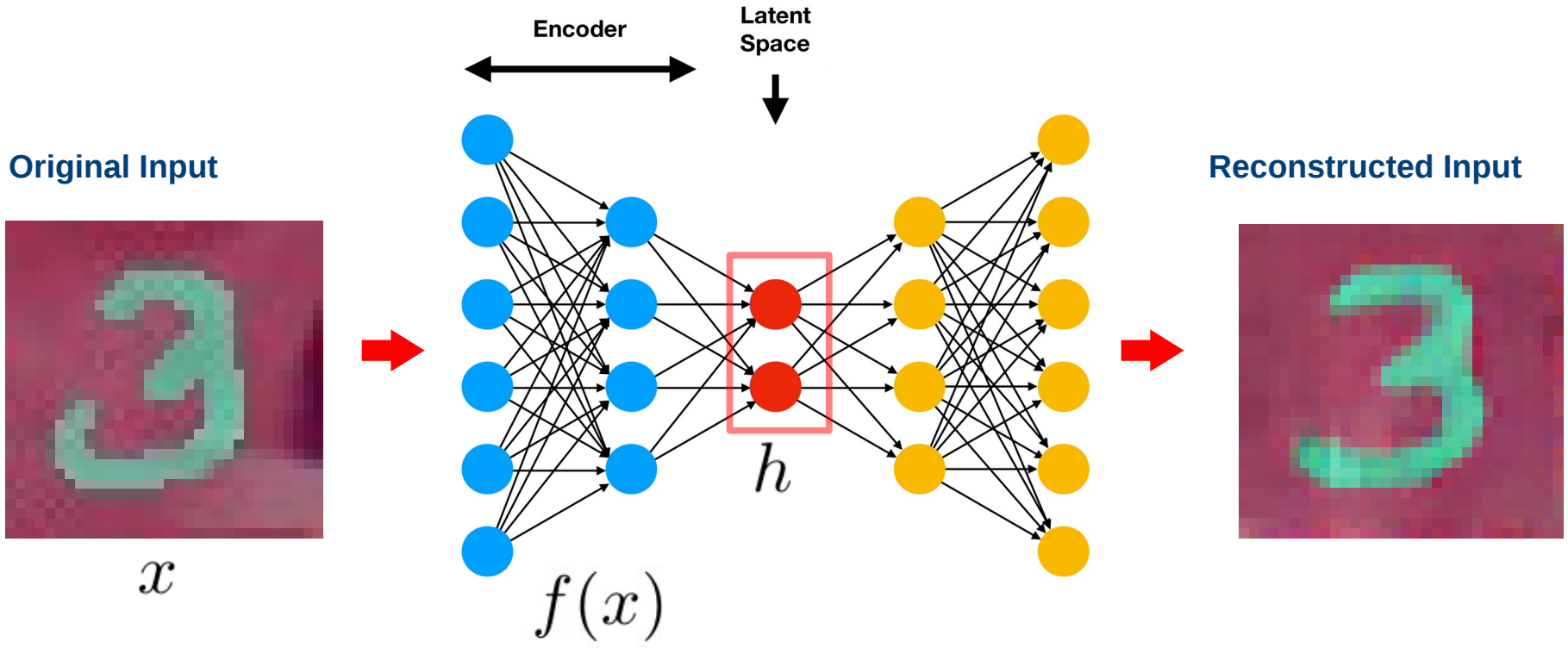
Autoencoders

Learn to reconstruct the input



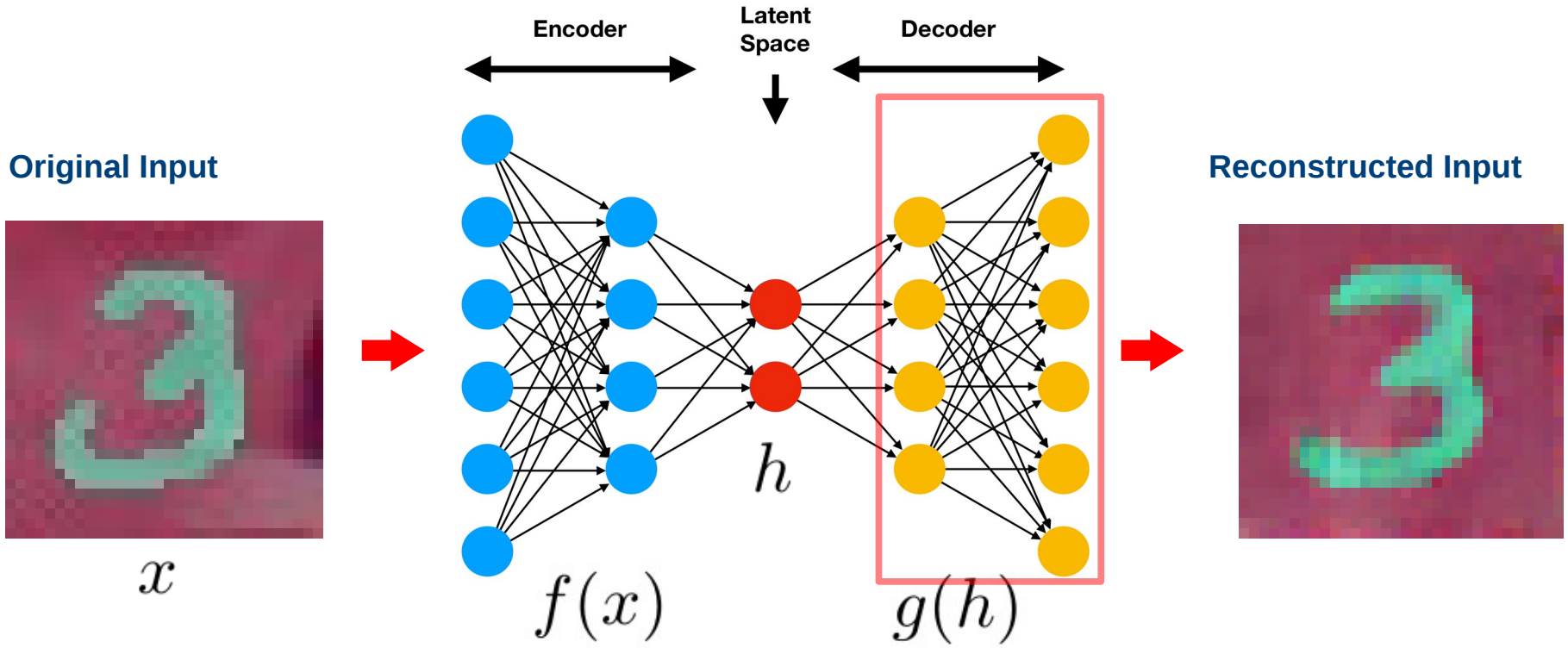
Autoencoders

Learn to reconstruct the input



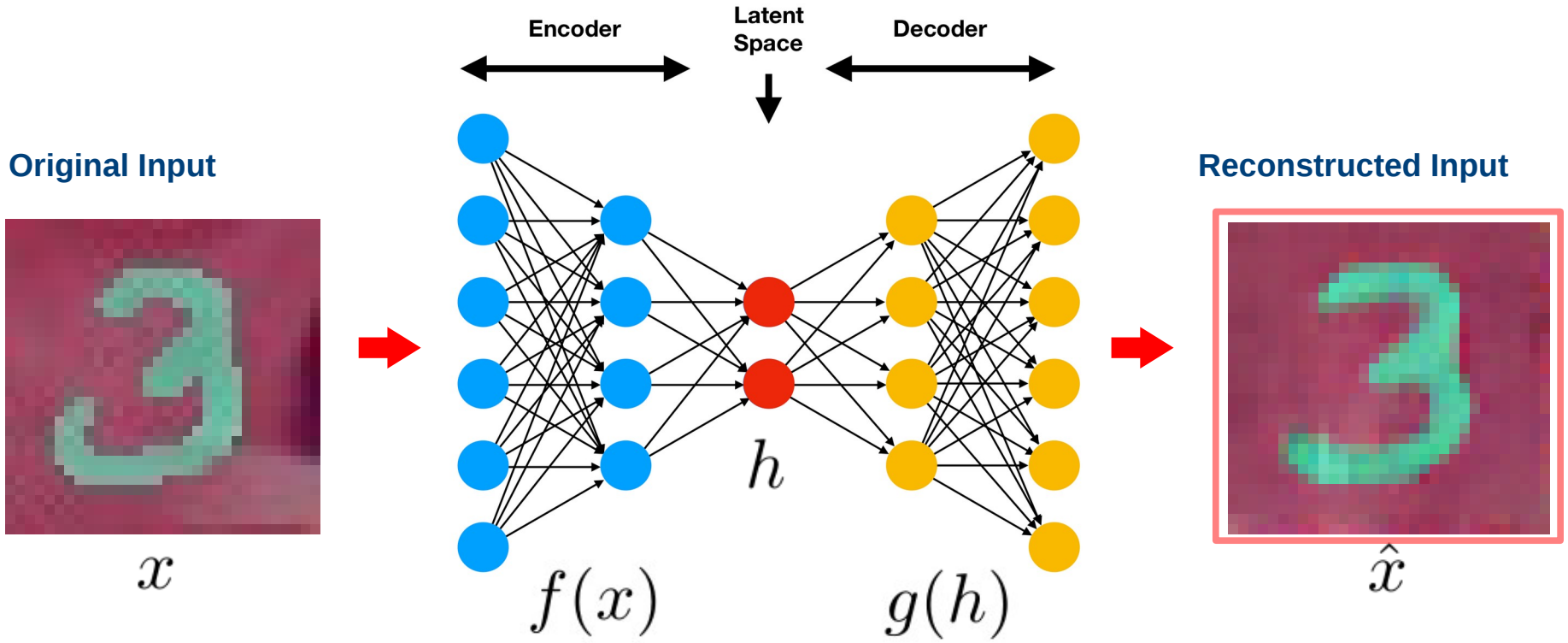
Autoencoders

Learn to reconstruct the input



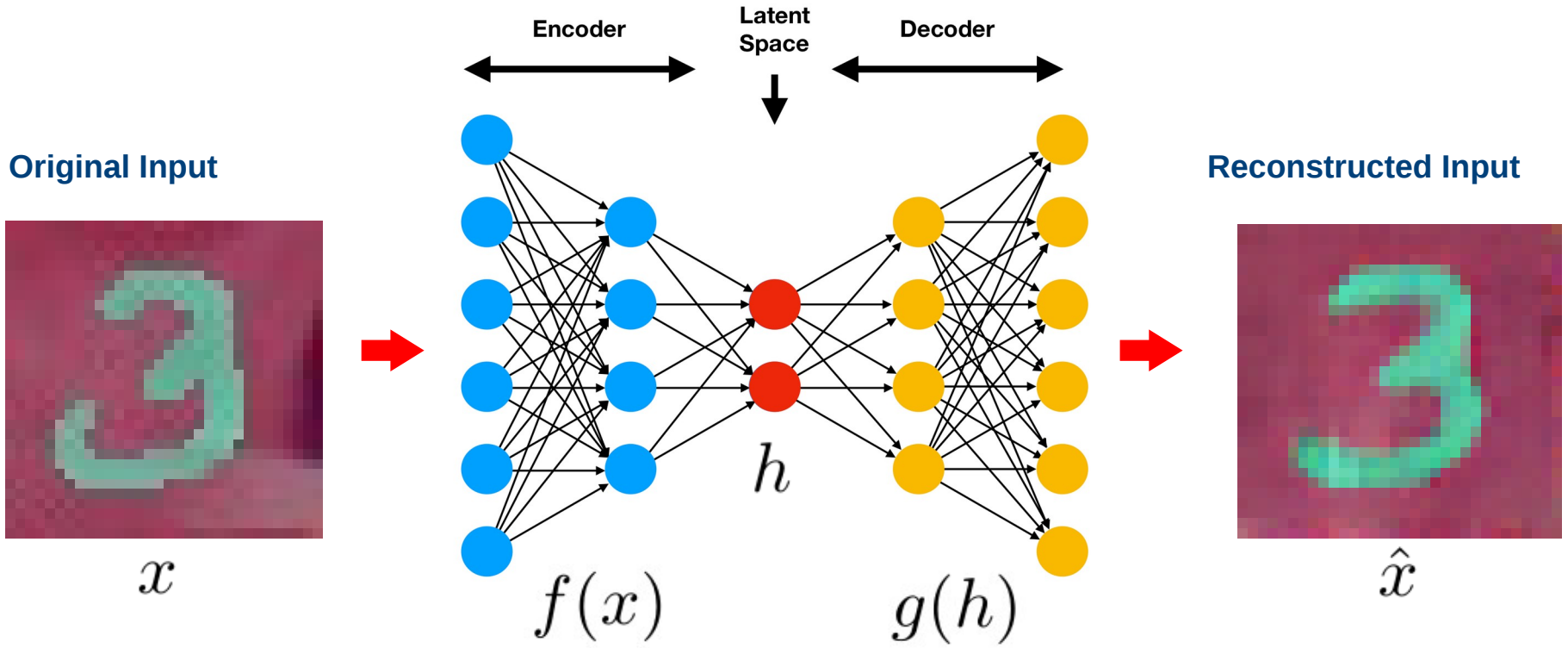
Autoencoders

Learn to reconstruct the input



Autoencoders

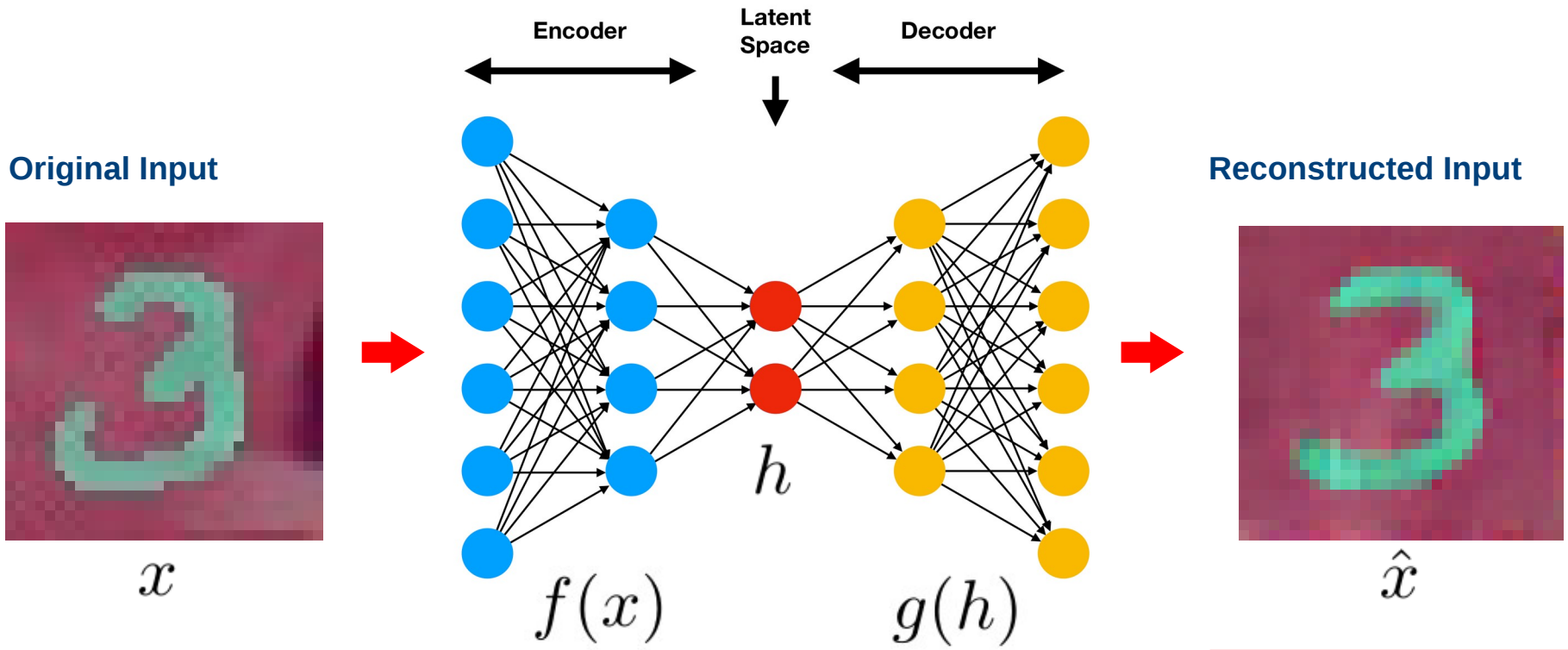
Learn to reconstruct the input



- Pick up data characteristics

Autoencoders – Training

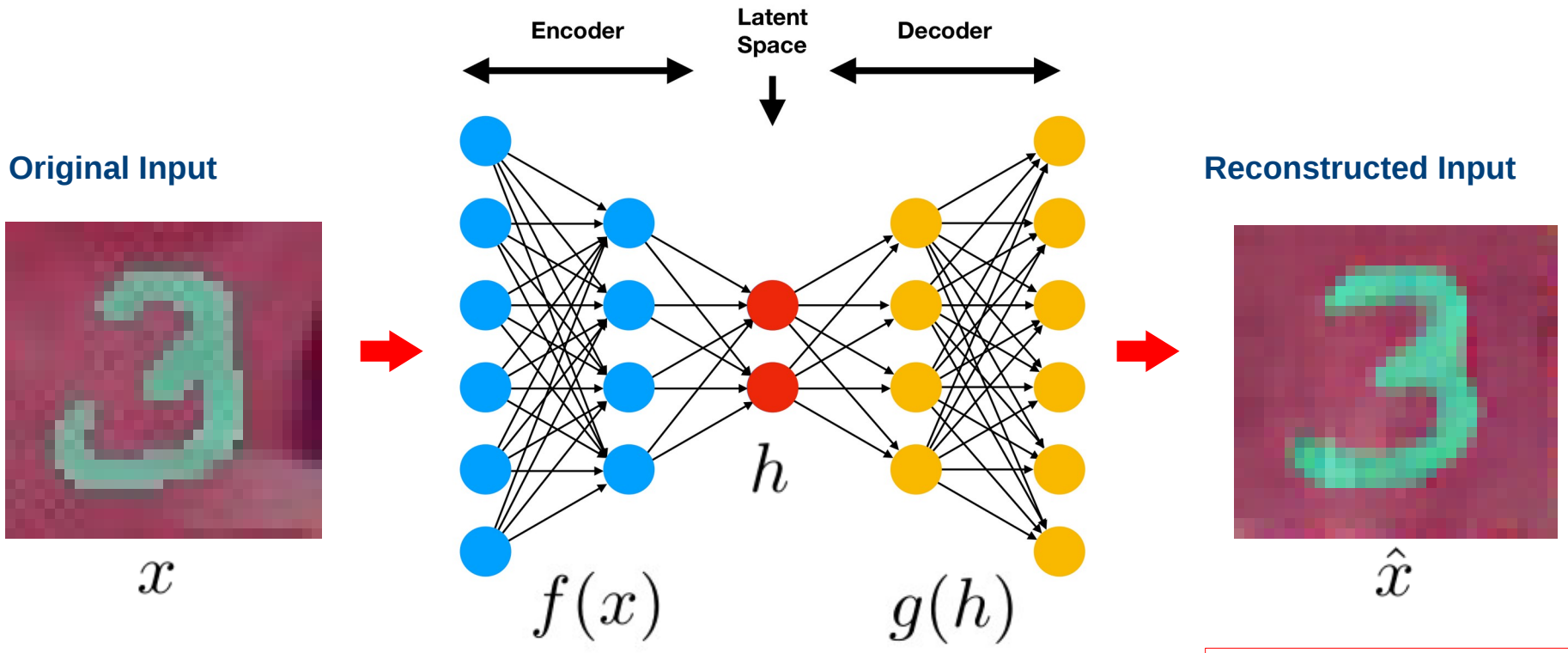
Measure reconstruction error



$$l(x, \hat{x}) = l(\ x,\ g(f(x))\ )$$

Autoencoders – Training

Measure reconstruction error

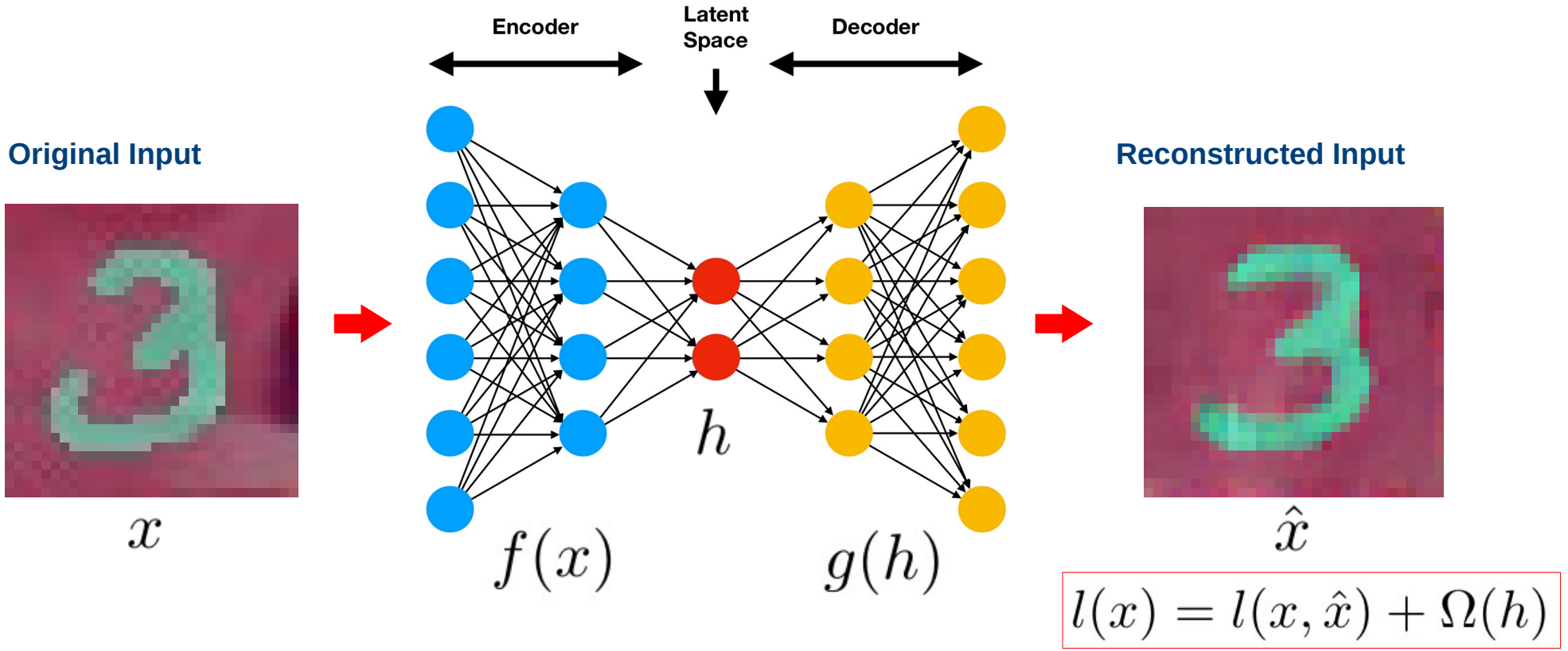


- No need for annotations
- Perfect reconstruction is discouraged

$$l(x, \hat{x}) = l(\ x,\ g(f(x))\ )$$

Sparse Autoencoders

Impose additional constrains on the latent space

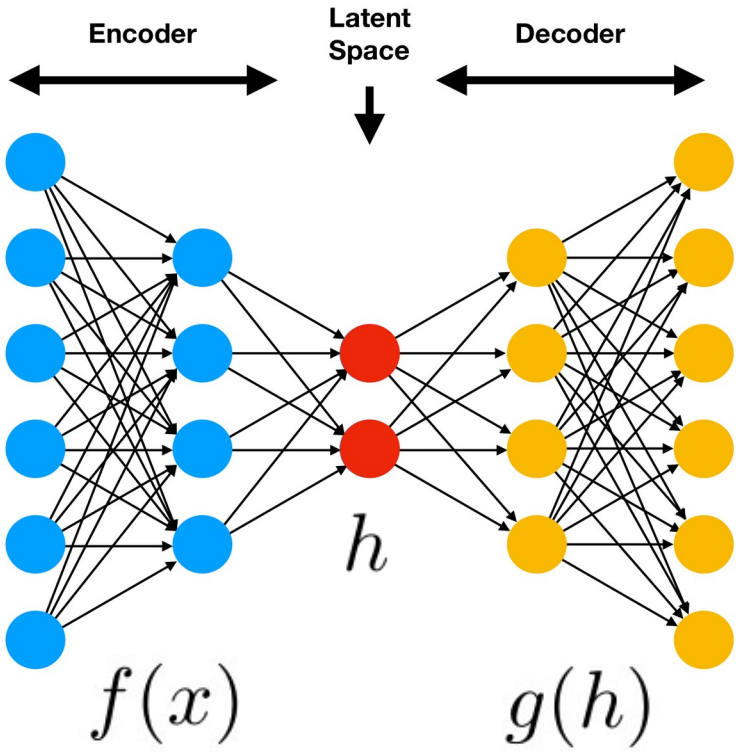


Sparse Autoencoders

Impose additional constrains on the latent space

Original Input

x



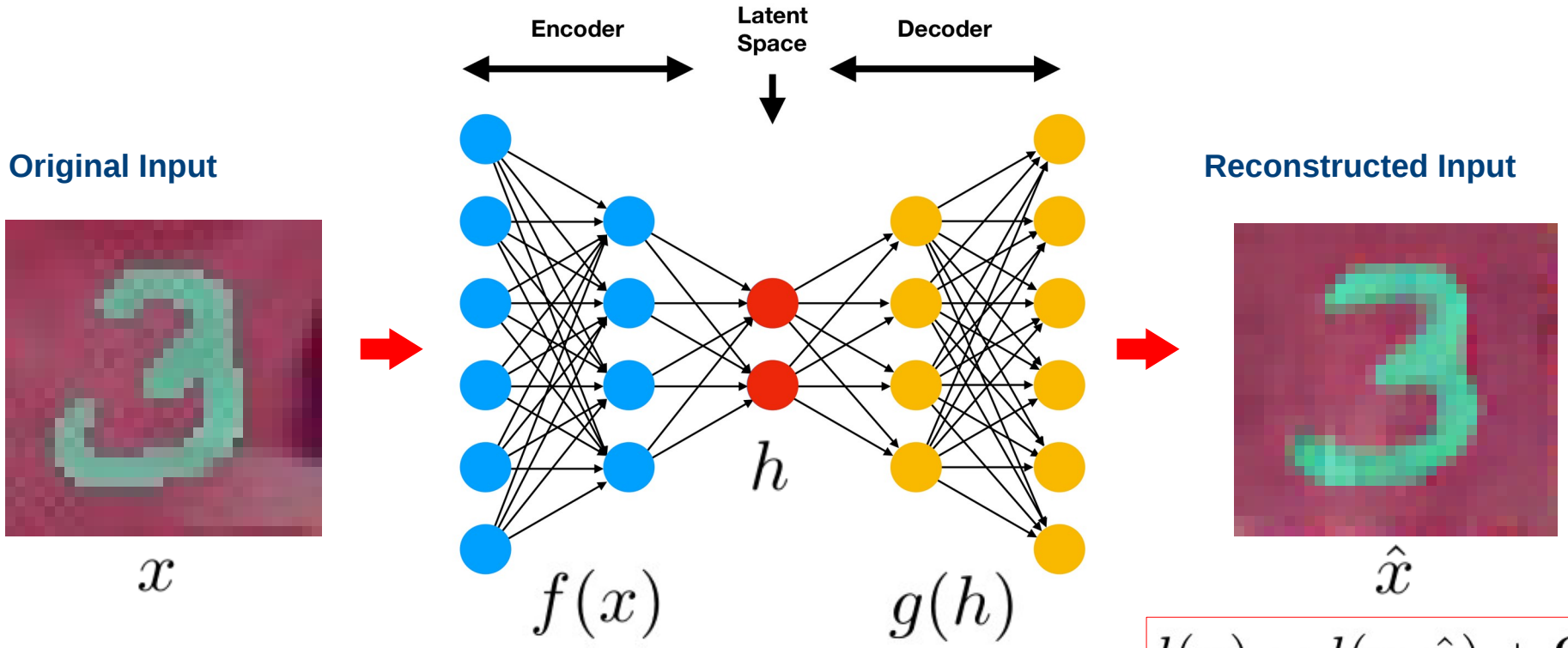
Reconstructed Input

$\hat{x}$

$$l(x) = l(x, \hat{x}) + \Omega(h)$$
$$l(x) = l(x, \hat{x}) + \sum_i |a_i^{(h)}|$$

Sparse Autoencoders

Impose additional constrains on the latent space

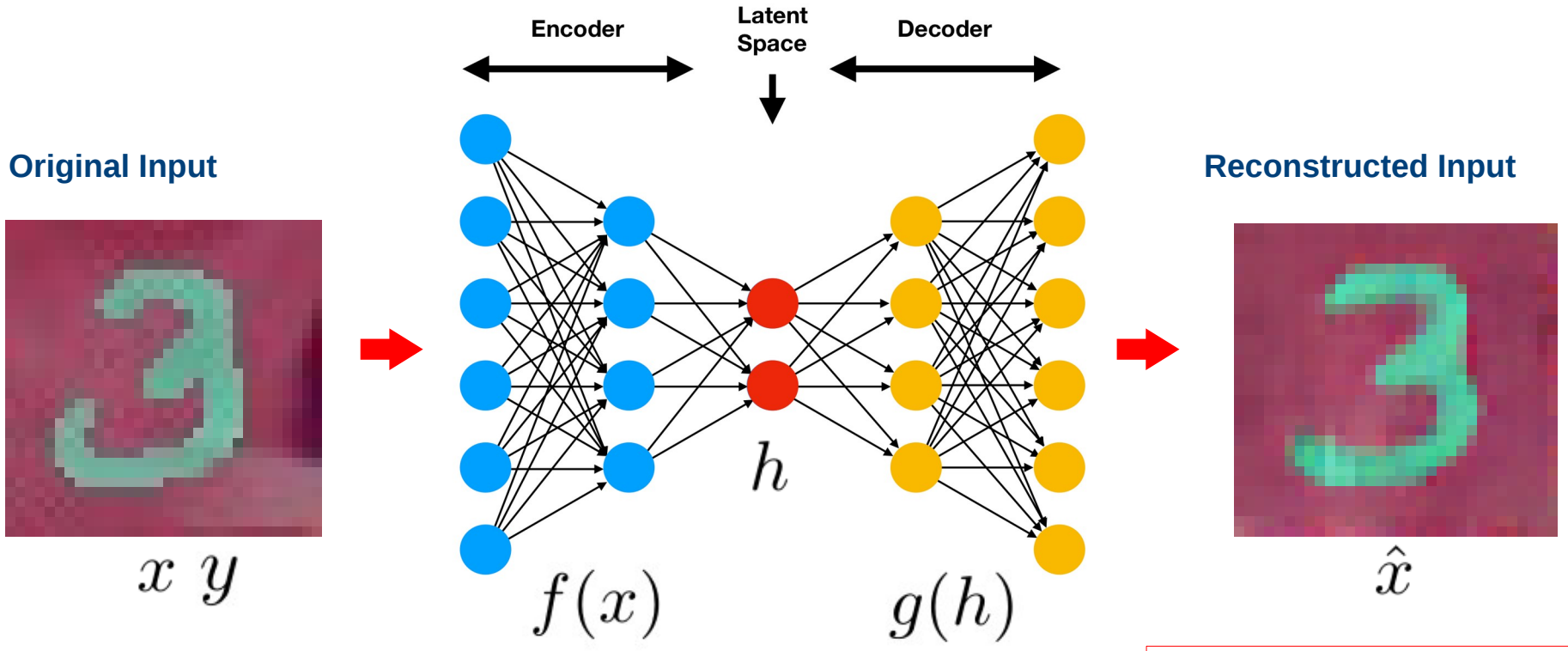


- Go beyond undercomplete
- Beyond learning identity functions

$$l(x) = l(x, \hat{x}) + \Omega(h)$$
$$l(x) = l(x, \hat{x}) + \sum_i |a_i^{(h)}|$$

Sparse Autoencoders

Impose additional constrains on the latent space

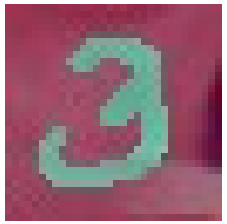


$$l(x) = l_{rec}(x, \hat{x}) + l_{class}(y, \hat{y})$$

Denoising Autoencoders (DAEs)

Obtaining a clean reconstruction from a noisy input

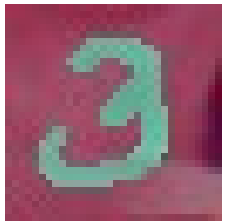
Original Input x



Denoising Autoencoders (DAEs)

Obtaining a clean reconstruction from a noisy input

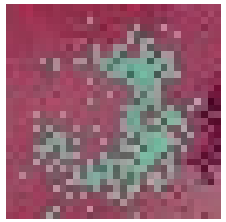
Original Input x



C

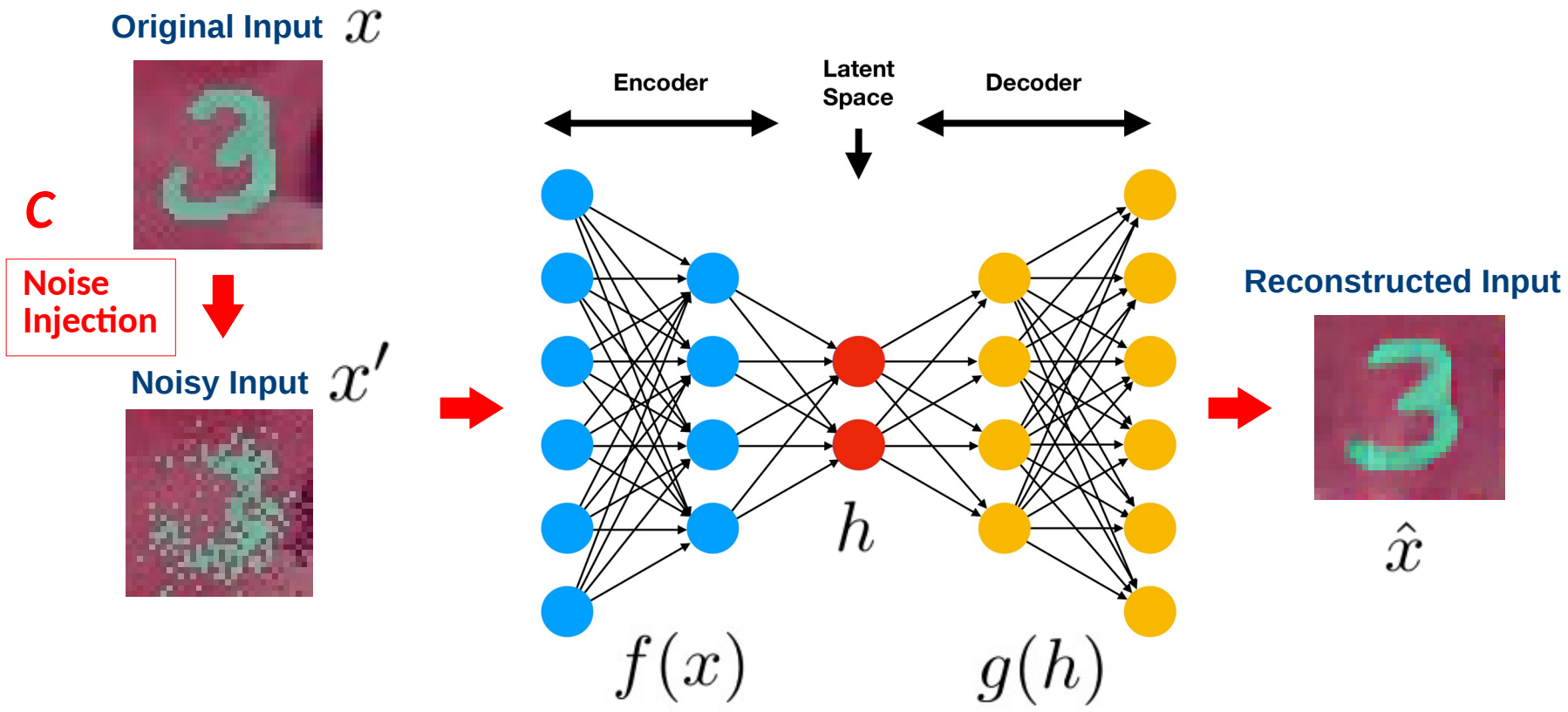
Noise Injection

Noisy Input x'



Denoising Autoencoders (DAEs)

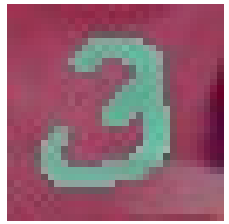
Obtaining a clean reconstruction from a noisy input



Denoising Autoencoders (DAEs)

Obtaining a clean reconstruction from a noisy input

Original Input x



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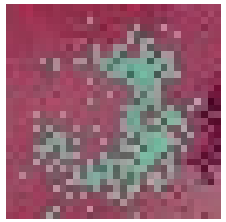
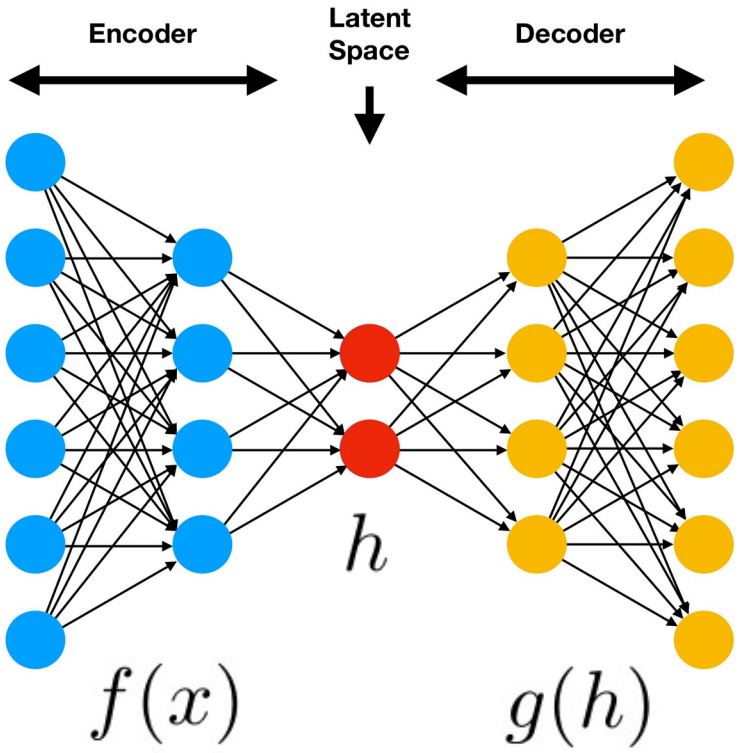
Noise Injection

Noisy Input x'





Reconstructed Input

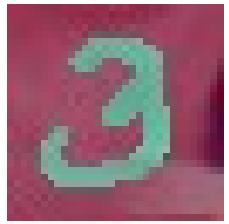
$\hat{x}$

$$l(x, \hat{x}) = l(\ x,\ g(f(x'))\ )$$

Denoising Autoencoders (DAEs)

Obtaining a clean reconstruction from a noisy input

Original Input x



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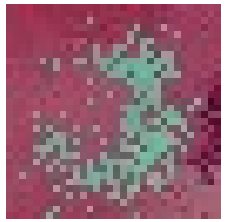
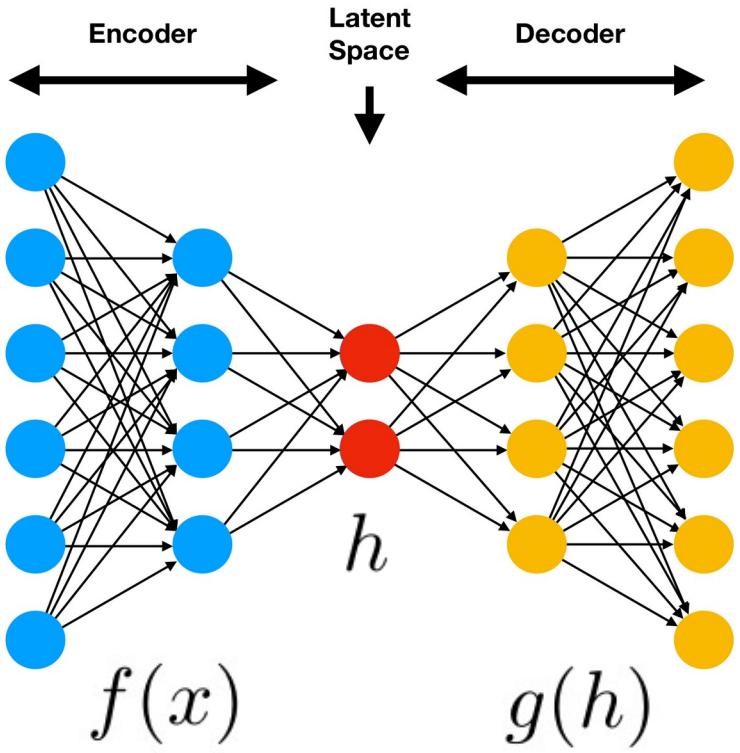
Noise Injection

Noisy Input x'





Reconstructed Input

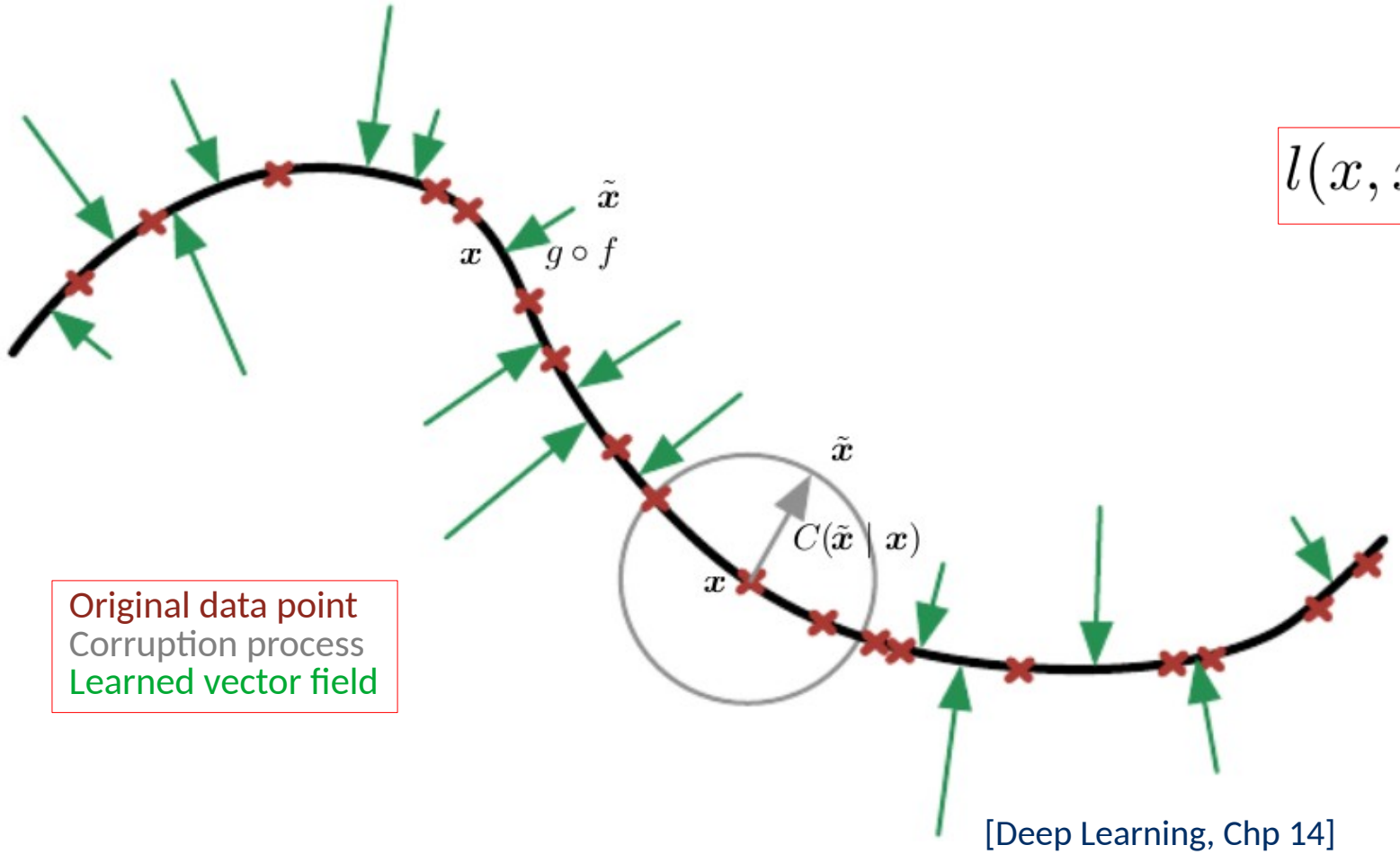
$\hat{x}$

- Learn how to undo the corruption

$$l(x, \hat{x}) = l(\ x,\ g(f(x'))\ )$$

Denoising Autoencoders (DAEs)

Obtaining a clean reconstruction from a noisy input



Original data point
Corruption process
Learned vector field

$$l(x, \hat{x}) = l(\ x,\ g(f(x'))\ )$$

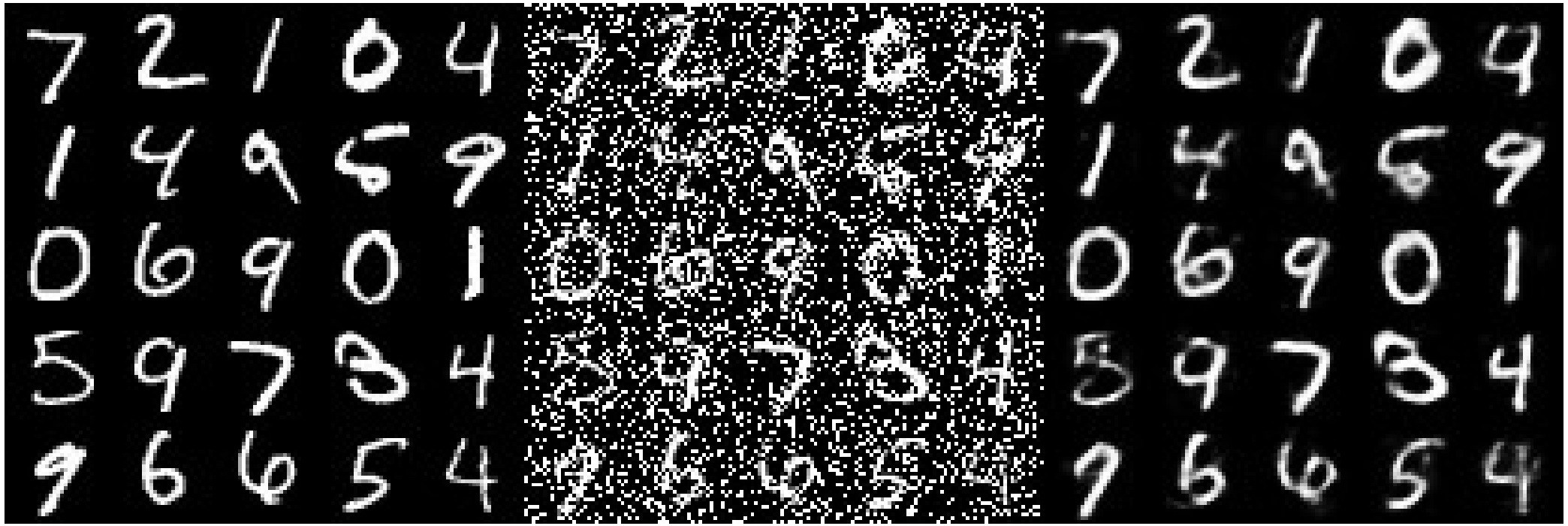
- Learn how to undo the corruption

[Deep Learning, Chp 14]

Denoising Autoencoders (DAEs)

Obtaining a clean reconstruction from a noisy input

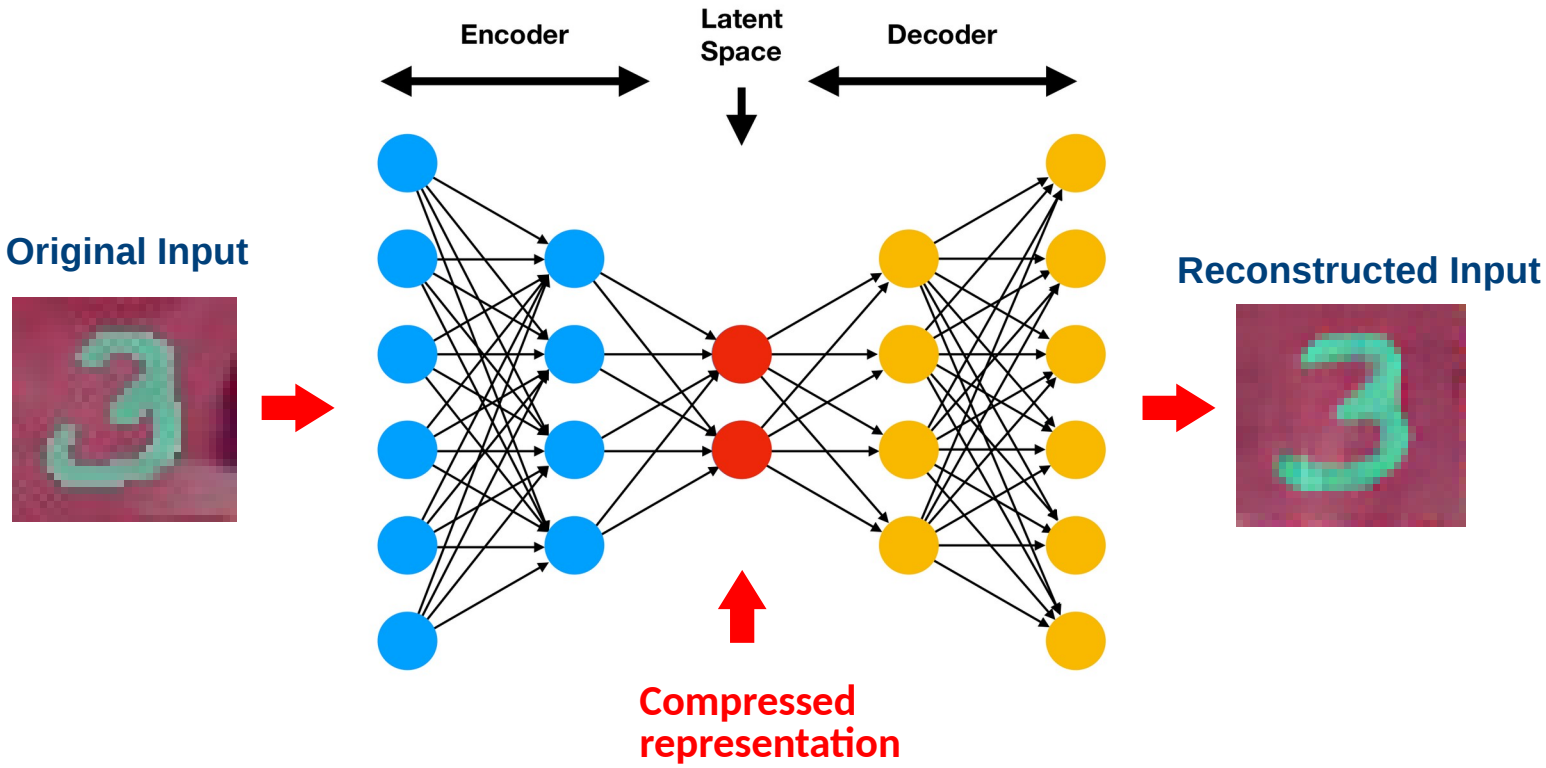
Original Input | Corrupted Input | Reconstructed Input



[opendeep.org]

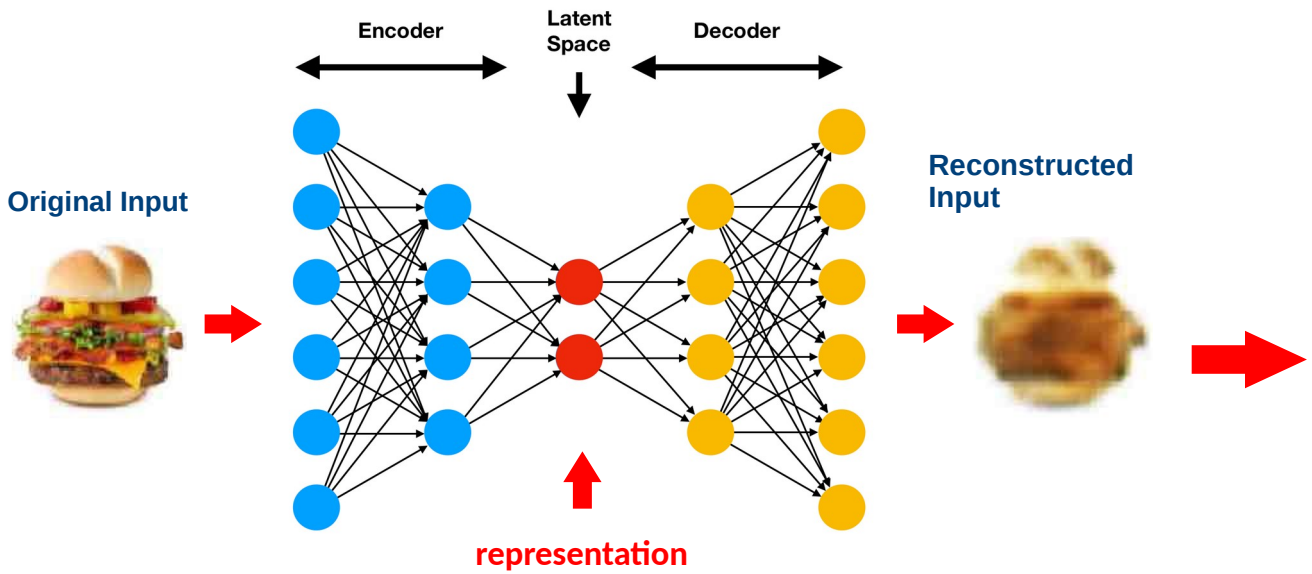
Autoencoders – Applications

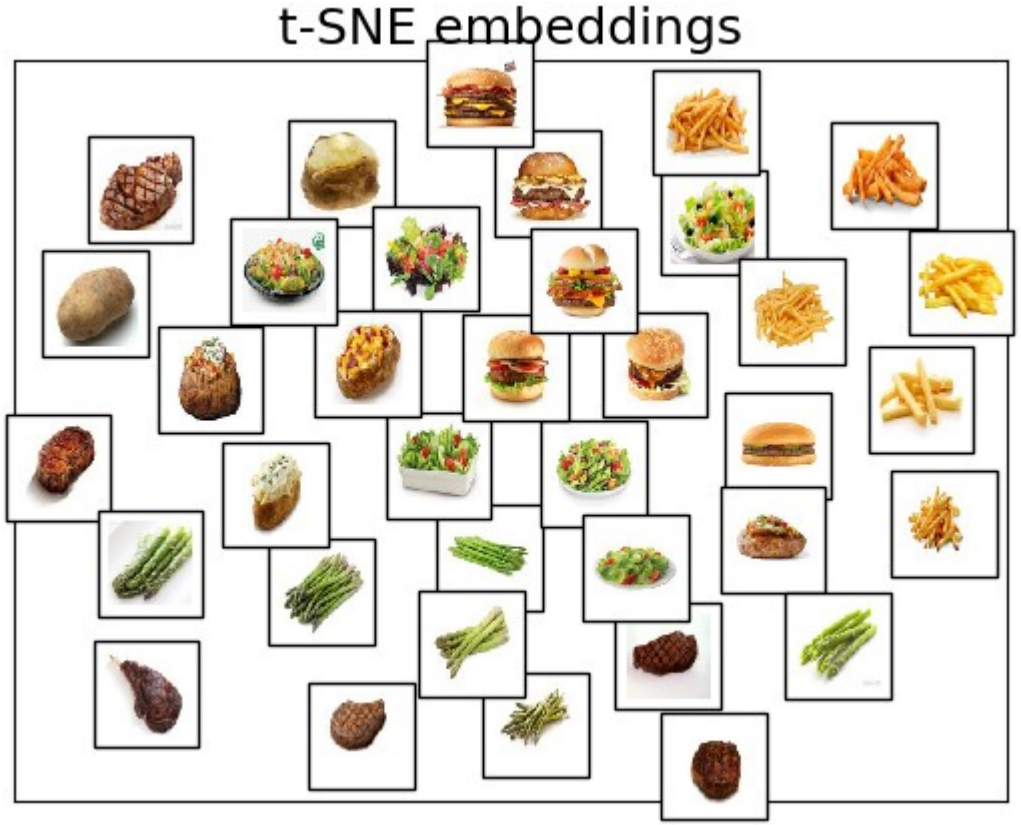
Compression & Retrieval



Autoencoders – Applications

Compression & Retrieval

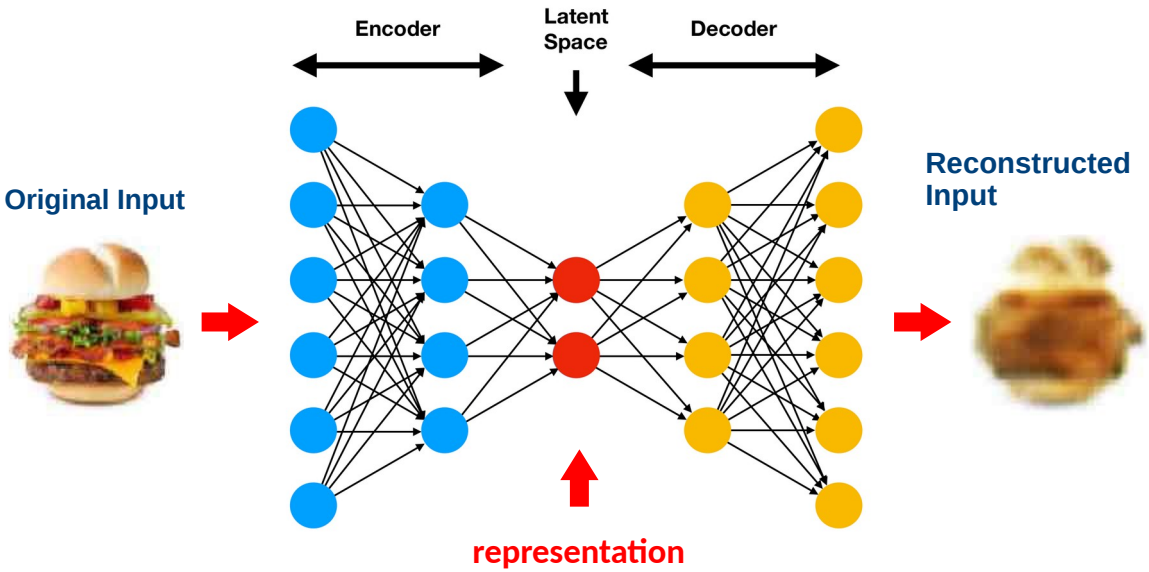


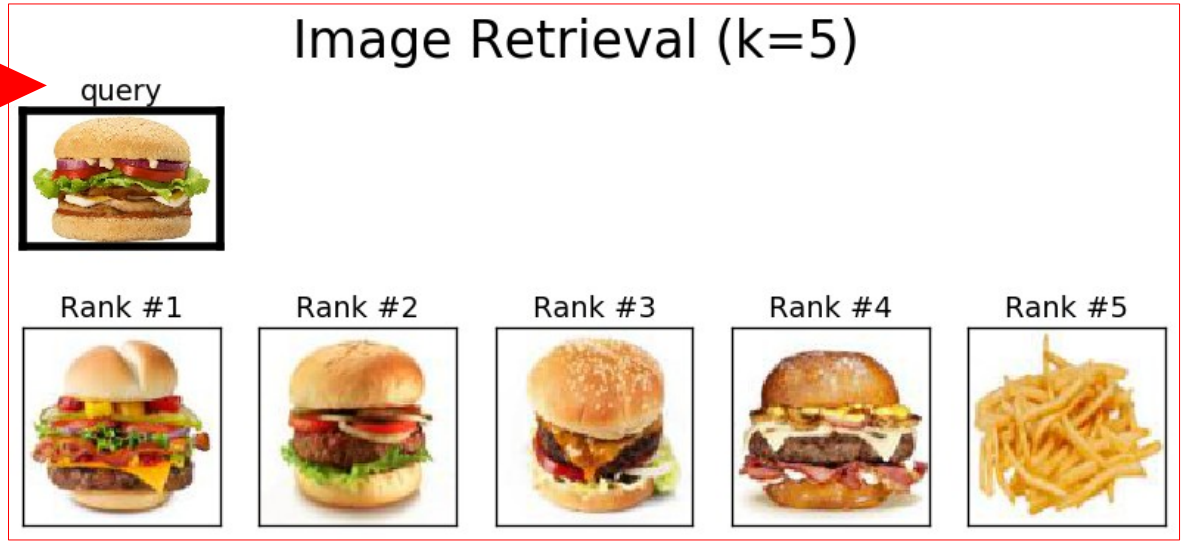


[A. Wong 2017]

Autoencoders – Applications

Compression & Retrieval

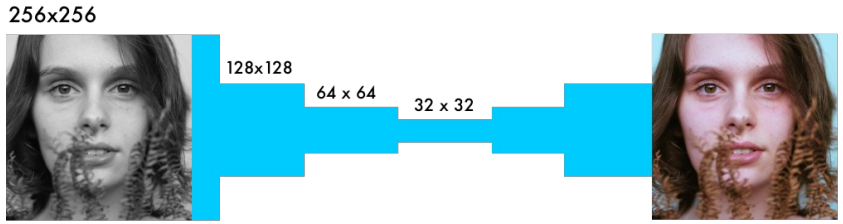




[A. Wong 2017]

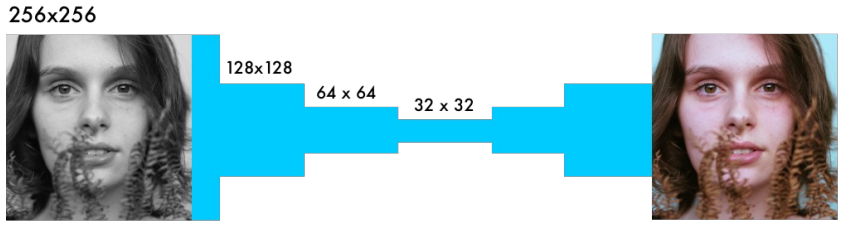
Autoencoders – Applications

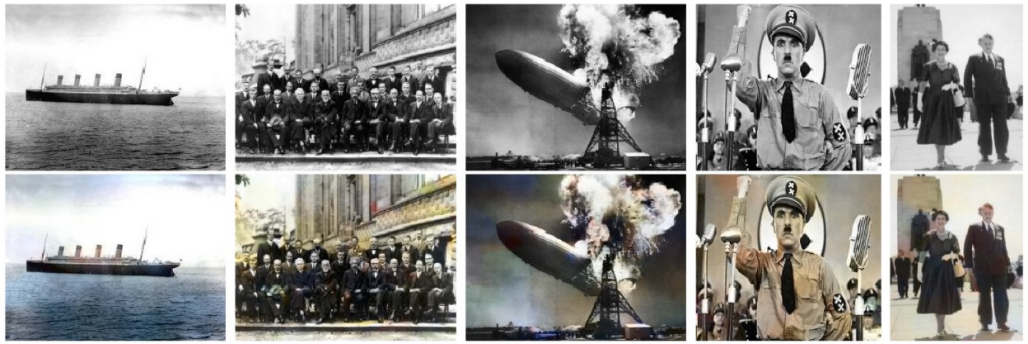
Image Colorization

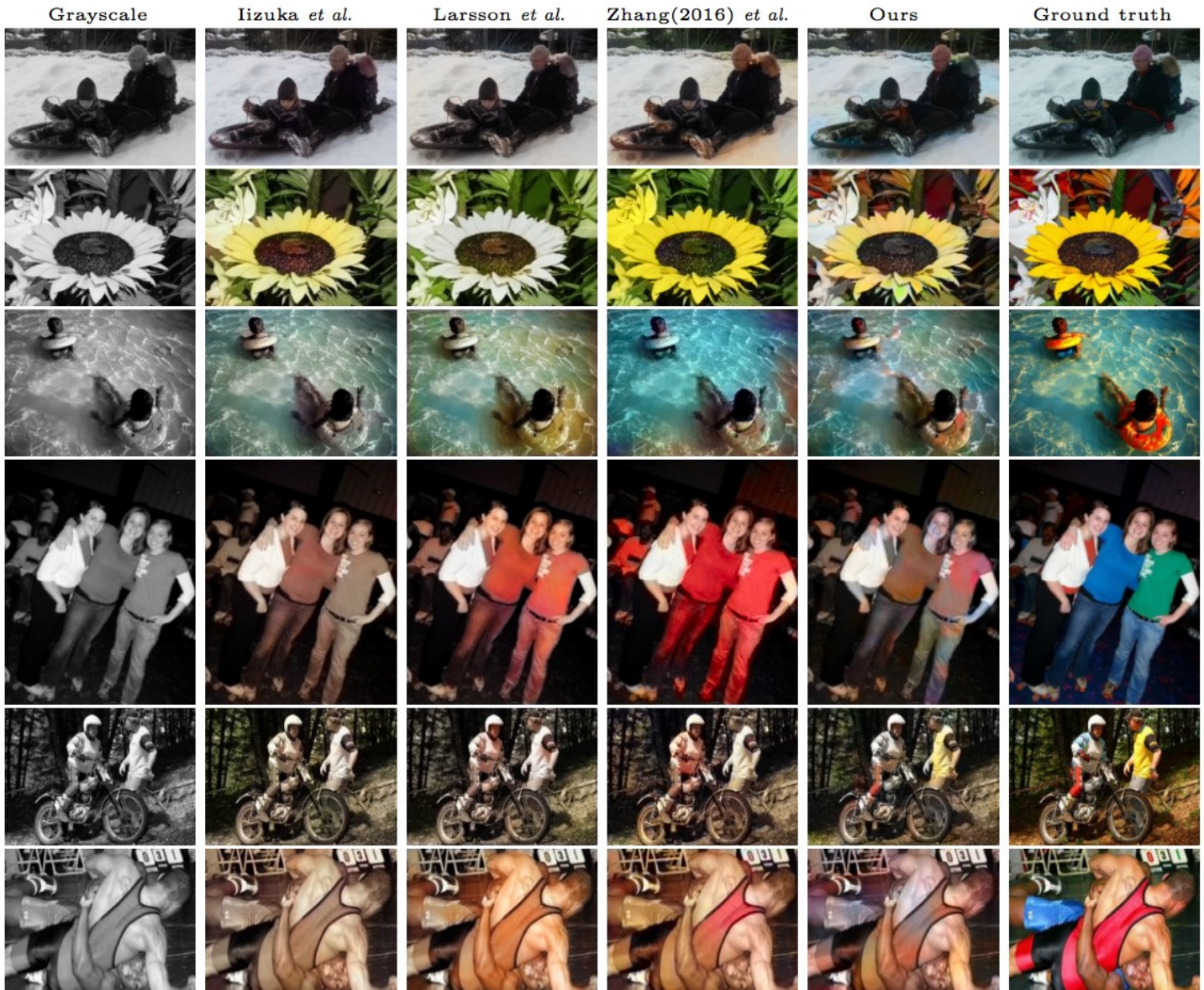


Autoencoders – Applications

Image Colorization



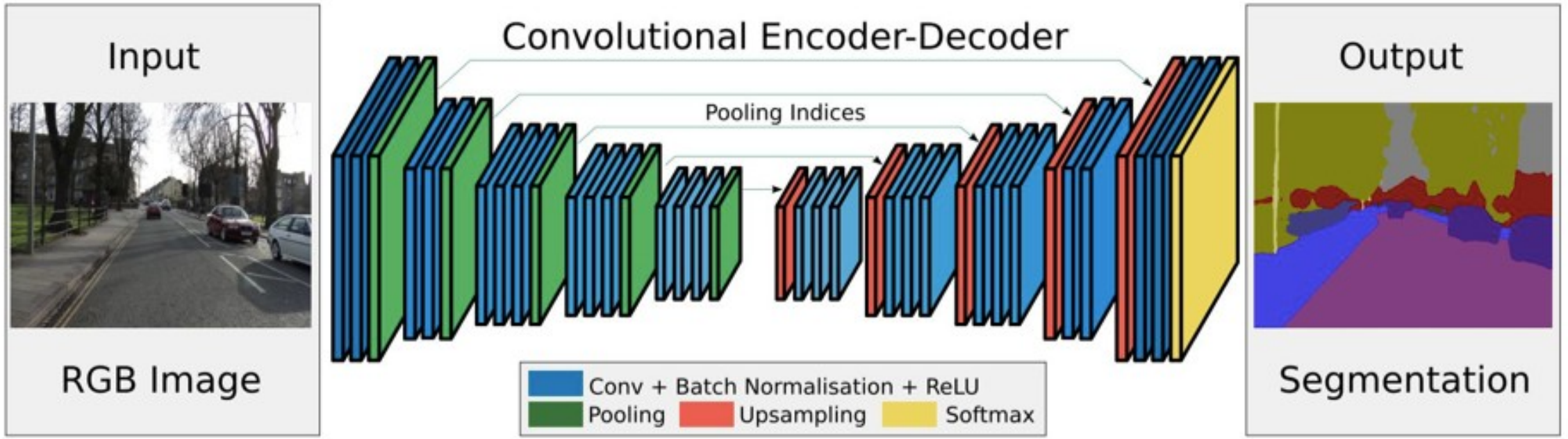




[Baldassarre, 2017]

Autoencoders – Applications

[Semantic] Segmentation



Autoencoders – Applications

Noise Reduction

Noise Removal

[Edureka!, 2018]

Autoencoders – Applications

Noise Reduction

Noise Removal

Watermark Removal

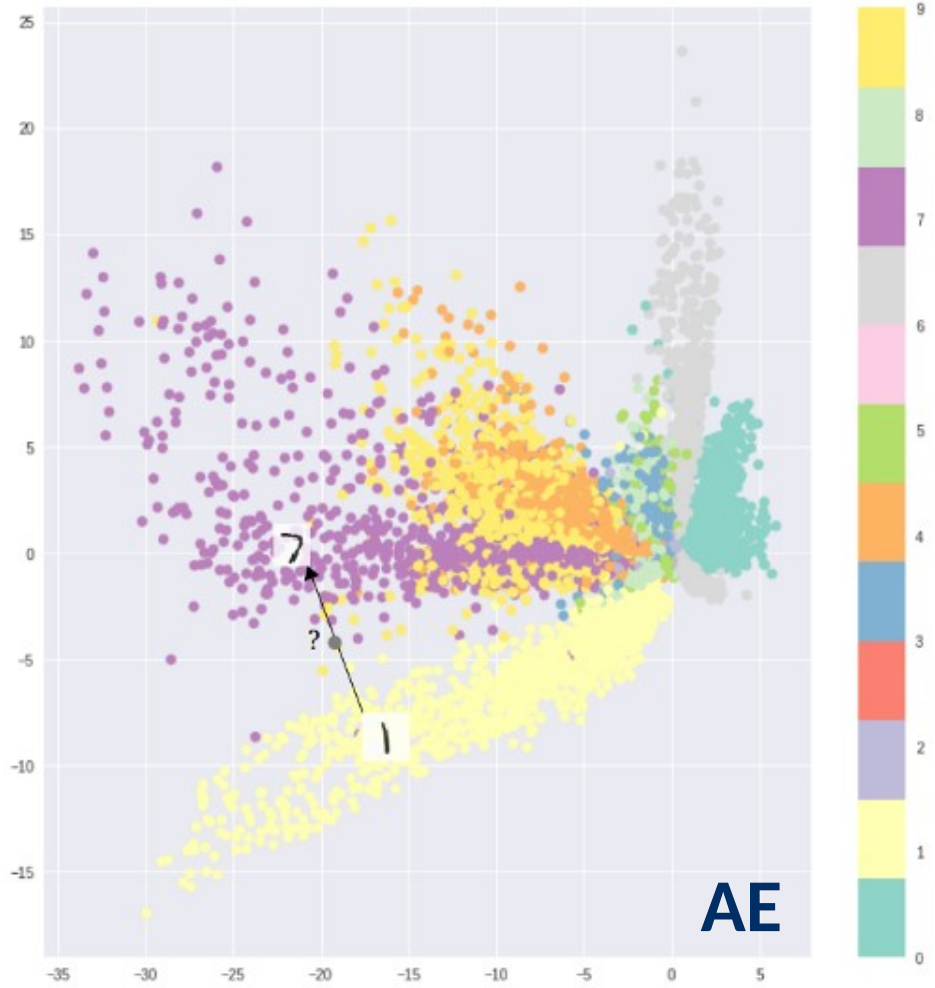
[Edureka!, 2018]

Variational Autoencoders

[autoencoders with continuous latent spaces]

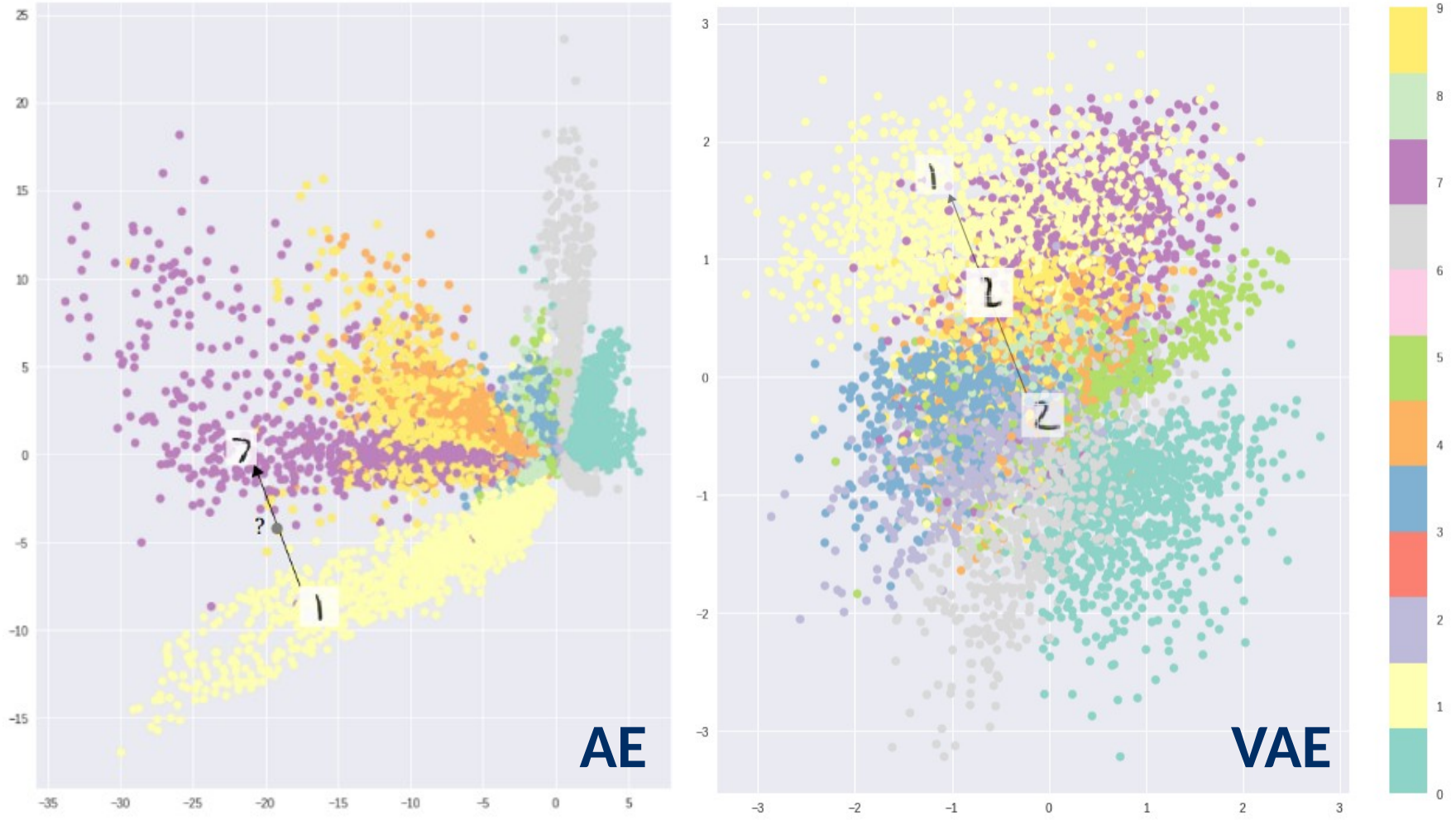
Autoencoders VS. Variational Autoencoders

Latent representations of MNIST digits



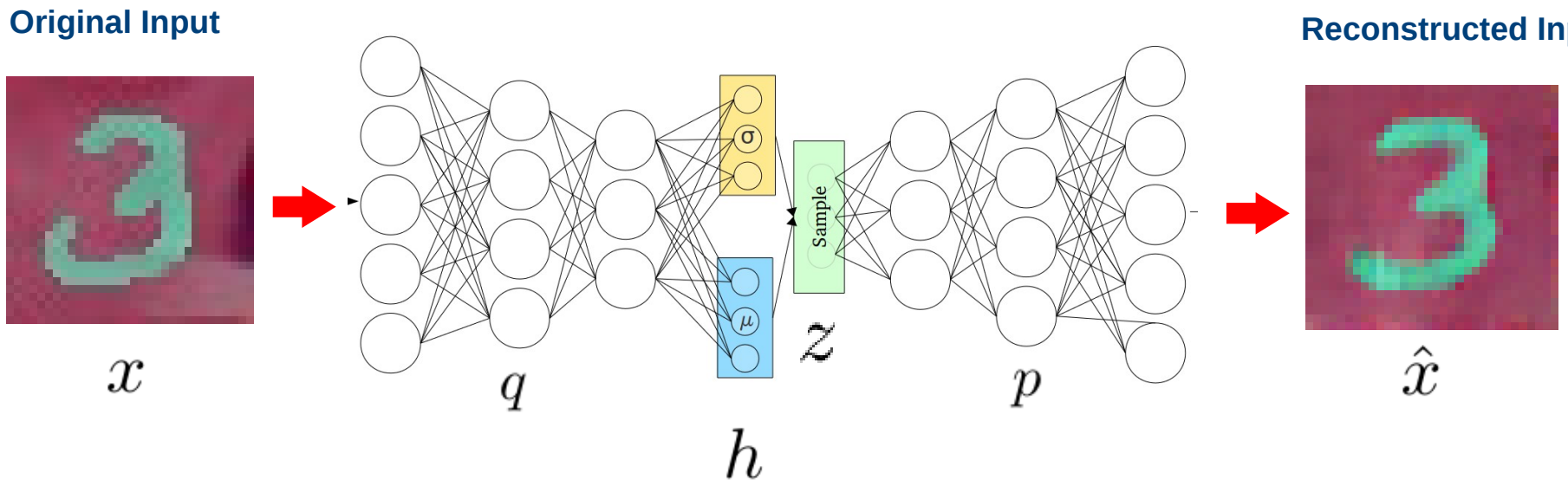
Autoencoders VS. Variational Autoencoders

Latent representations of MNIST digits



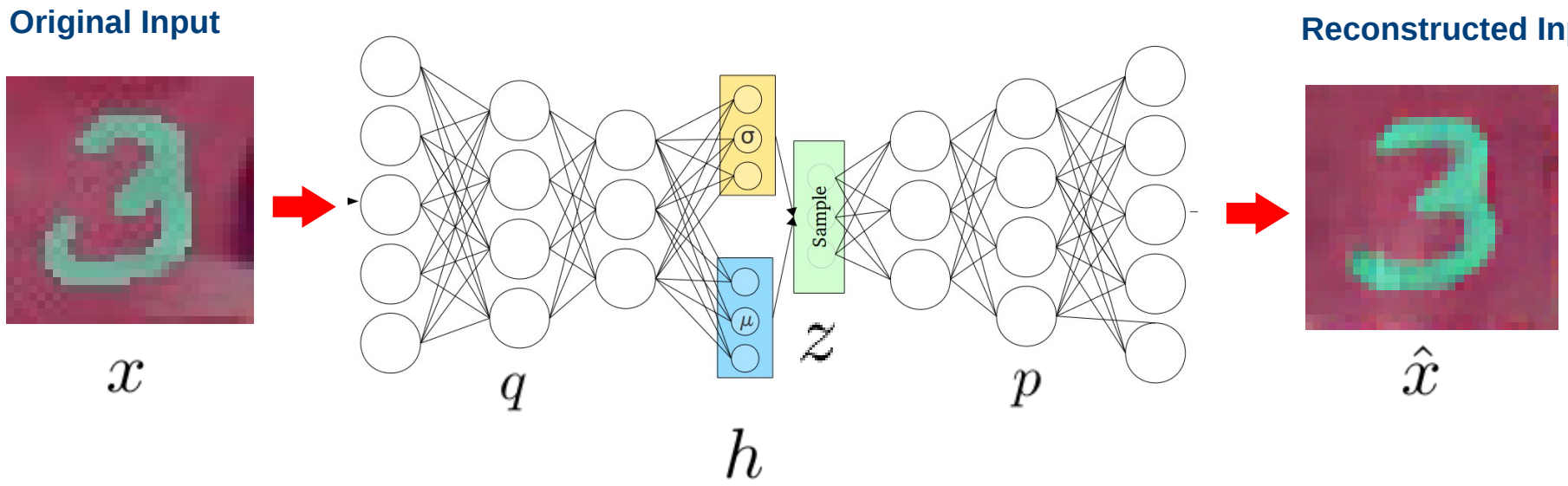
Variational Autoencoders

Mapping inputs to a distributions



Variational Autoencoders

Mapping inputs to a distributions



- Bottleneck now includes components μ and σ.
- *Generate variations of the input from a continuous latent space*
- Decoder feeds from sample from distribution (μ,σ).

Variational Autoencoders – Training

Desirable properties of the representation

$$l(q) = \mathbb{E}_{z \sim q(z|x)} \, log(p(x|z)) - D_{KL}((q(\mathbf{z}|x)||p(\mathbf{z}))$$

Variational Autoencoders – Training

Desirable properties of the representation

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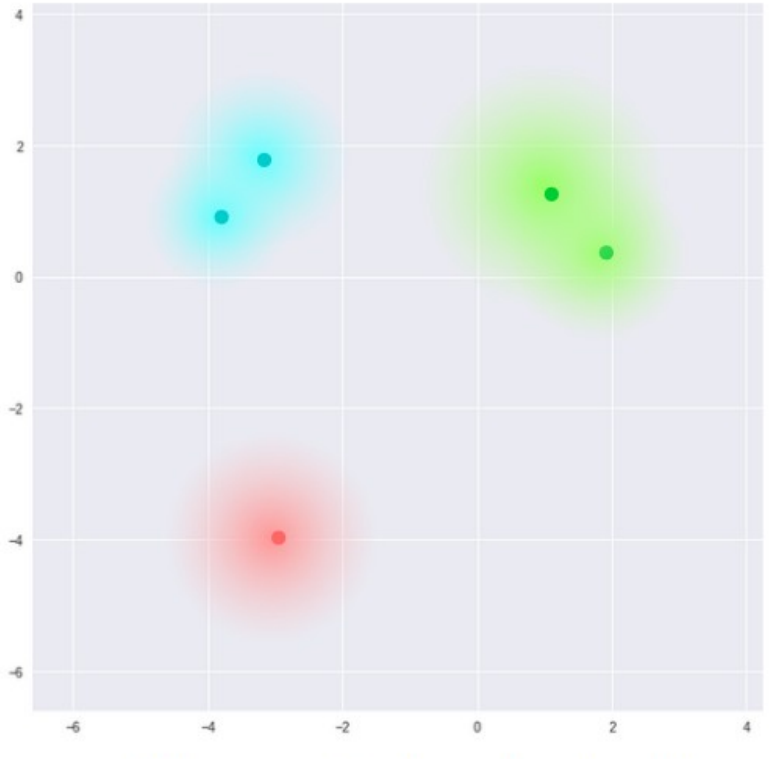
P1:Model local variations



Variational Autoencoders – Training

Desirable properties of the representation

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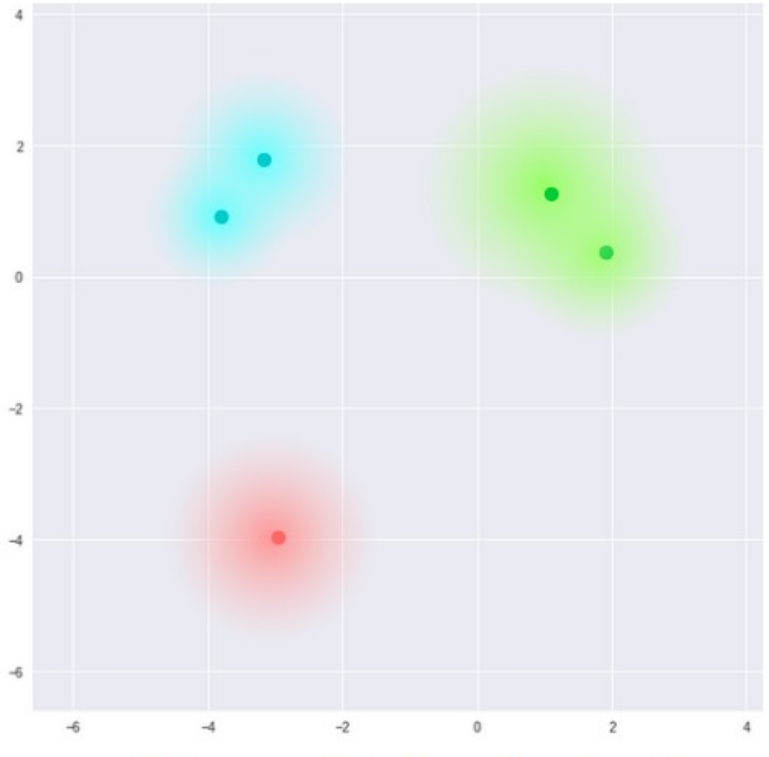
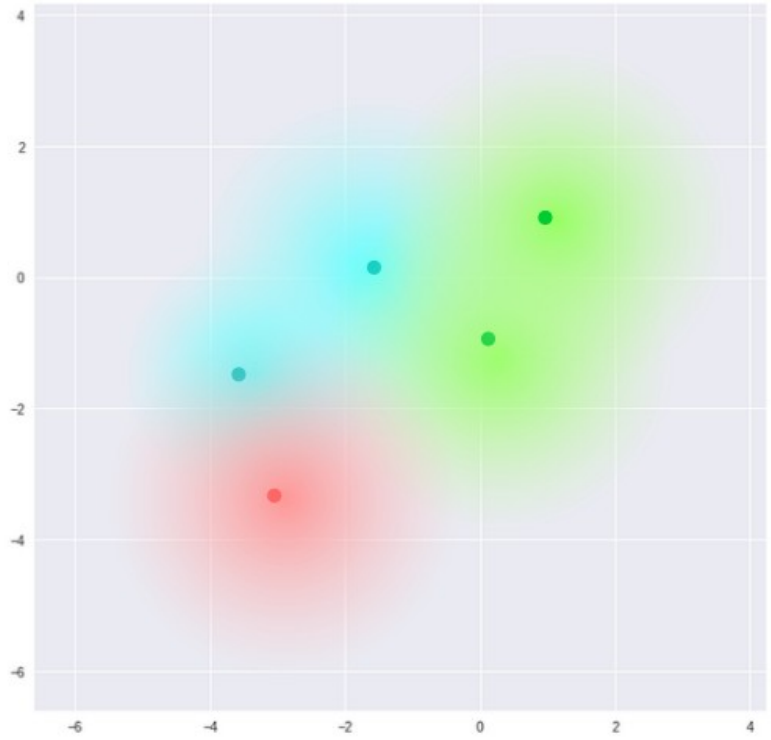
P1:Model local variations



P2: Close encodings even when different

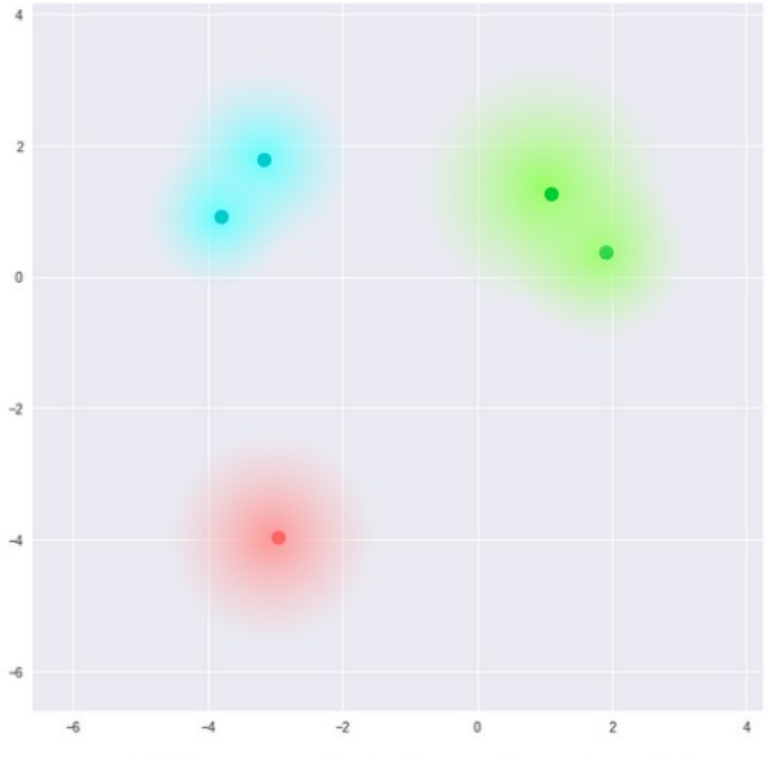


Variational Autoencoders – Training

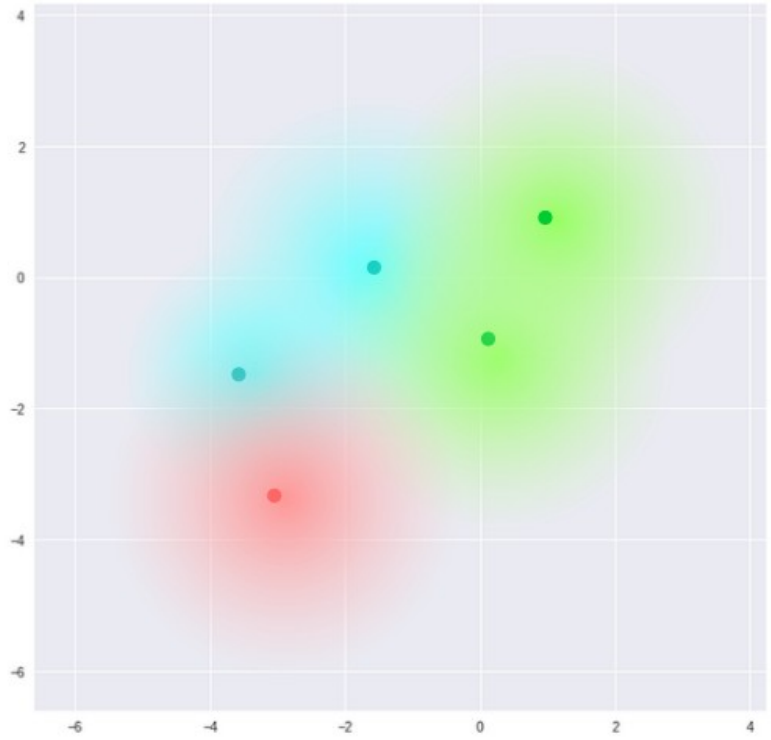
Desirable properties of the representation

$$l(q) = \mathbb{E}_{z \sim q(z|x)}\ log(p(x|z)) - D_{KL}((q(\mathbf{z}|x)||p(\mathbf{z}))$$

P1:Model local variations



P2: Close encodings even when different



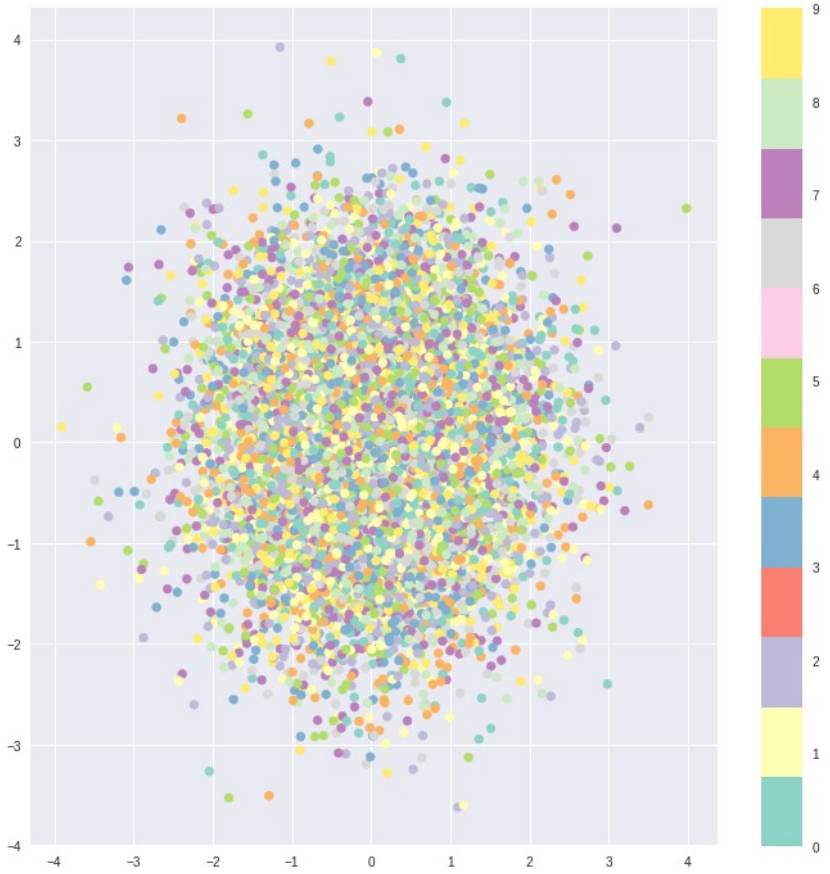
- P1 enabled by components *(μ,σ)*
- P2 enforced via the KL-divergence

Variational Autoencoders – Training

Desirable properties of the representation

$$l(q) = \mathbb{E}_{z \sim q(z|x)}\ log(p(x|z)) - D_{KL}((q(\mathbf{z}|x)||p(\mathbf{z}))$$

Optimizing only the KL-divergence



Variational Autoencoders – Training

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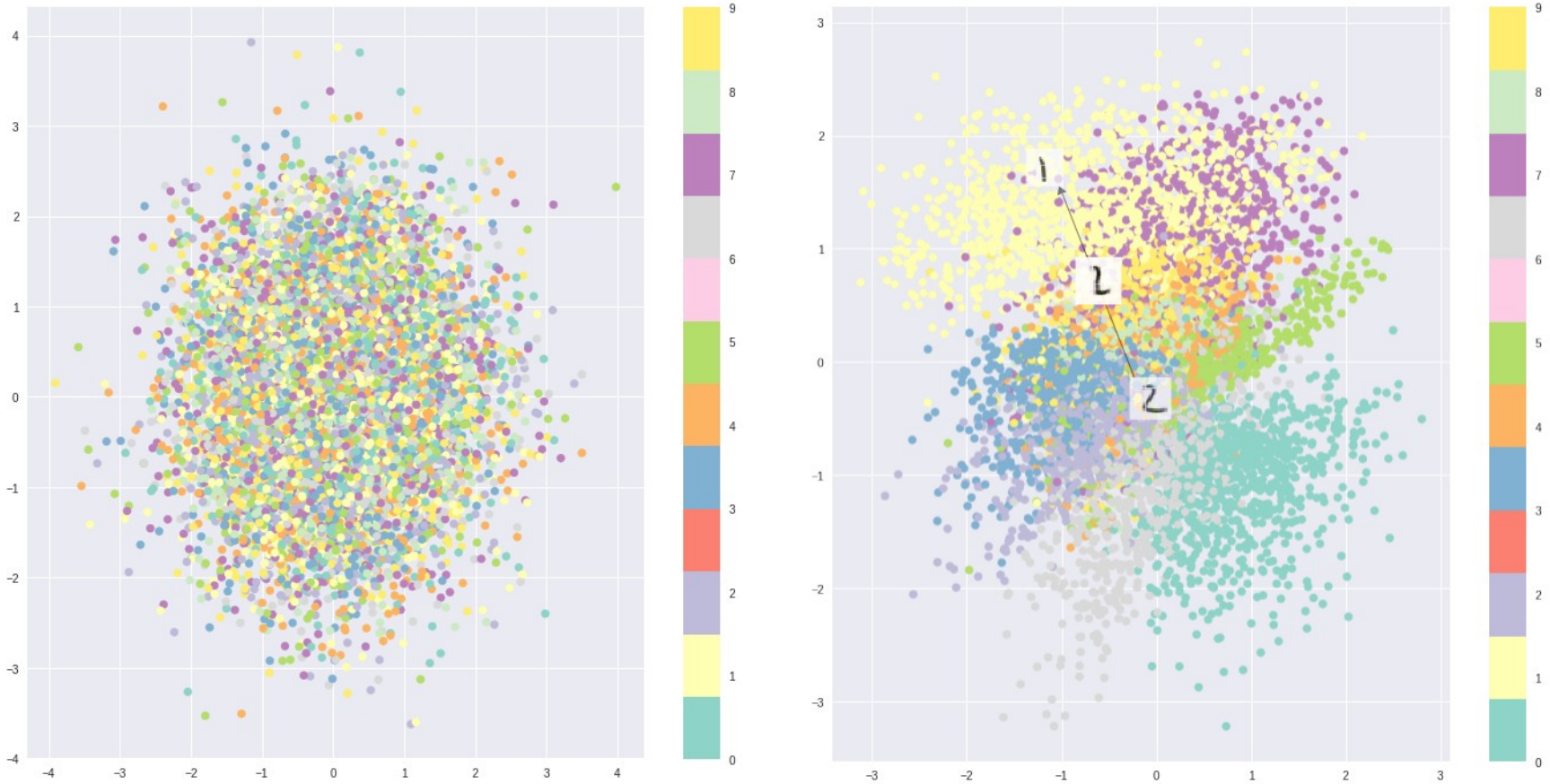
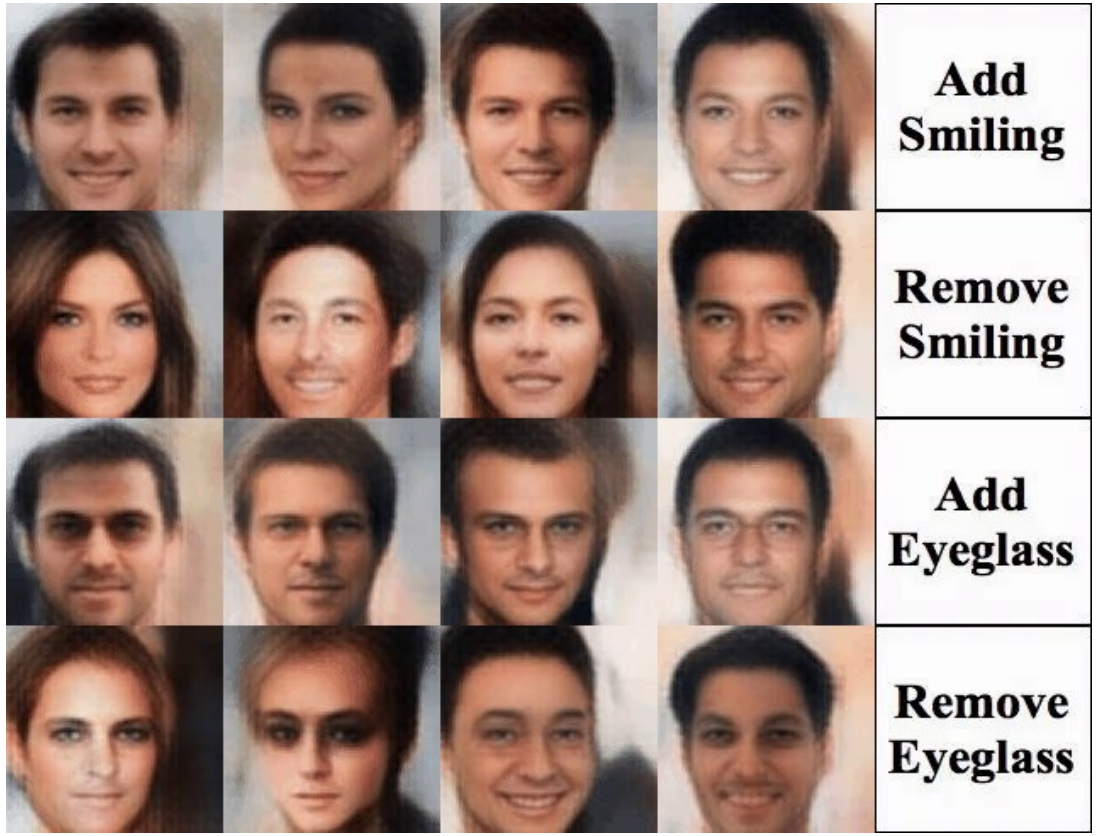


Optimizing the Reconstruction Loss + KL-divergence

Variational Autoencoders – Training

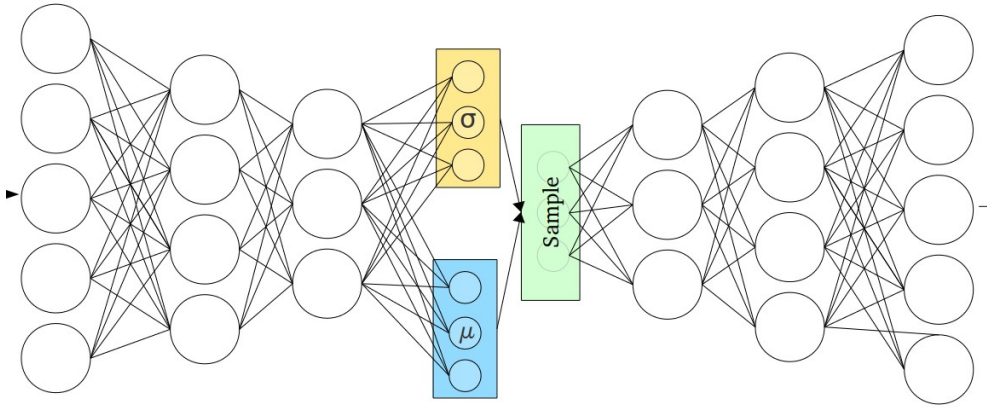
Interpolation accross the latent space



[Hou et al., 2017]

Variational Autoencoders – Training

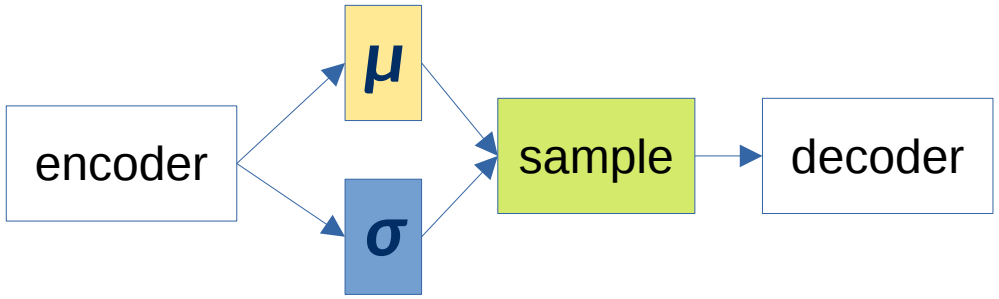
Difficulty → the sampling component is not differentiable



Variational Autoencoders – Training

Difficulty → the sampling component is not differentiable

- **Original**



Variational Autoencoders – Training

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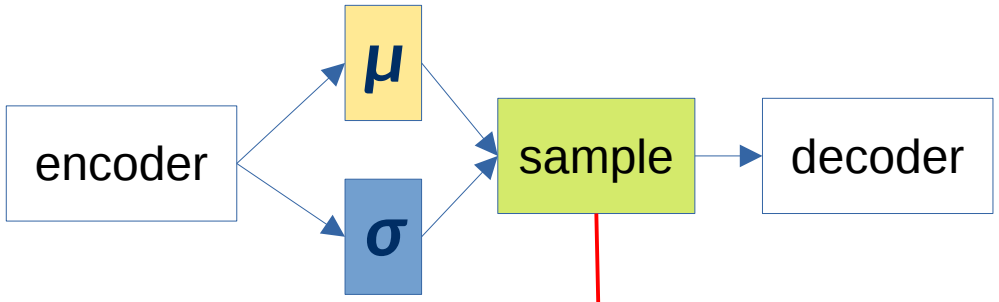

$$z = \mu + \sigma \odot \epsilon$$

Variational Autoencoders – Training

Difficulty → the sampling component is not differentiable

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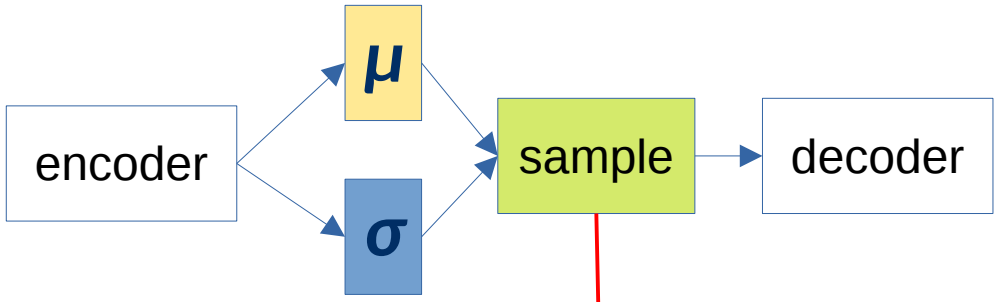
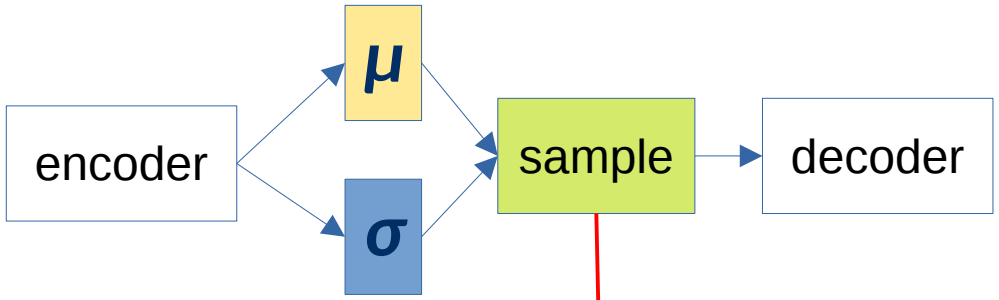


$$z = \mu + \sigma \odot \epsilon$$
$$\epsilon \sim N(0, 1)$$

Variational Autoencoders – Training

Difficulty → the sampling component is not differentiable

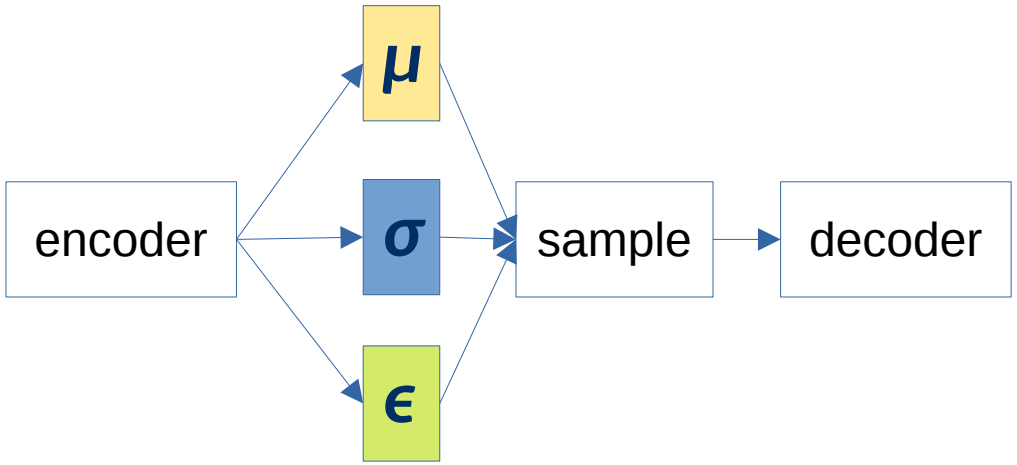
- **Original**



$$z = \mu + \sigma \odot \epsilon$$

$$\epsilon \sim N(0, 1)$$

- **Reparametrized**



Variational Autoencoders – Training

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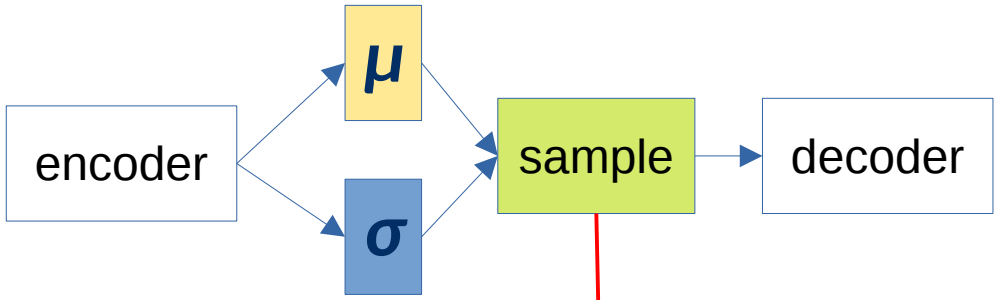

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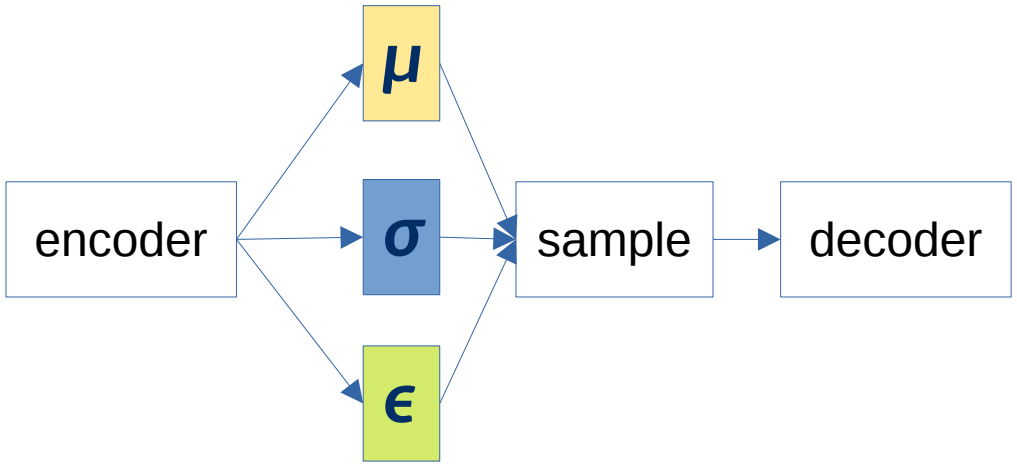


$$z = \mu + \sigma \odot \epsilon$$
$$\epsilon \sim N(0, 1)$$

- *No backprop through* ***ϵ***
- ***ϵ*** *remains stochastic.*
- ***(μ,σ)*** *are learnable*

Generative Adversarial Networks

[*something-something*-GAN]

Generative Adversarial Networks (GANs)

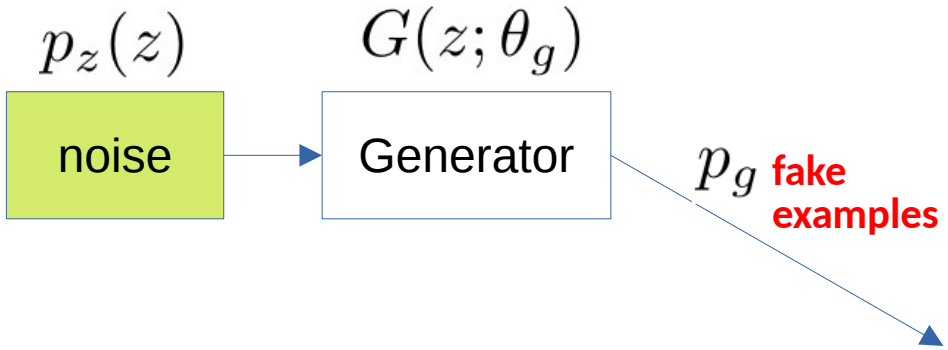
[Goodfellow et al., 2014]

Adversarial Training with Neural Networks

Generative Adversarial Networks (GANs)

[Goodfellow et al., 2014]

Adversarial Training with Neural Networks



Generative Adversarial Networks (GANs)

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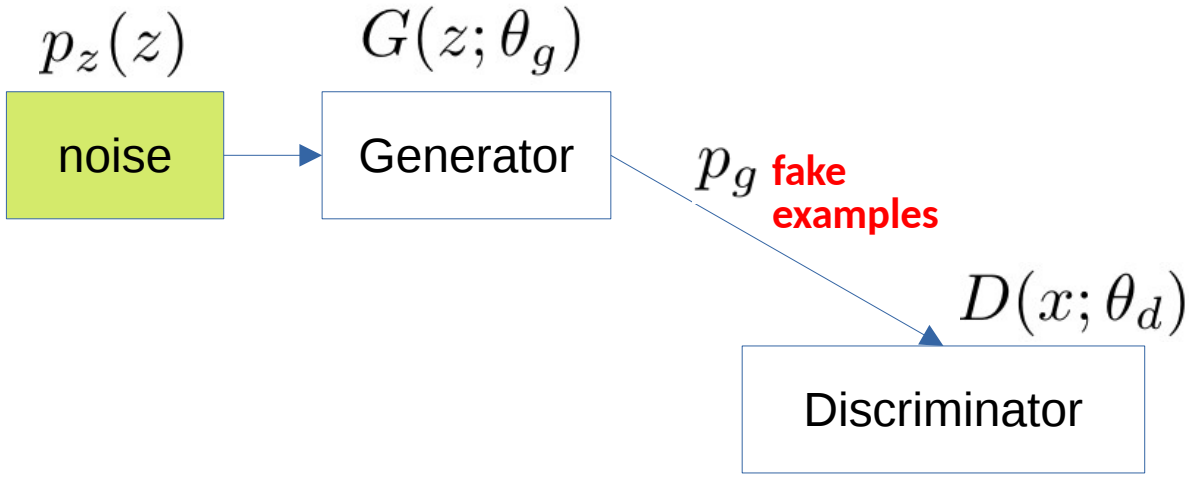
Adversarial Training with Neural Networks



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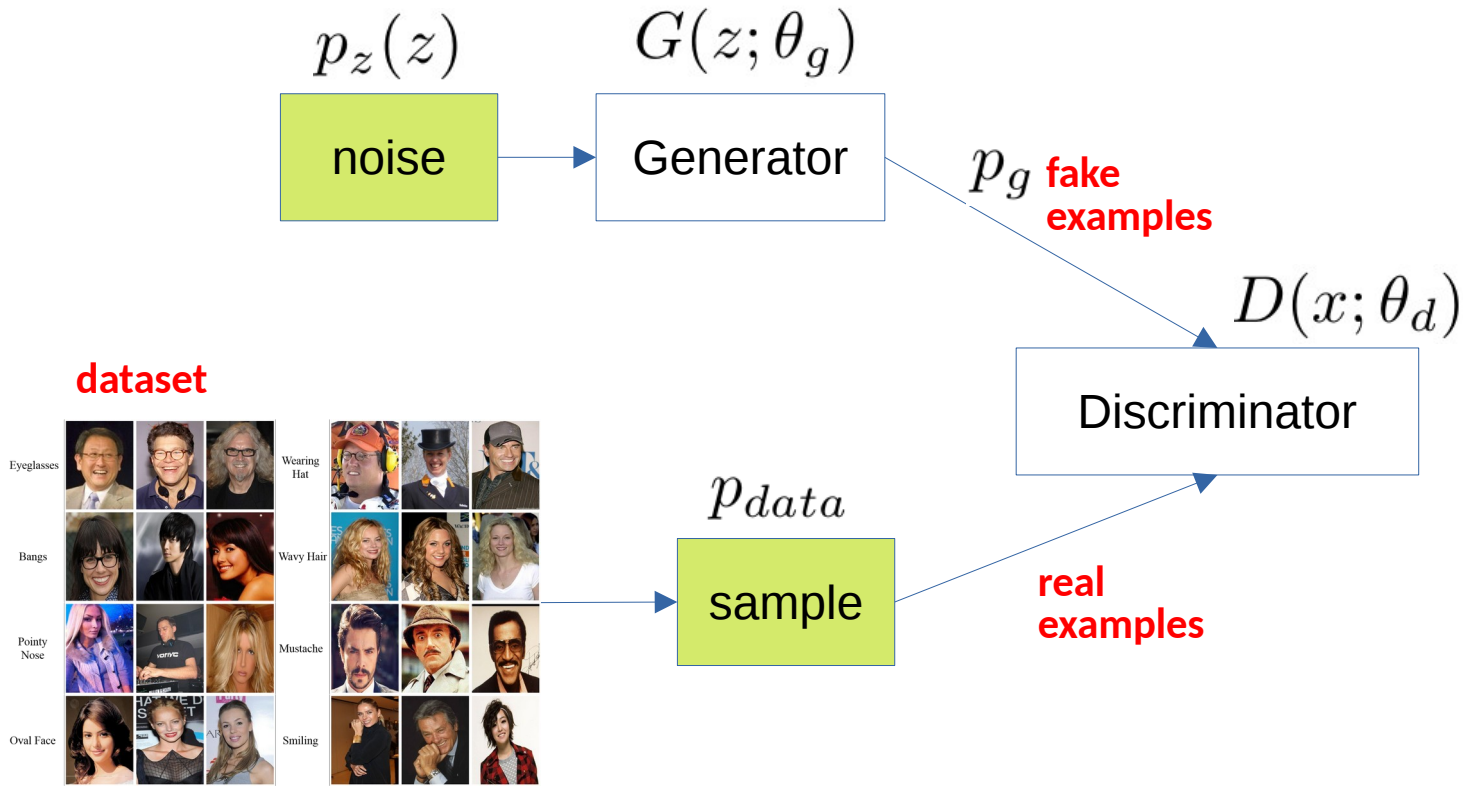
Adversarial Training with Neural Networks



Generative Adversarial Networks (GANs)

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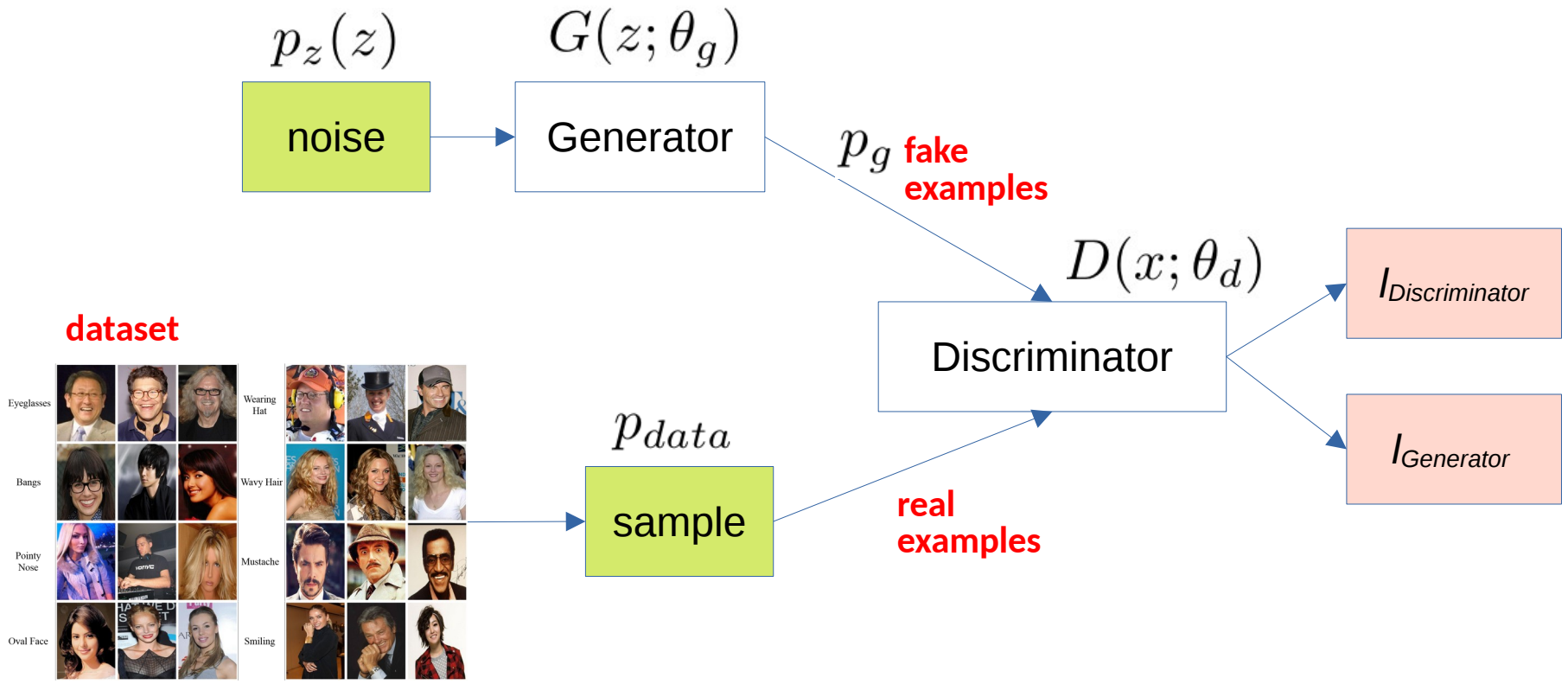
Adversarial Training with Neural Networks



Generative Adversarial Networks (GANs)

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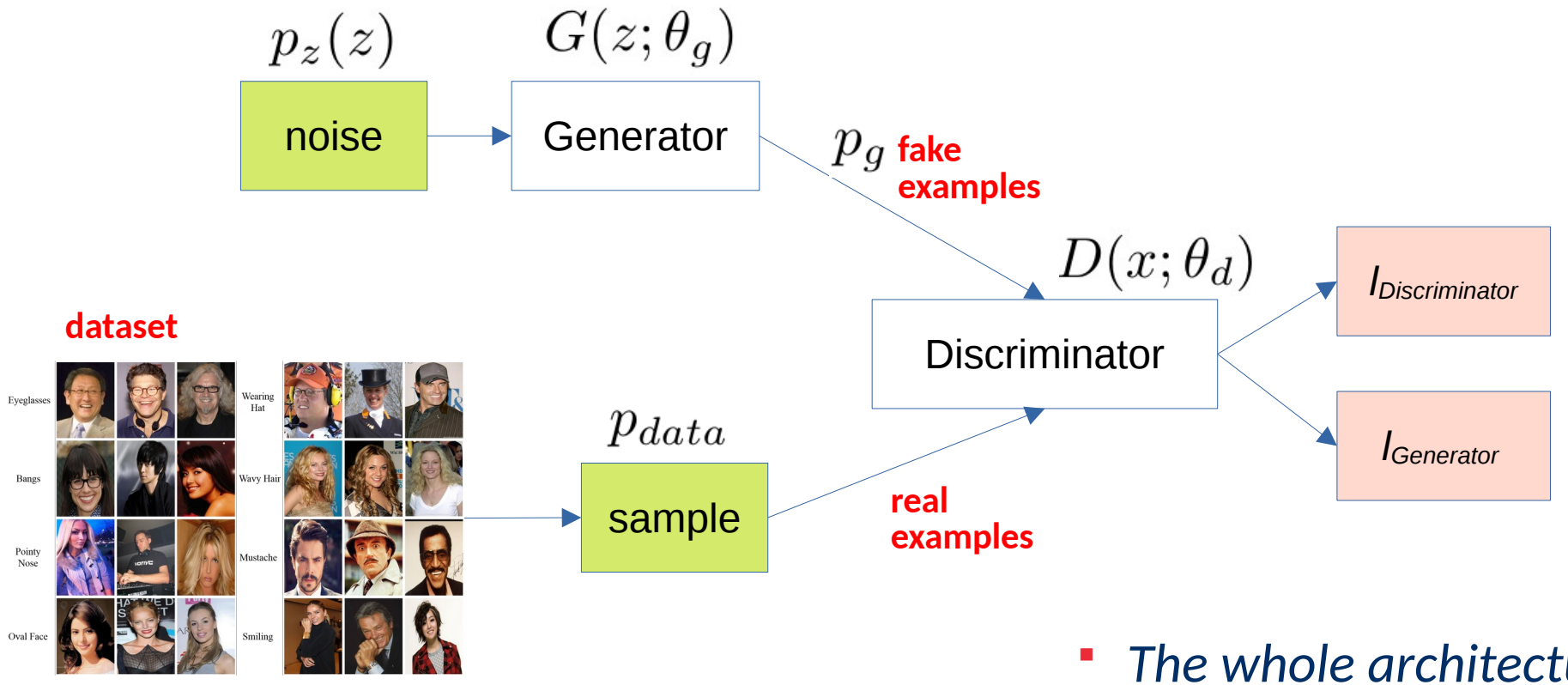
Adversarial Training with Neural Networks

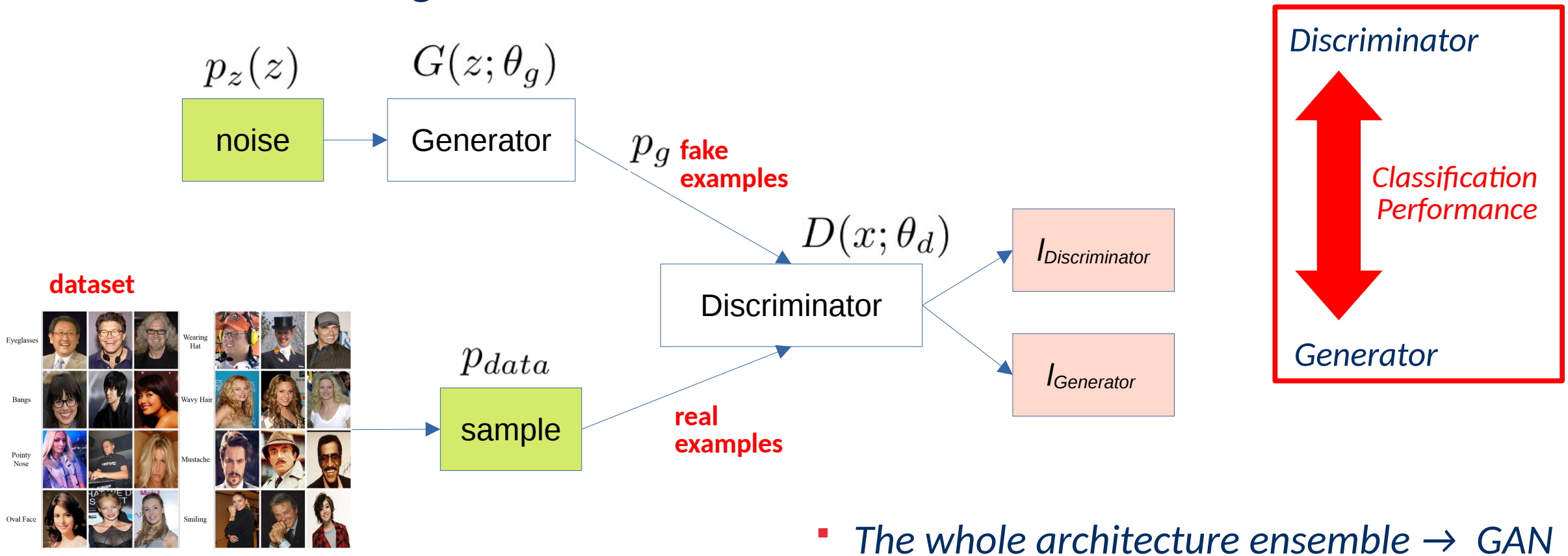


- *The whole architecture ensemble → GAN*

Generative Adversarial Networks (GANs)

[Goodfellow et al., 2014]

Adversarial Training with Neural Networks

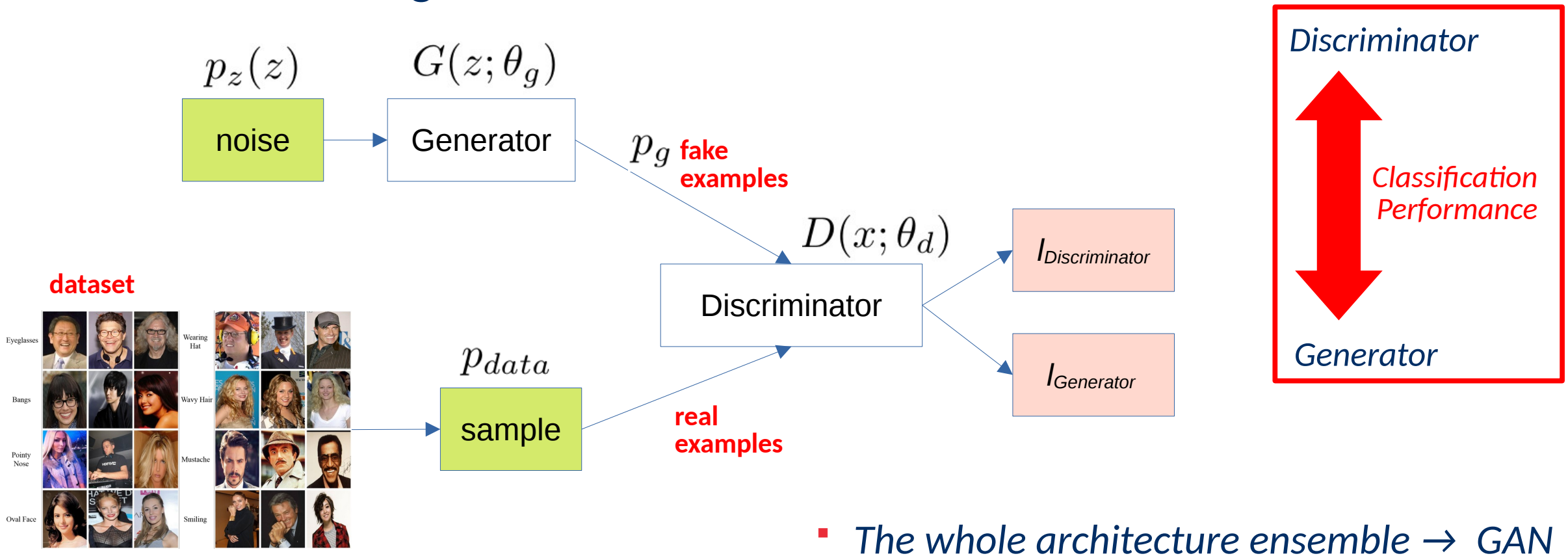


- *The whole architecture ensemble → GAN*

Generative Adversarial Networks (GANs)

[Goodfellow et al., 2014]

Adversarial Training with Neural Networks



- *The whole architecture ensemble → GAN*

Q: How would the *Generator* and *Discriminator* behave when reaching equilibrium?

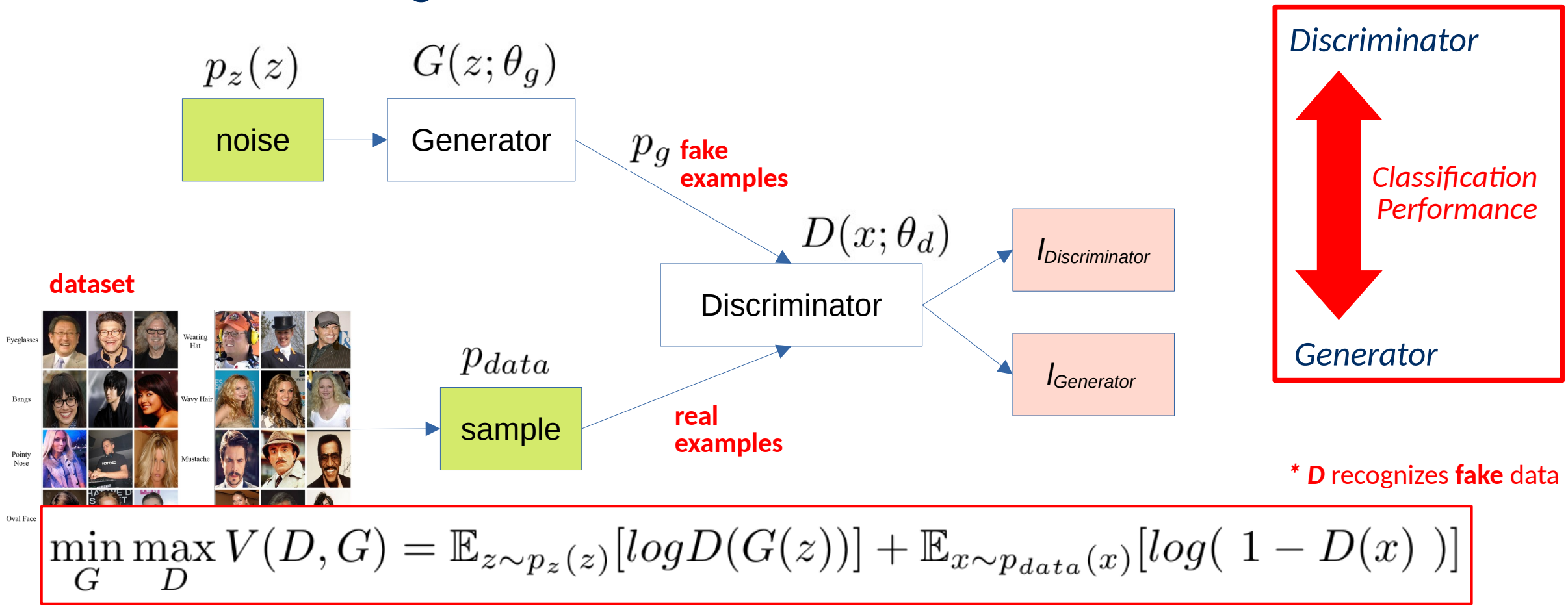
ok, but…

How do we enforce the competing behaviour?

Generative Adversarial Networks – Training

[Goodfellow et al., 2014]

Adversarial Training with Neural Networks

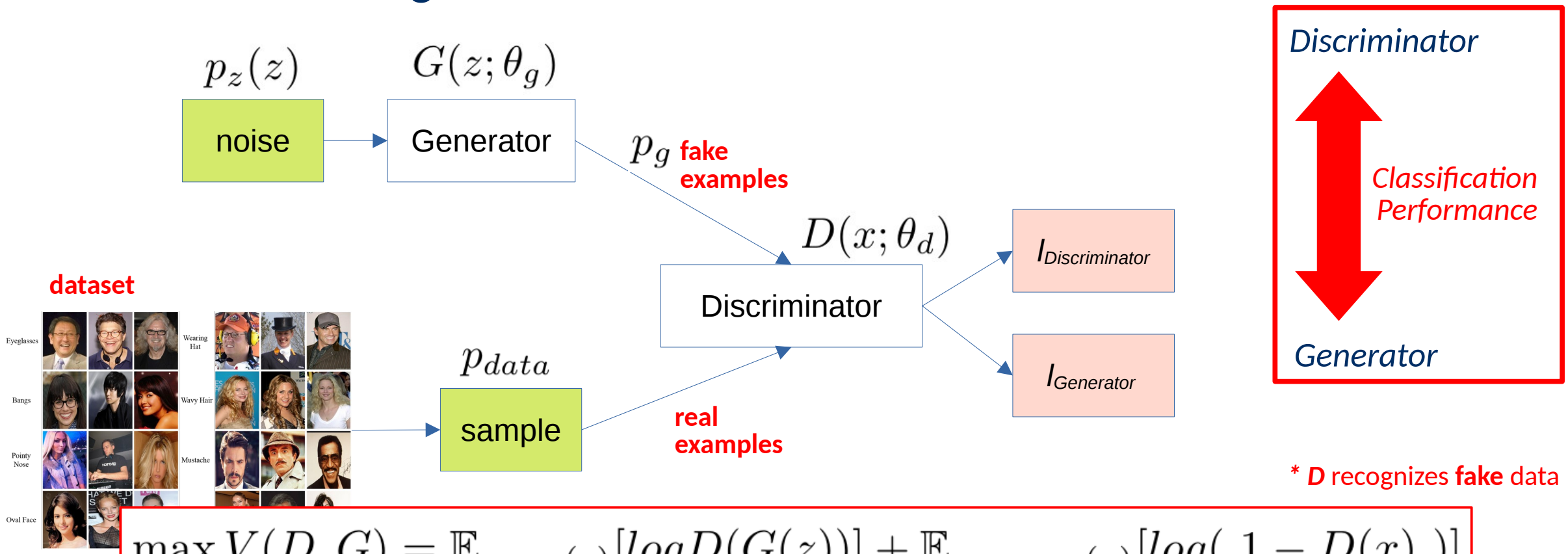


$$\min_G \max_D V(D,G) = \mathbb{E}_{z\sim p_z(z)}[logD(G(z))] + \mathbb{E}_{x\sim p_{data}(x)}[log(\ 1 - D(x)\ )]$$

Generative Adversarial Networks – Training

[Goodfellow et al., 2014]

Adversarial Training with Neural Networks



Generative Adversarial Networks – Training

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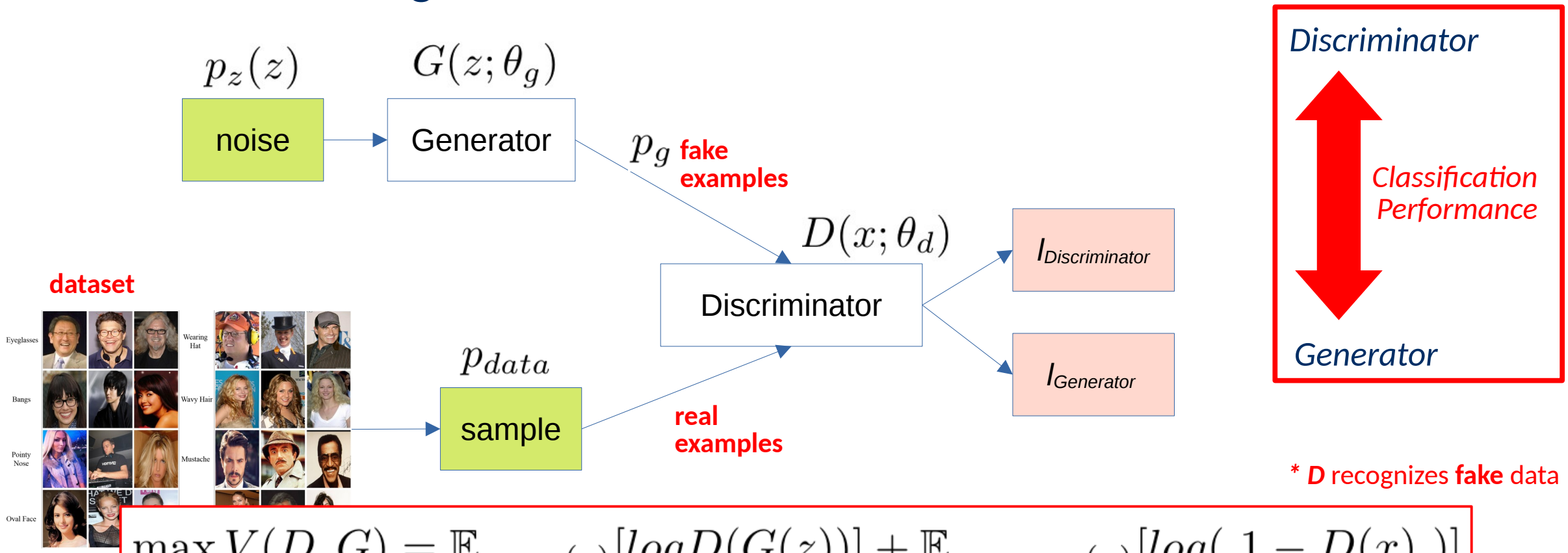
Adversarial Training with Neural Networks



Generative Adversarial Networks – Training

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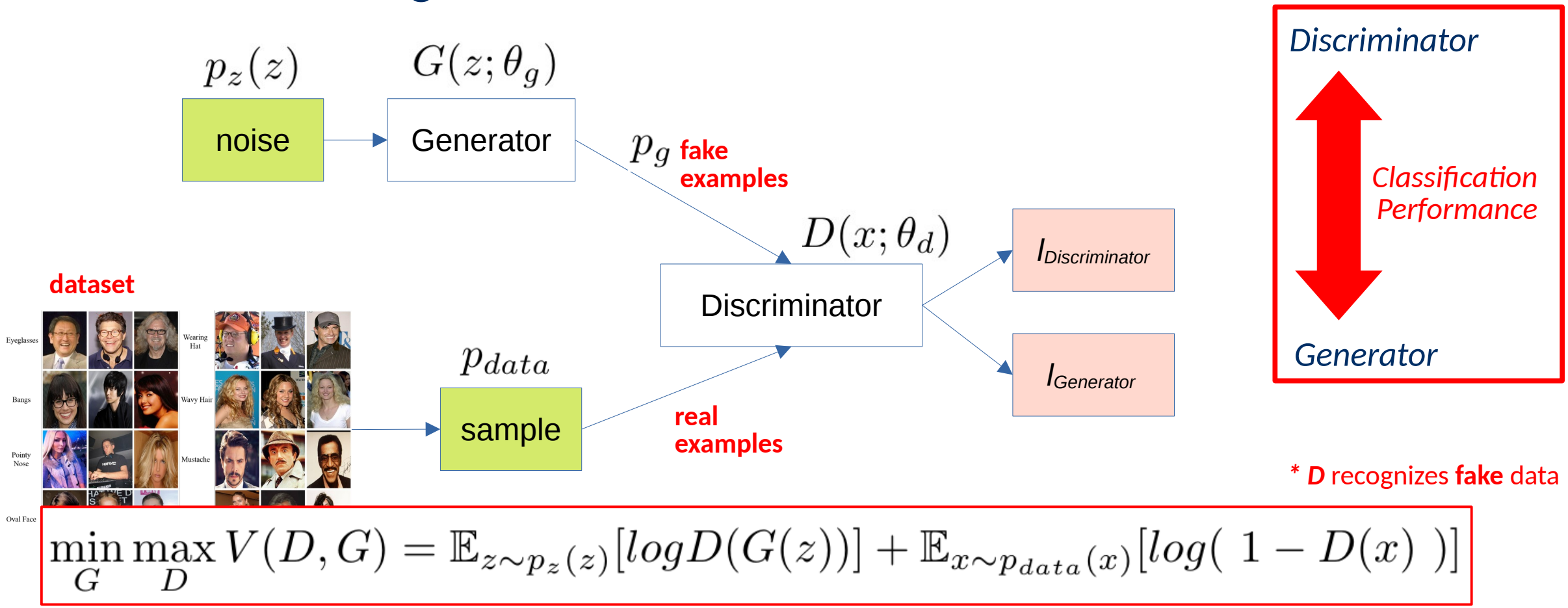
Adversarial Training with Neural Networks



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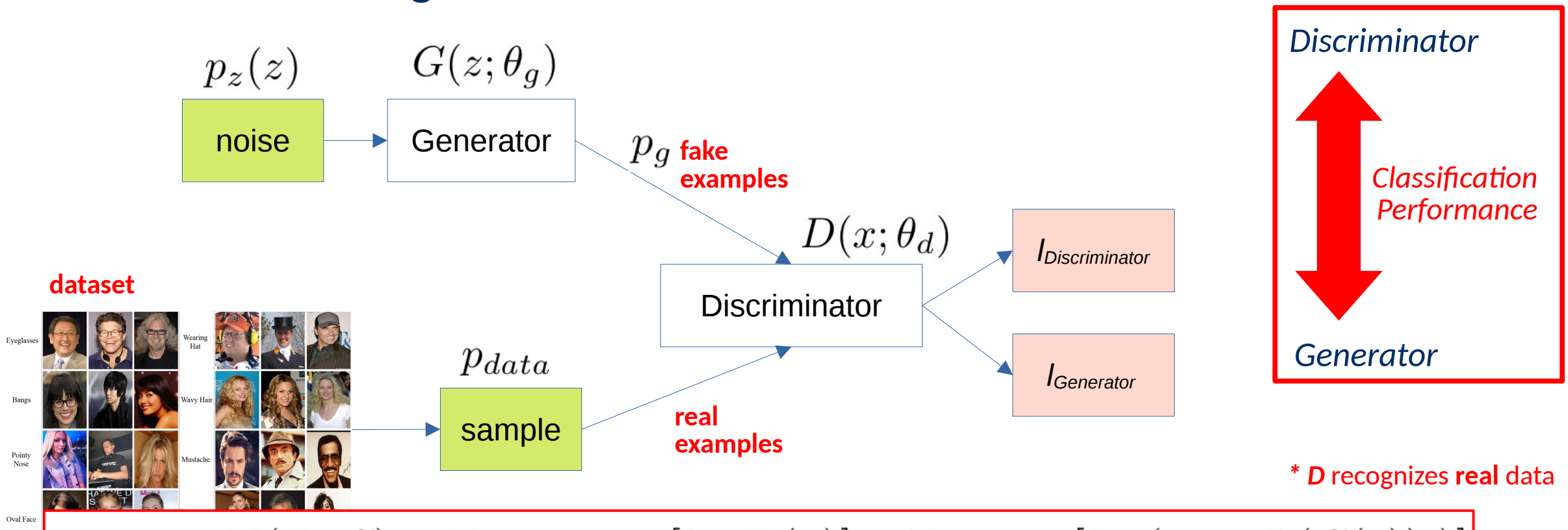
Generative Adversarial Networks – Training

[Goodfellow et al., 2014]

Adversarial Training with Neural Networks



* ***D*** recognizes **real** data

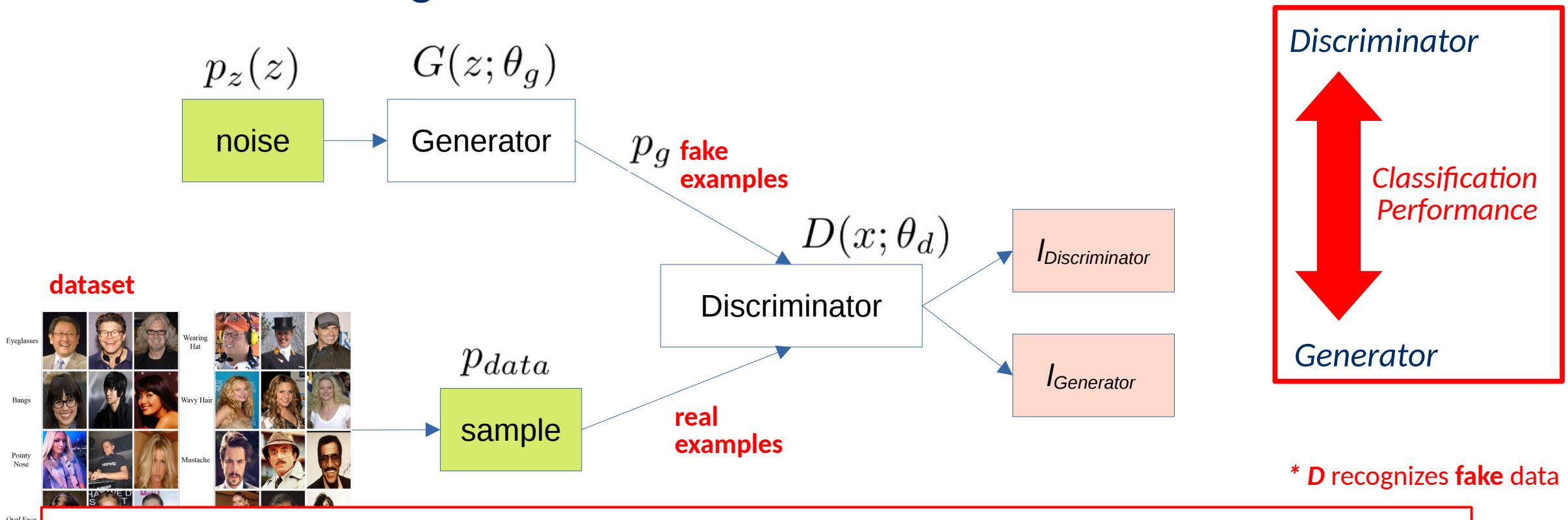
$$\min_G \max_D V(D,G) = \mathbb{E}_{x\sim p_{data}(x)}[logD(x)] + \mathbb{E}_{z\sim p_z(z)}[log(\ 1 - D(G(z))\ )]$$

Alternatively Formulation

Generative Adversarial Networks – Training

[Goodfellow et al., 2014]

Adversarial Training with Neural Networks



* ***D*** recognizes **fake** data

$$\min_G \max_D V(D,G) = \mathbb{E}_{z\sim p_z(z)}[logD(G(z))] + \mathbb{E}_{x\sim p_{data}(x)}[log(\ 1 - D(x)\ )]$$

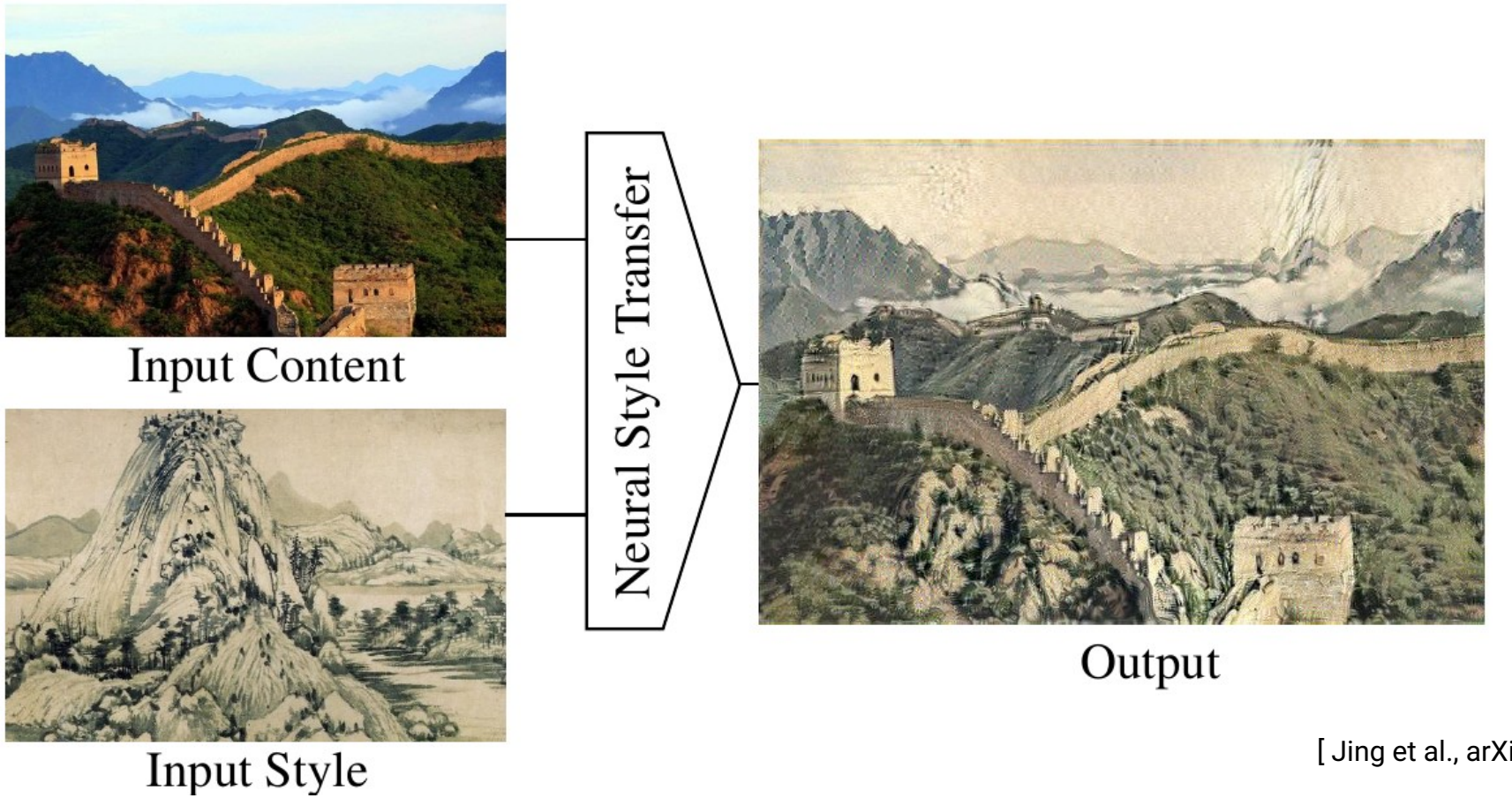
Q: How to train this?

Applications

[*something-something*-GAN]

Generative Adversarial Networks – Applications

Style Transfer



[Jing et al., arXiv:1705.04058]

Generative Adversarial Networks – Applications

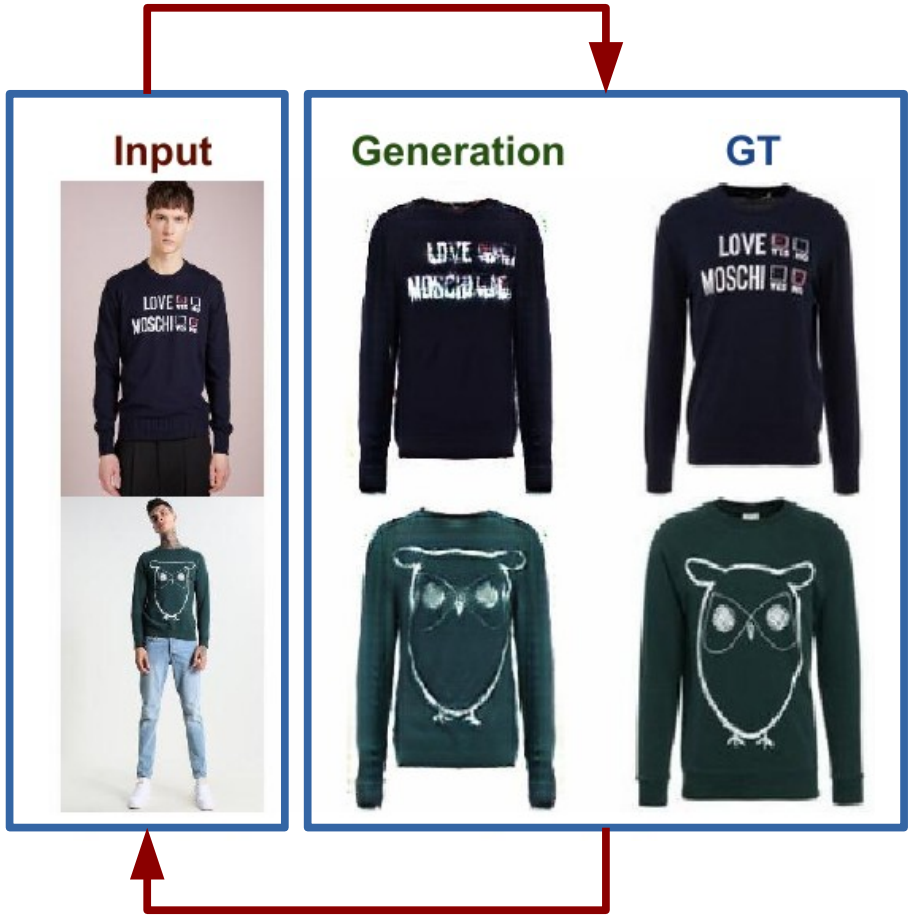
Style Transfer

[Zhu et al., ICCV'17]

Generative Adversarial Networks – Applications

Transfering shape, Preserving Style

People images



Catalog images

[Wang et al., ICIP'20]
[Wang et al., arXiv:1812.02134]

Generative Adversarial Networks – Applications

Transfering shape, Preserving Style

Virtual Clothing Try-On

[Wang et al., ICIP'20]
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Generative Adversarial Networks – Applications

Transfering shape, Preserving Style

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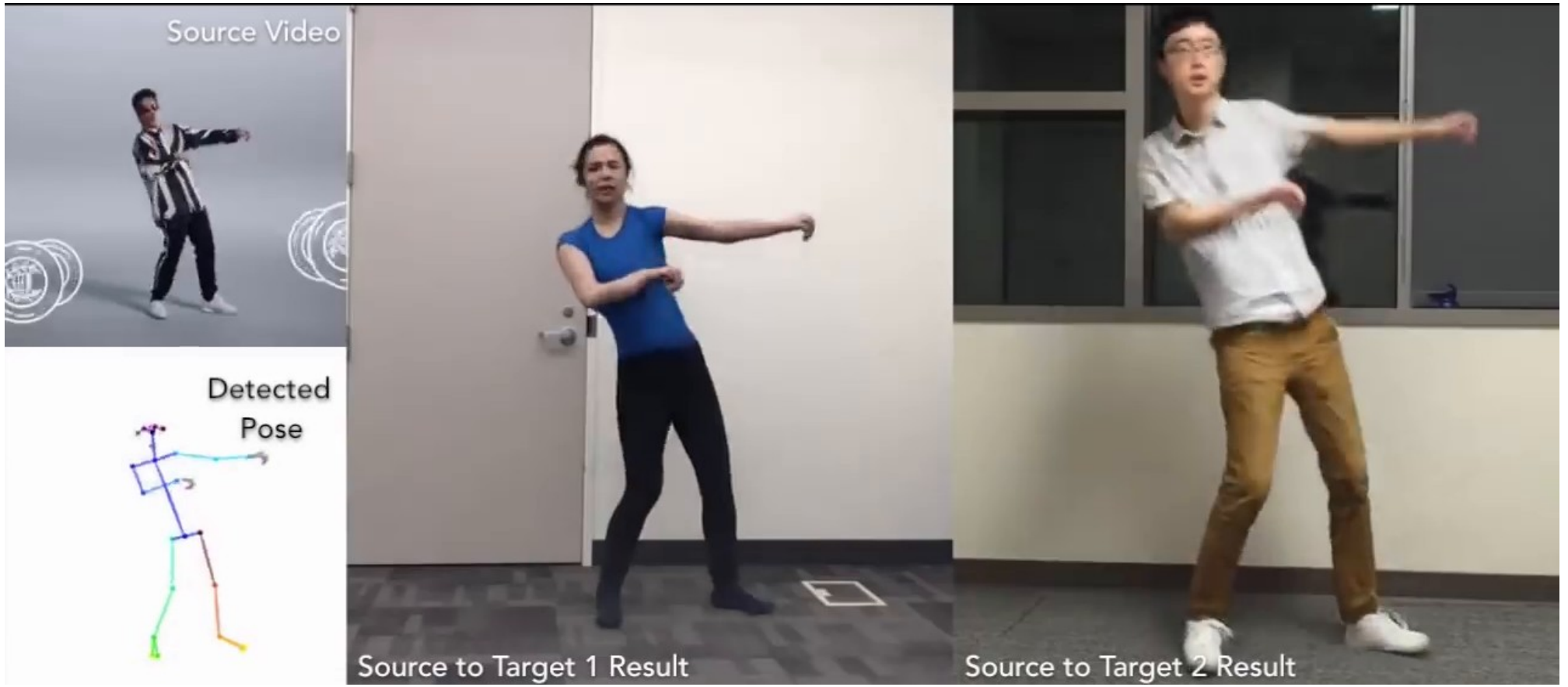
Generative Adversarial Networks – Applications

Transfering appearance to pose



[Chan et al., ICCV'19]

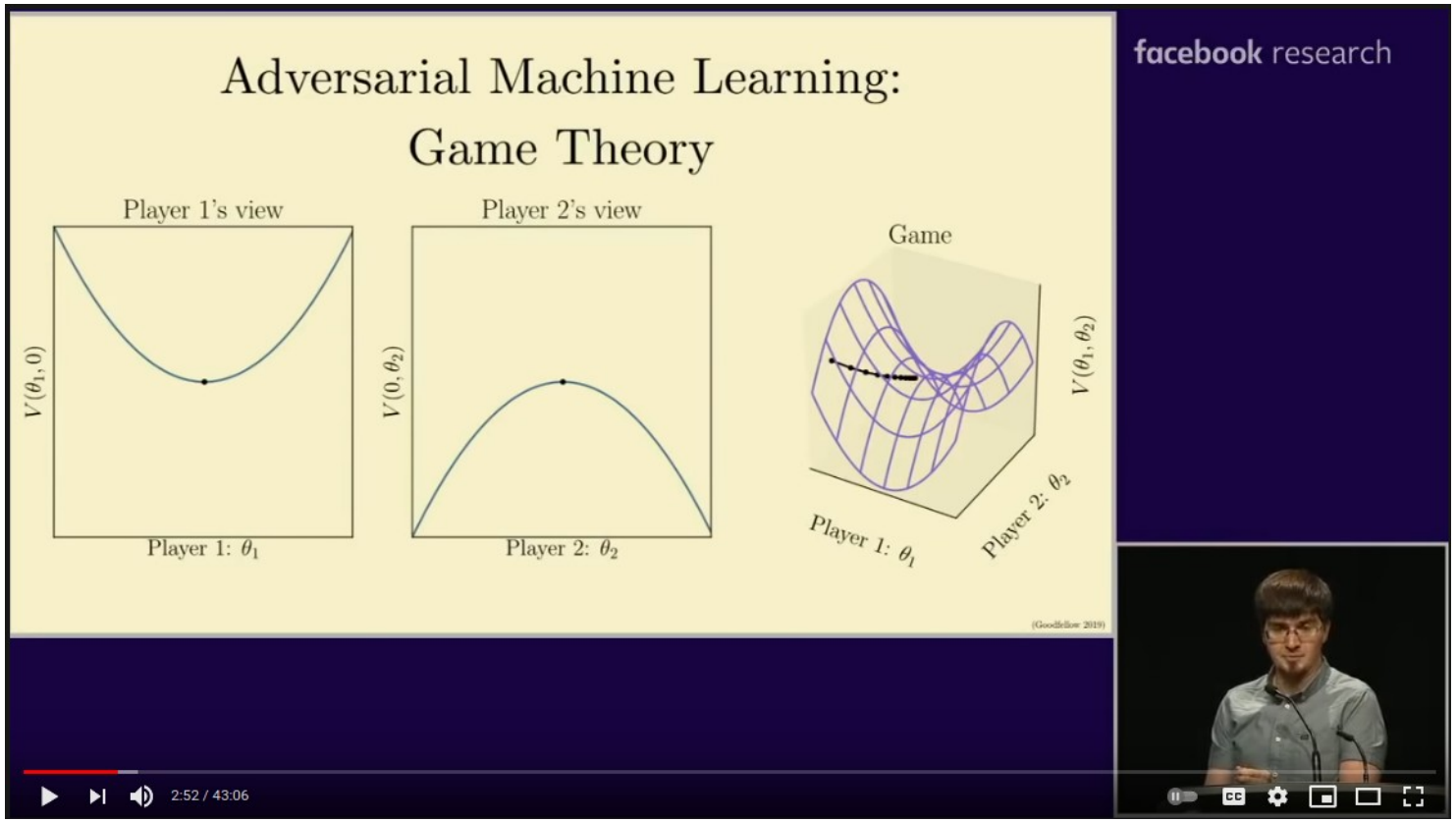
Generative Adversarial Networks – Applications

Transfering appearance to pose

[Chan et al., ICCV'19]

Generative Adversarial Networks – Applications

For more: have a look at Ian Goodfellow's talk at ICLR'19



[Ian Goodfellow: Adversarial Machine Learning (ICLR 2019 invited talk)]

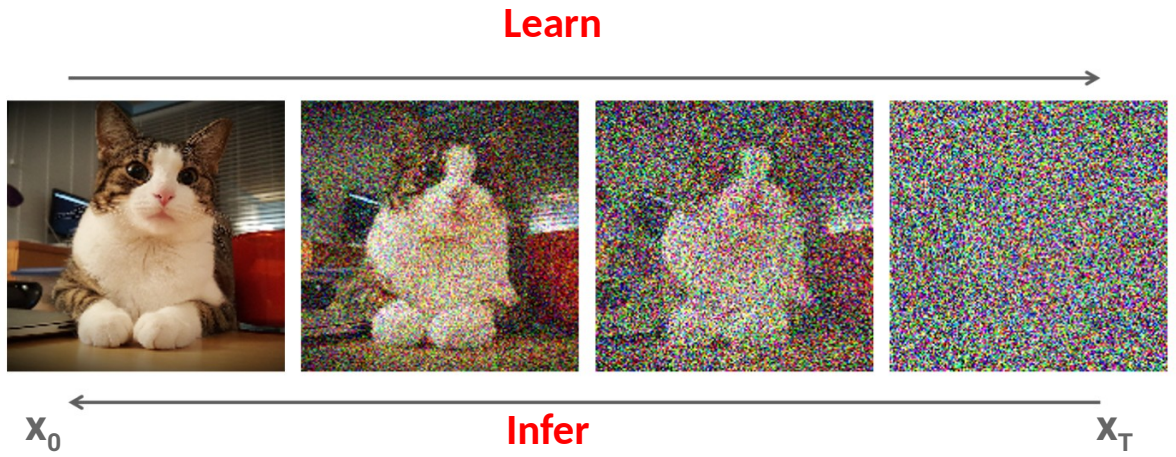
Difusion

[One Step at a Time]

Diffusion Models

Learning to Generate One Step at a Time

[Sohl-Dickstein, Weiss et al., 2015]



Diffusion Models

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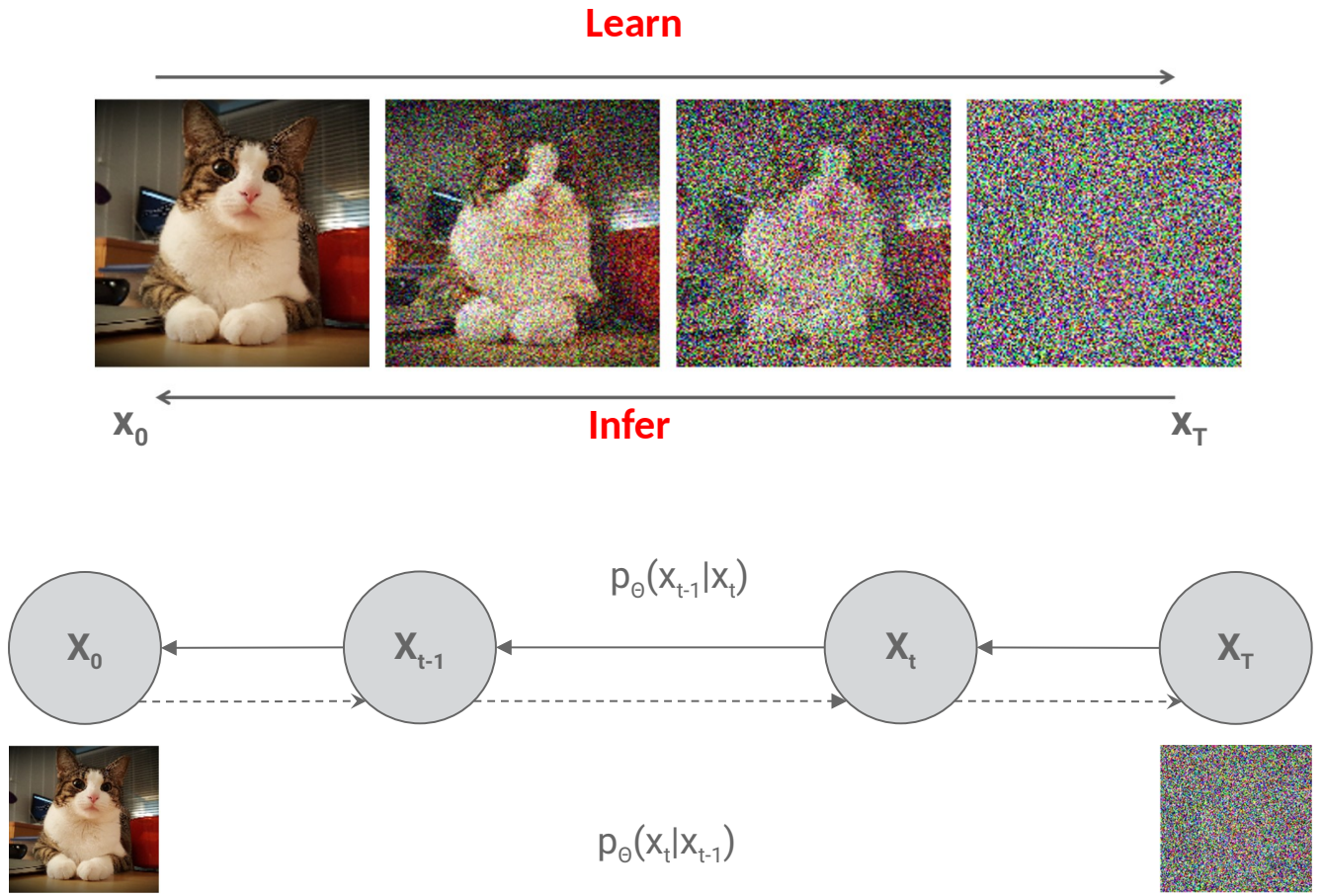


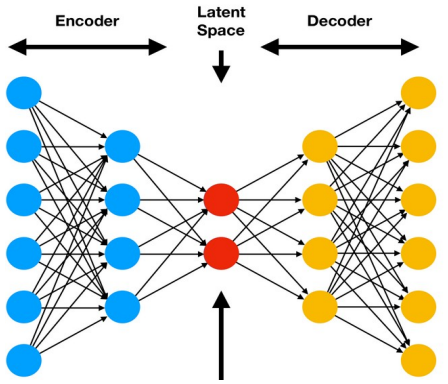
- **Conditioning**
  - **← Class labels**
  - **← Text / Visual Prompts**

Summarizing

[Finally :D]

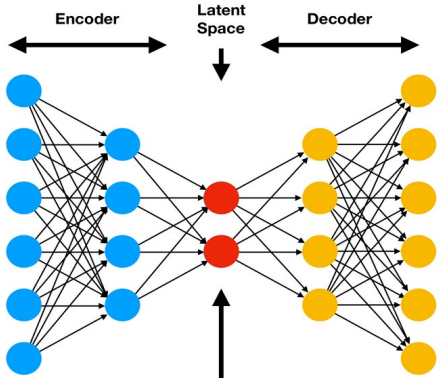
Summarizing

- **Autoencoders map data points to compressed vectors**
  - → Does not require additional annotations
  - → Learn how to preserve relevant properties from the data

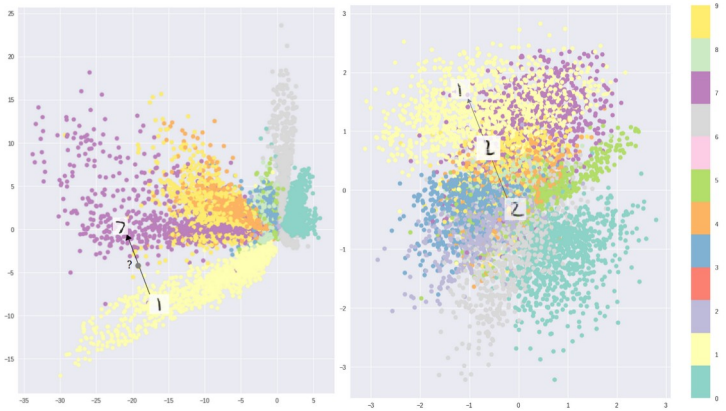


Summarizing

- **Autoencoders map data points to compressed vectors**
  - → Does not require additional annotations
  - → Learn how to preserve relevant properties from the data



- **VAEs map data points to continuous spaces**
  - → Enables the generation of new examples
  - → Enables for interpollation across data examples



Summarizing

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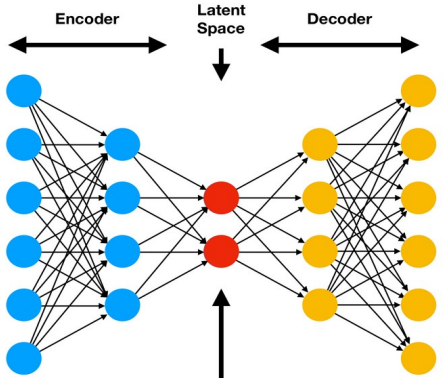

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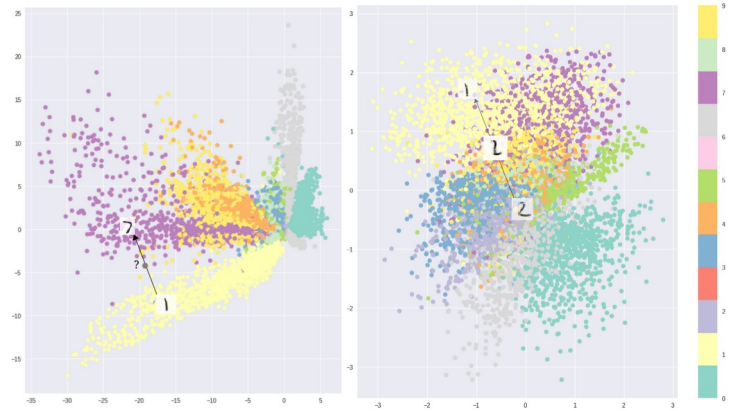

- **GANs: adversarial learning with DNNs**
  - → Enables the generation of new examples
  - → Training can become complex

Questions?

References

- Autoencoders - Deep Learning Book - Chapter 14. https://www.deeplearningbook.org/contents/autoencoders.html
- Vaiational Autoencoders - Deep Learning Book - Chapter 20.10.3 https://www.deeplearningbook.org/contents/generative_models.html
- P. Vincent, H. Larochelle, Y. Bengio, P. Manzagol.Extracting and Composing Robust Features with Denoising Autoencoders ICML 2008
- F. Baldassarre, D. González Morín, L. Rodés-Guirao. Deep Koalarization: Image Colorization using CNNs and Inception-Resnet-v2. ArXiv:1712.03400
- I. Higgins, Loic Matthey, A. Pal, Christopher P. Burgess, Xavier Glorot, M. Botvinick, S. Mohamed, A. Lerchner. beta-VAE: Learning Basic Visual Concepts with a Constrained Variational Framework. ICLR 2017
- X Hou, L. Shen, K. Sun, G. Qiu. Deep Feature Consistent Variational Autoencoder. WACV 2017.

References

- I. Shafkat, Intuitively Understanding Variational Autoencoders https://towardsdatascience.com/intuitively-understanding-variational-autoencoders-1bfe67eb5daf
- A. Wong. Similar Image Retrieval using Autoencoders, 2017. https://towardsdatascience.com/find-similar-images-using-autoencoders-315f374029ea
- I. J. Goodfellow∗, J. Pouget-Abadie†, M. Mirza, B. Xu, D. Warde-Farley, S. Ozair, A. Courville, Y. Bengio§. Generative Adversarial Nets, NeurIPS, 2014.
- J, Zhu, T. Park, P. Isola, A. A. Efros. Unpaired Image-to-Image Translation using Cycle-Consistent Adversarial Networks. ICCV 2017. https://junyanz.github.io/CycleGAN/
- J. Brownlee. A Gentle Introduction to CycleGAN for Image Translation. https://machinelearningmastery.com/what-is-cyclegan

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