Deep Generative Models
MIT 6.S191

Alexander Amini

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Which face is fake?

Supervised vs unsupervised learning

Supervised Learning

Data: (x, y)
x is data, y is label

Goal: Learn function to map

$$x \rightarrow y$$

Examples: Classification, regression, object detection, semantic segmentation, etc.

Unsupervised Learning

Data: x
x is data, no labels!

Goal: Learn some *hidden* or *underlying structure* of the data

Examples: Clustering, feature or dimensionality reduction, etc.

Supervised vs unsupervised learning

Supervised Learning

Data: (x, y)
x is data, y is label

Goal: Learn function to map

$$x \to y$$

Examples: Classification, regression, object detection, semantic segmentation, etc.

Unsupervised Learning

Data: x
x is data, no labels!

Goal: Learn some *hidden* or *underlying structure* of the data

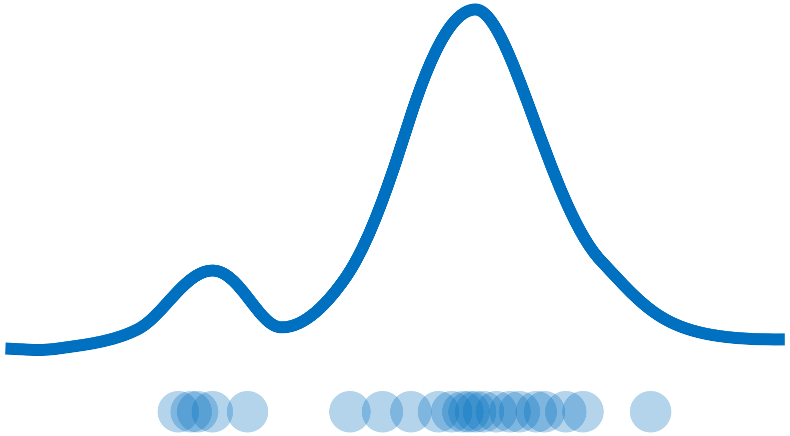
Examples: Clustering, feature or dimensionality reduction, etc.

Generative modeling

Goal: Take as input training samples from some distribution and learn a model that represents that distribution

Density Estimation

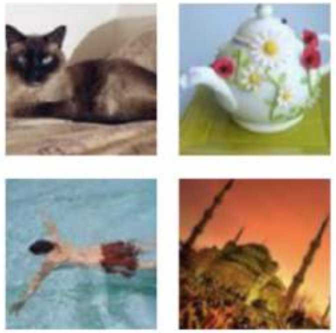
samples



Sample Generation

Input samples

Training data $\sim P_{data}(x)$



Generated samples

Generated $\sim P_{model}(x)$

How can we learn $P_{model}(x)$ similar to $P_{data}(x)$?

Why generative models? Debiasing

Capable of uncovering **underlying latent variables** in a dataset

vs

Homogeneous skin color, pose

Diverse skin color, pose, illumination

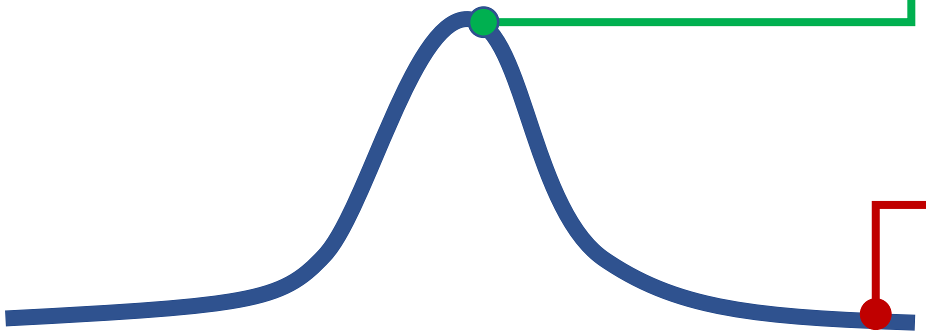
How can we use latent distributions to create fair and representative datasets?

Why generative models? Outlier detection

- **Problem:** How can we detect when we encounter something new or rare?
- **Strategy:** Leverage generative models, detect outliers in the distribution
- Use outliers during training to improve even more!

95% of Driving Data:
(1) sunny, (2) highway, (3) straight road

Detect outliers to avoid unpredictable behavior when training



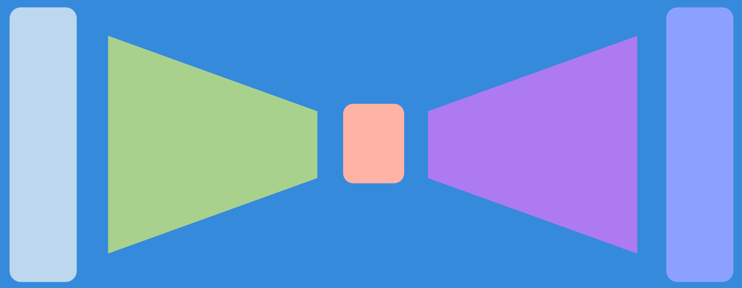
Edge Cases

Harsh Weather

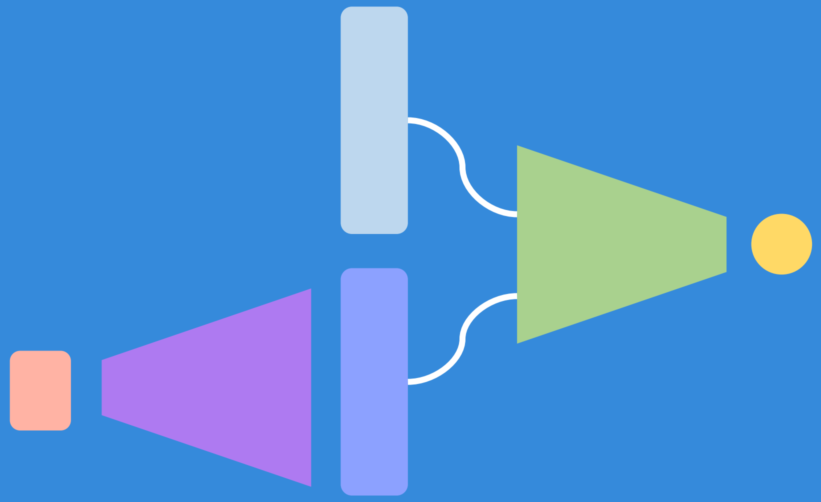
Pedestrians

Latent variable models

Autoencoders and Variational Autoencoders (VAEs)



Generative Adversarial Networks (GANs)



What is a latent variable?

Myth of the Cave

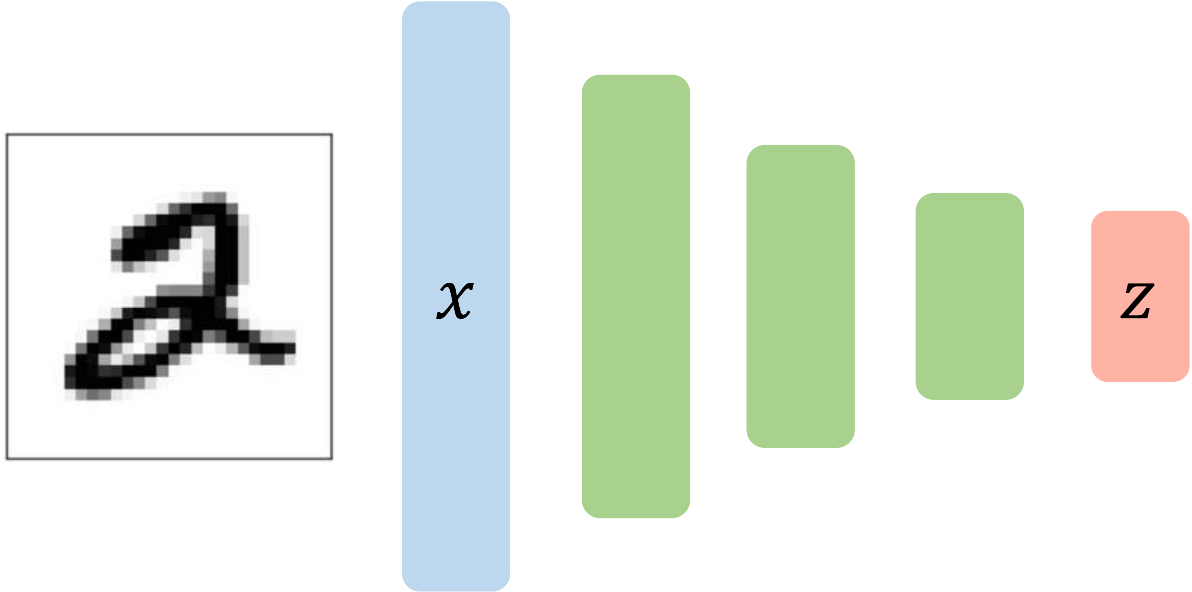
What is a latent variable?

Can we learn the **true explanatory factors**, e.g. latent variables, from only observed data?

Autoencoders

Autoencoders: background

Unsupervised approach for learning a **lower-dimensional** feature representation from unlabeled training data

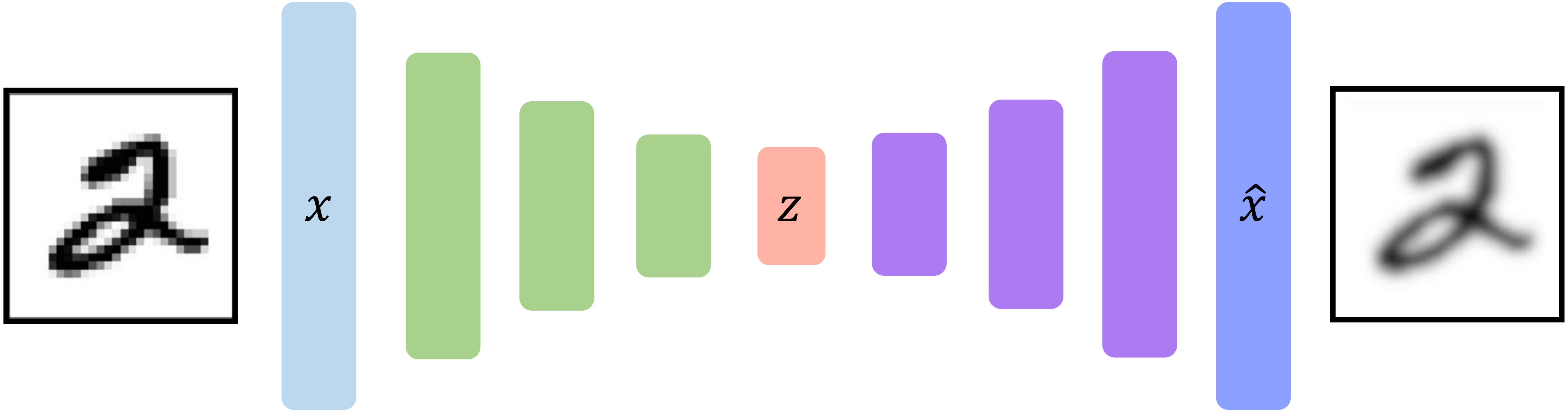


Why do we care about a low-dimensional z?

"Encoder" learns mapping from the data, x, to a low-dimensional latent space, z

Autoencoders: background

How can we learn this latent space?
Train the model to use these features to **reconstruct the original data**

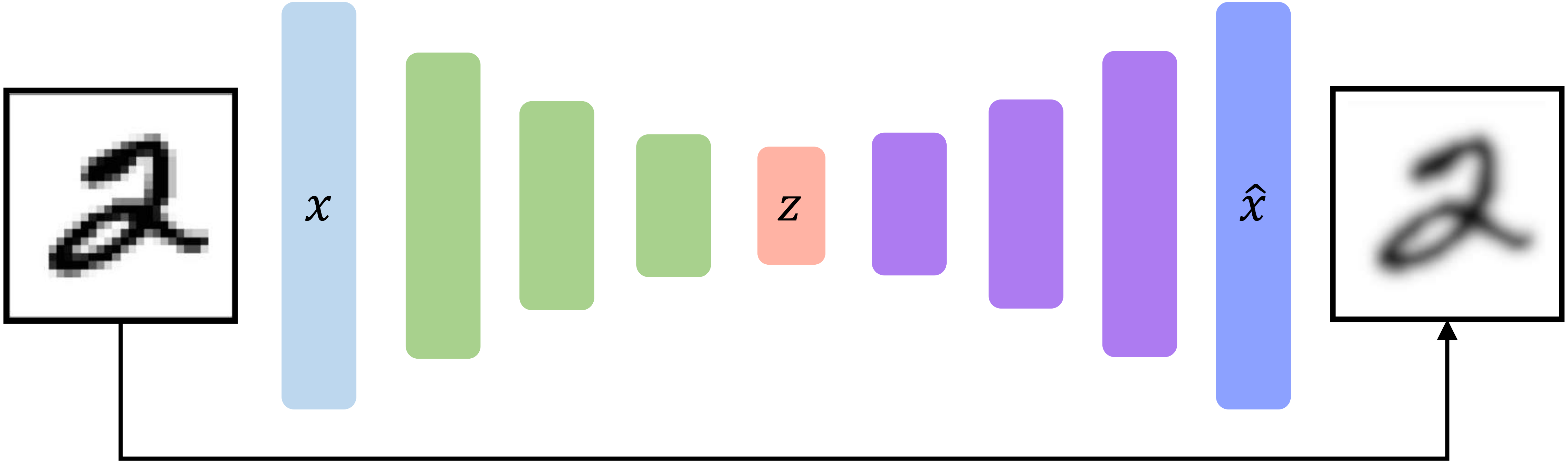


"Decoder" learns mapping back from latent, z, to a reconstructed observation, $\hat{x}$

Autoencoders: background

How can we learn this latent space?

Train the model to use these features to **reconstruct the original data**



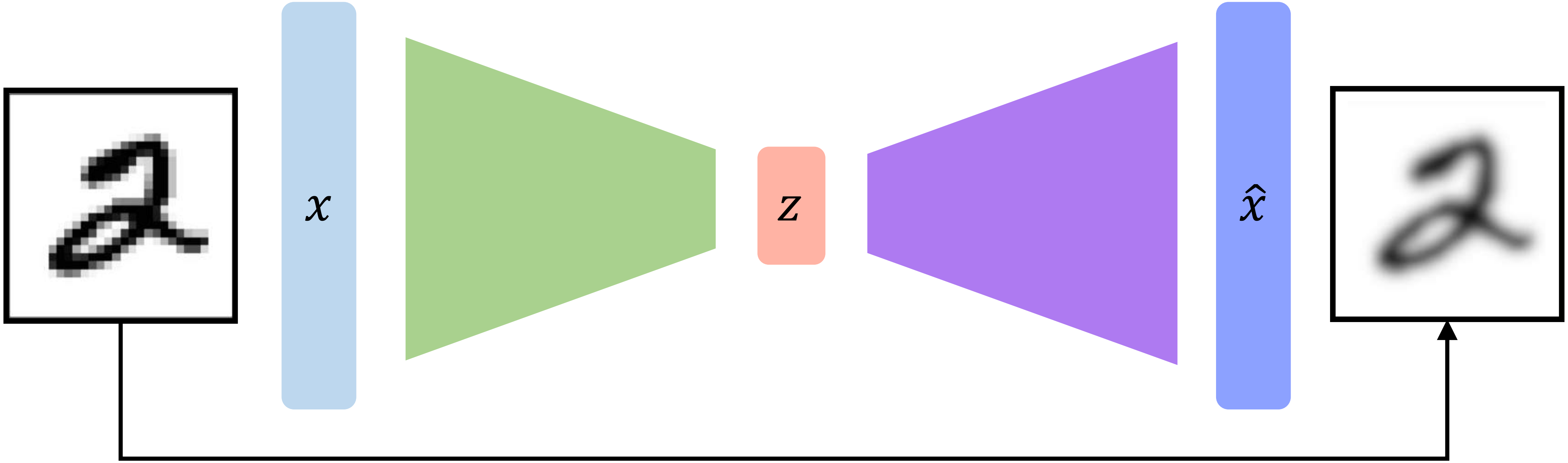
$$\mathcal{L}(x, \hat{x}) = \|x - \hat{x}\|^2$$

Loss function doesn't use any labels!!

Autoencoders: background

How can we learn this latent space?

Train the model to use these features to **reconstruct the original data**



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Dimensionality of latent space → reconstruction quality

Autoencoding is a form of compression!
Smaller latent space will force a larger training bottleneck

2D latent space

5D latent space

Ground Truth

Autoencoders for representation learning

Bottleneck hidden layer forces network to learn a compressed latent representation

Reconstruction loss forces the latent representation to capture (or encode) as much "information" about the data as possible

Autoencoding = **Auto**matically **encoding** data

Variational Autoencoders (VAEs)

Latent Variable Models

- The Variational Autoencoder model:
  - Kingma and Welling, *Auto-Encoding Variational Bayes*, *International Conference on Learning Representations (ICLR)* 2014.
  - Rezende, Mohamed and Wierstra, *Stochastic back-propagation and variational inference in deep latent Gaussian models*. ICML 2014.

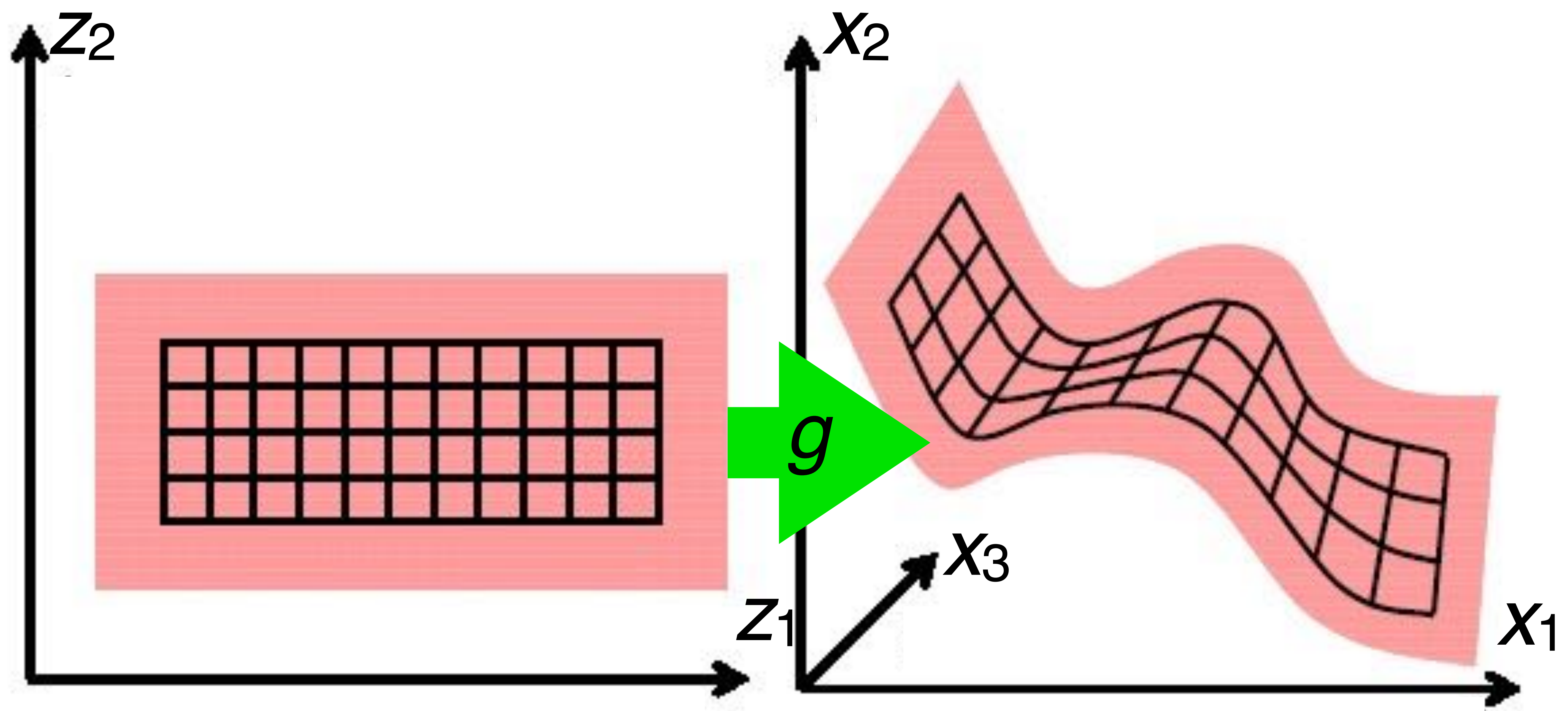
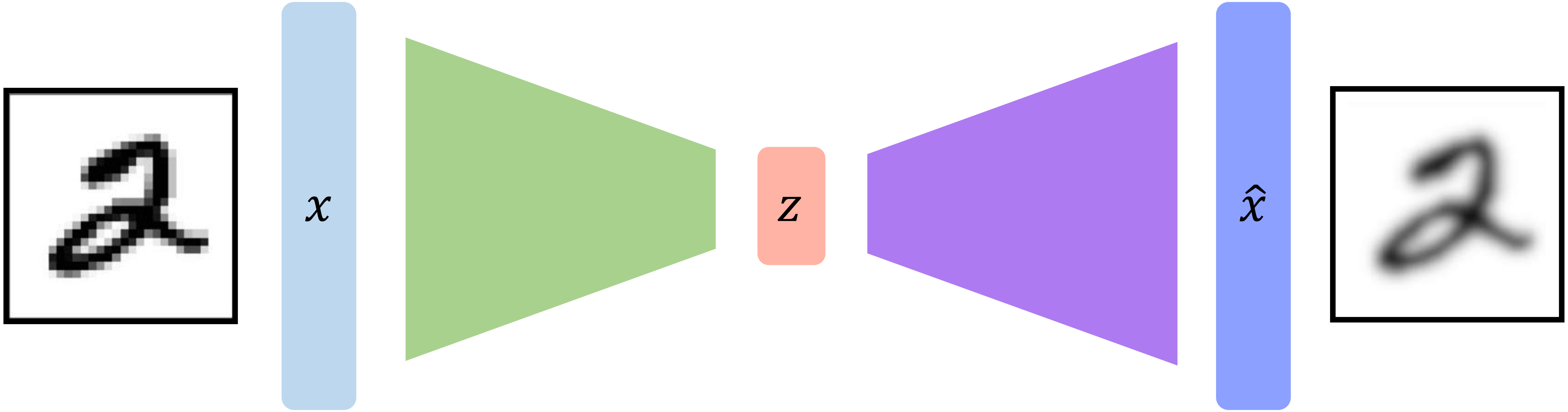


Image from: Ward, A. D., Hamarneh, G.: **3D Surface Parameterization Using Manifold Learning for Medial Shape Representation**, *Conference on Image Processing, Proc. of SPIE Medical Imaging*, 2007

VAEs: key difference with traditional autoencoder



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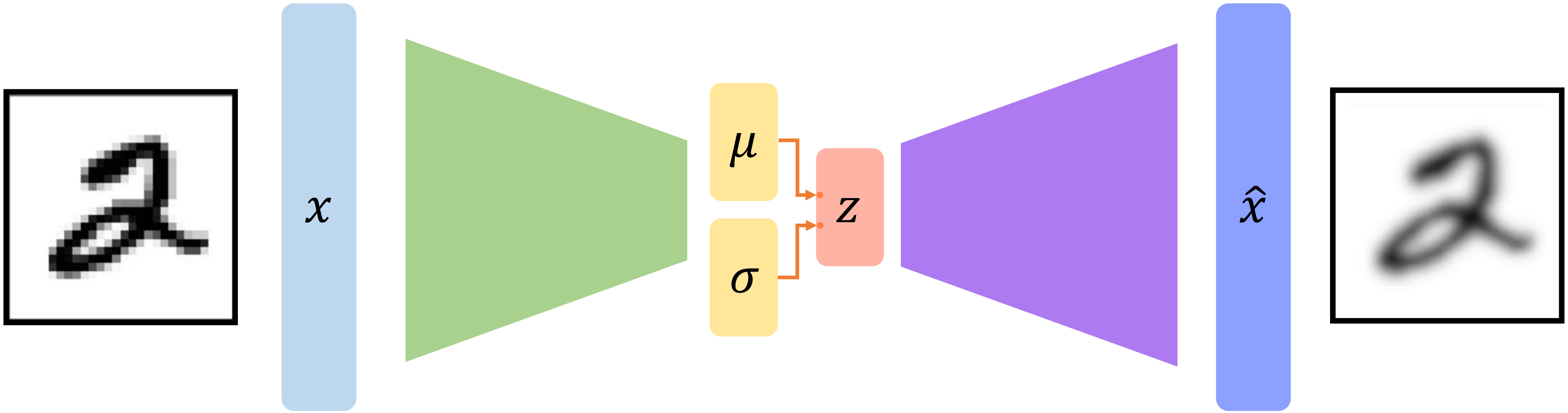

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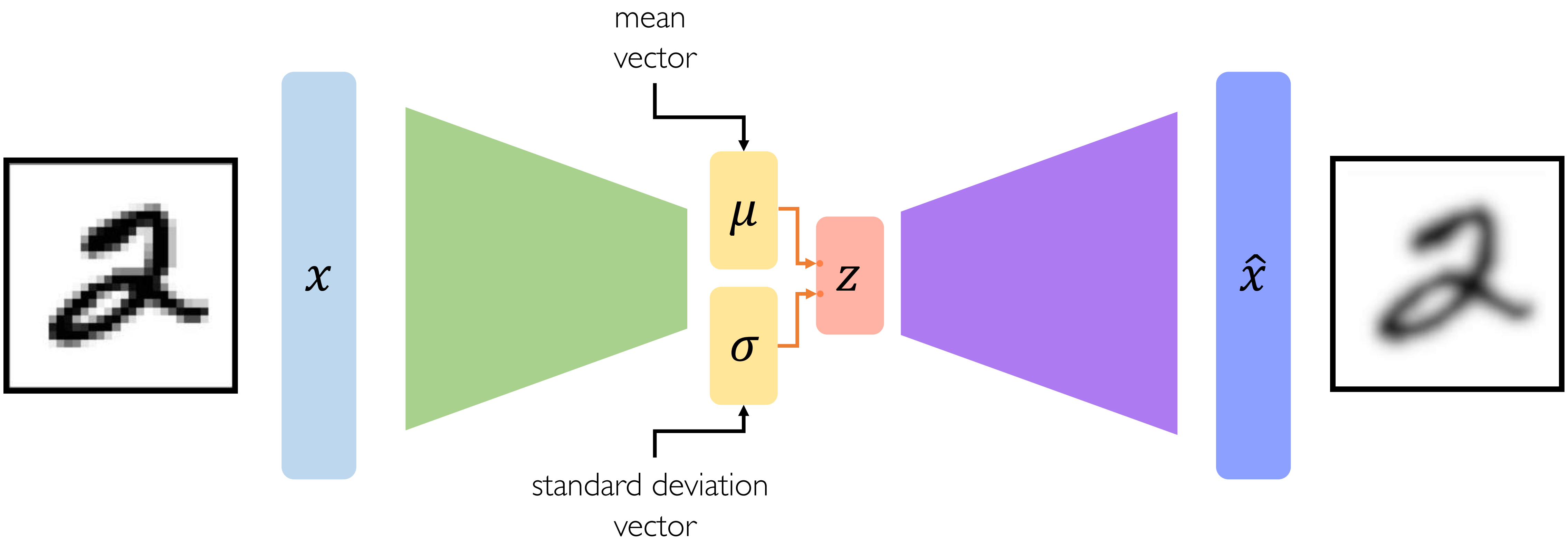
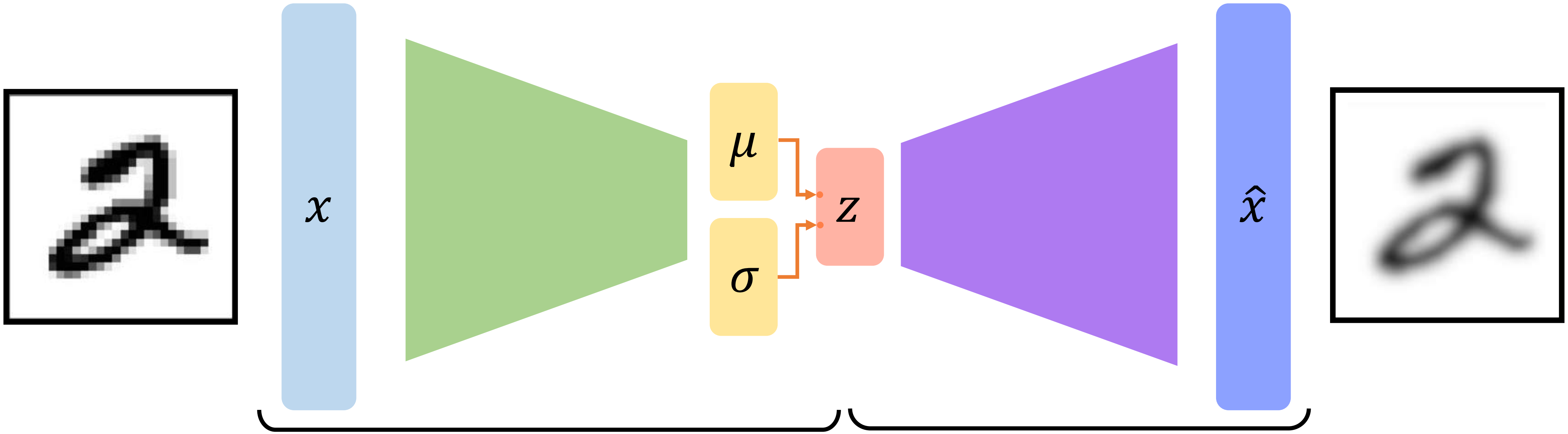


Variational autoencoders are a probabilistic twist on autoencoders!

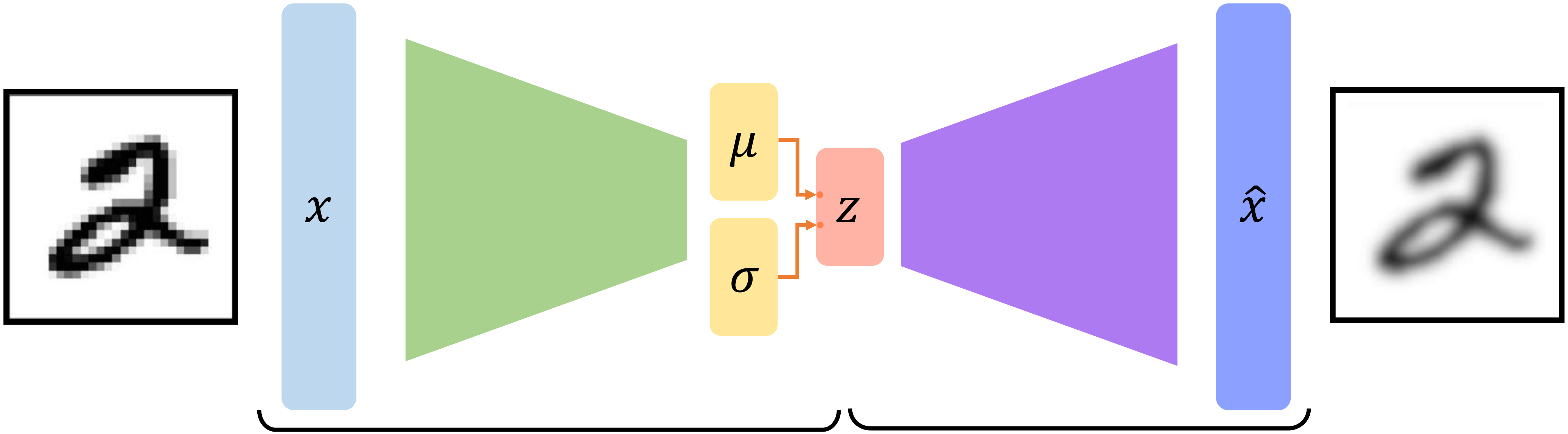
Sample from the mean and standard dev. to compute latent sample

VAE optimization



Encoder computes: $p_\phi(\mathrm{z}|x)$ Decoder computes: $q_\theta(\mathrm{x}|z)$

VAE optimization



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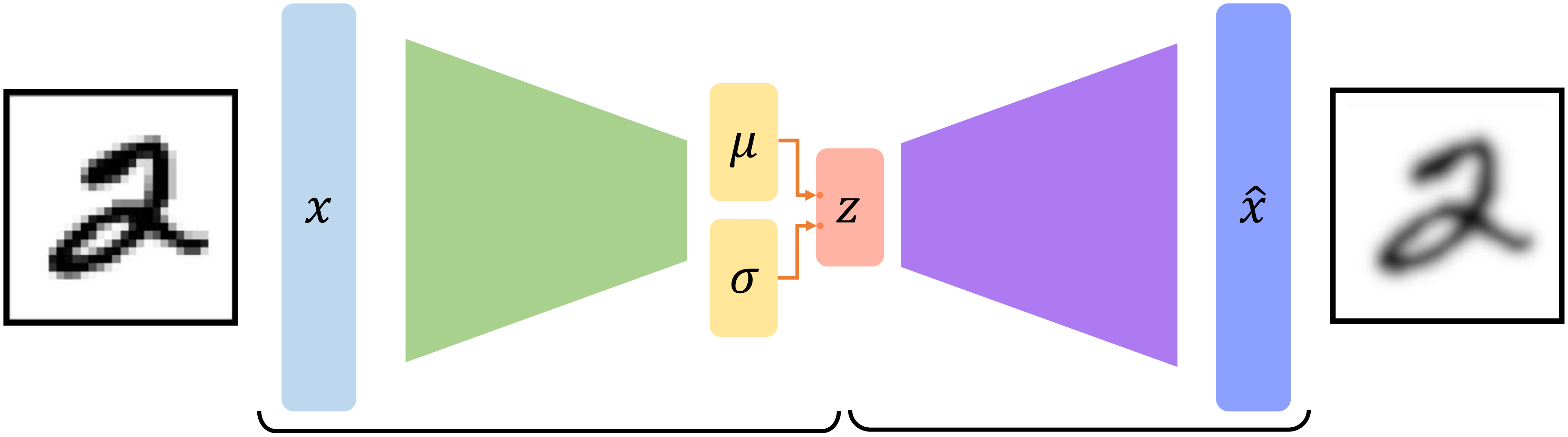
$$\mathcal{L}(\phi, \theta) = \text{(reconstruction loss)} + \text{(regularization term)}$$

VAE optimization



Encoder computes: $p_\phi(z|x)$ Decoder computes: $q_\theta(x|z)$

$$\mathcal{L}(\phi, \theta, x) = (\text{reconstruction loss}) + (\text{regularization term})$$

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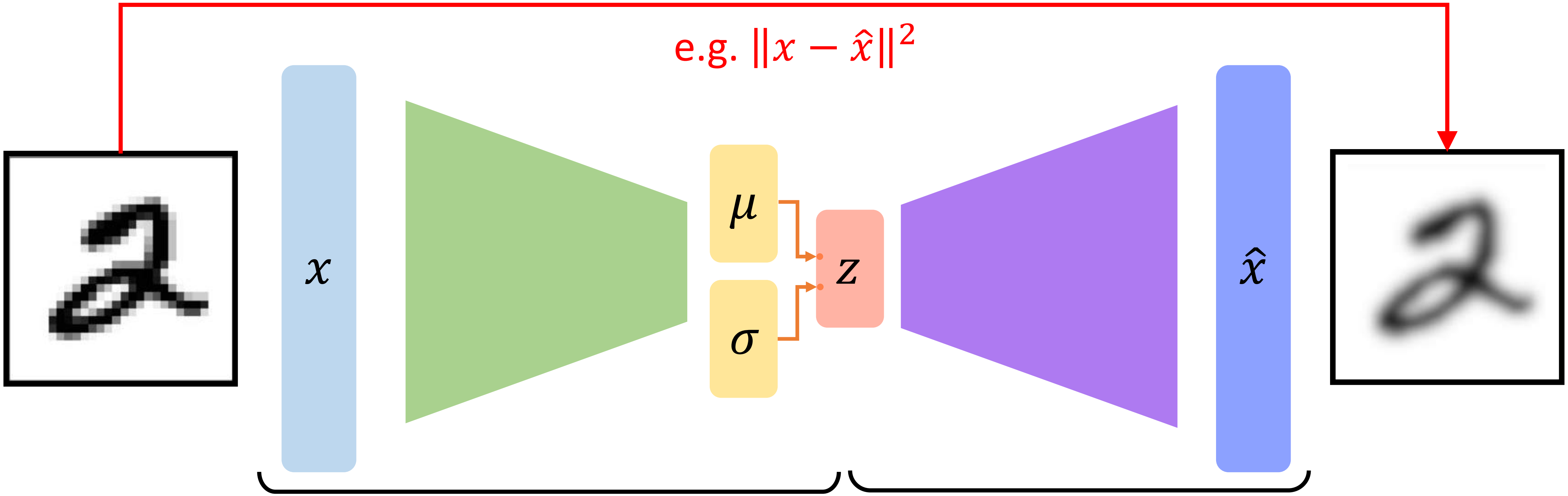

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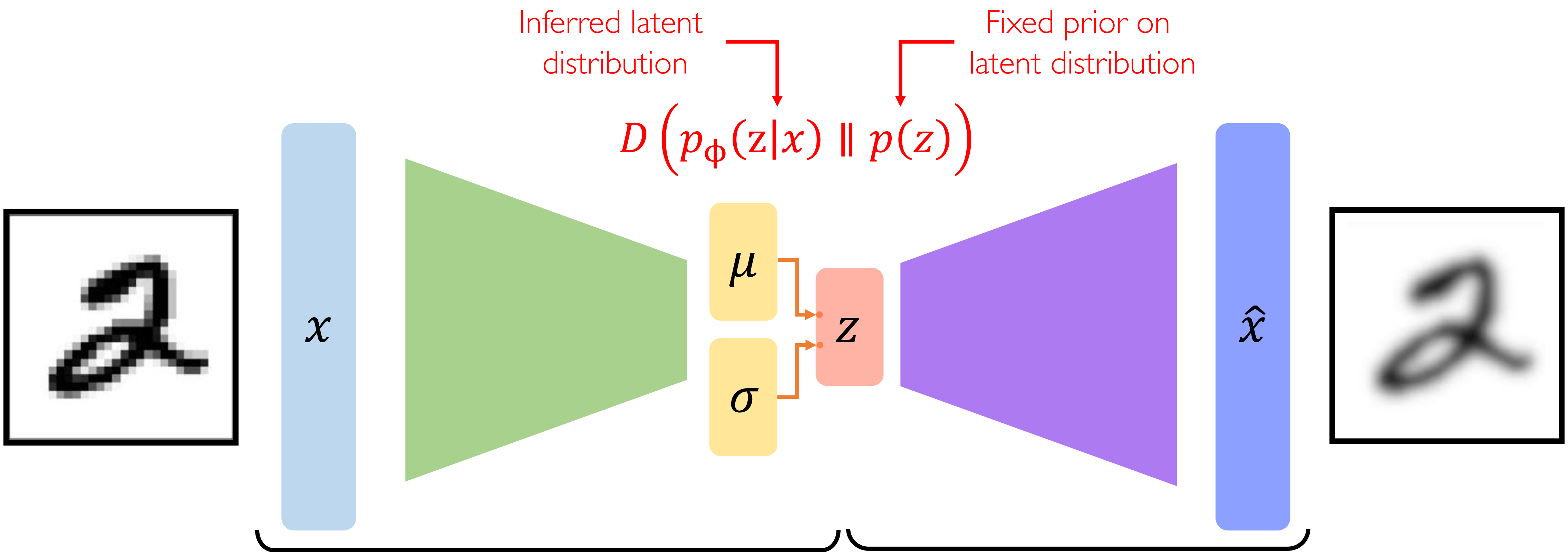
VAE optimization

$$D_{\mathrm{KL}}(P \parallel Q) = \sum_{x \in \mathcal{X}} P(x) \log\left(\frac{P(x)}{Q(x)}\right).$$



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Priors on the latent distribution

$$D\left(p_{\phi}(z|x)\ \|\ p(z)\right)$$

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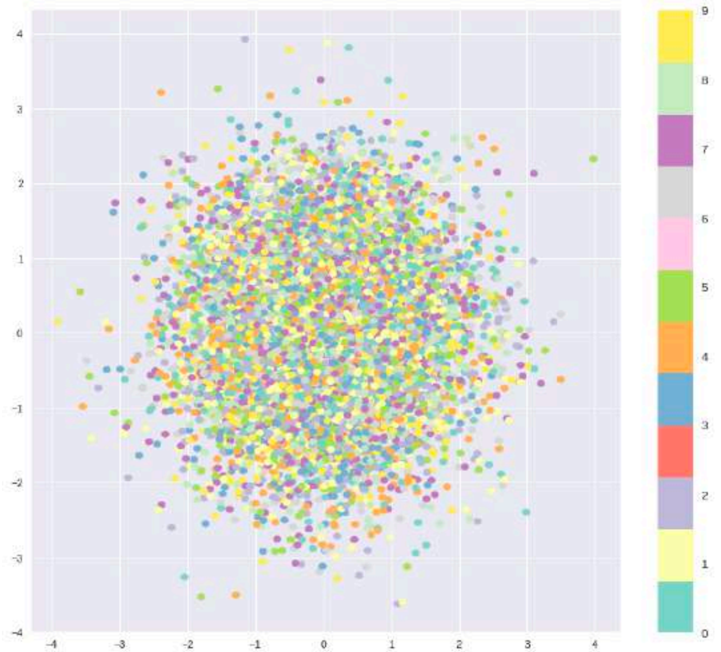
Inferred latent distribution

Fixed prior on latent distribution



Common choice of prior:

$$p(z) = \mathcal{N}(\mu = 0, \sigma^2 = 1)$$

- Encourages encodings to distribute encodings evenly around the center of the latent space
- Penalize the network when it tries to "cheat" by clustering points in specific regions (ie. memorizing the data)

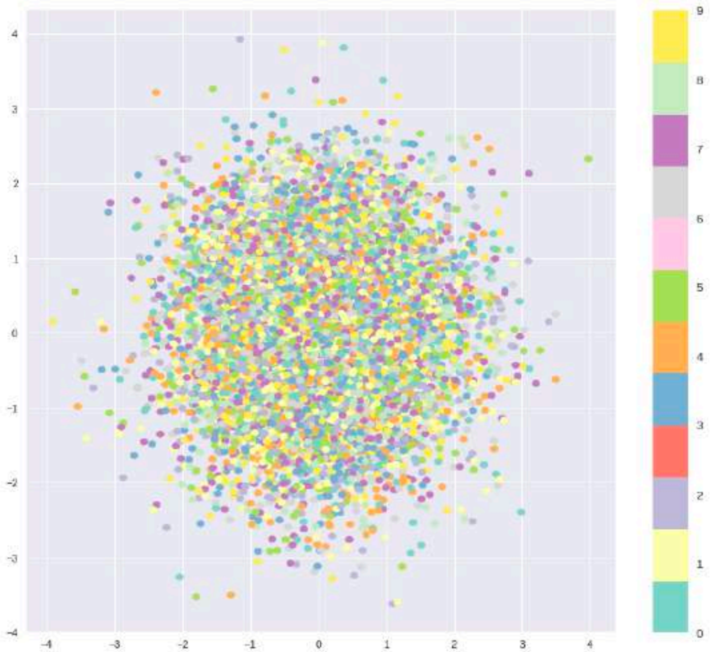
Priors on the latent distribution

$$D\left(p_\phi(\mathrm{z}|x)\ \|\ p(z)\right)$$

$$= -\frac{1}{2}\sum_{j=0}^{k-1}\left(\sigma_j + \mu_j^2 - 1 - \log\sigma_j\right)$$

$$D_{\mathrm{KL}}(P \parallel Q) = \sum_{x\in\mathcal{X}} P(x)\log\left(\frac{P(x)}{Q(x)}\right).$$

KL-divergence between the two distributions



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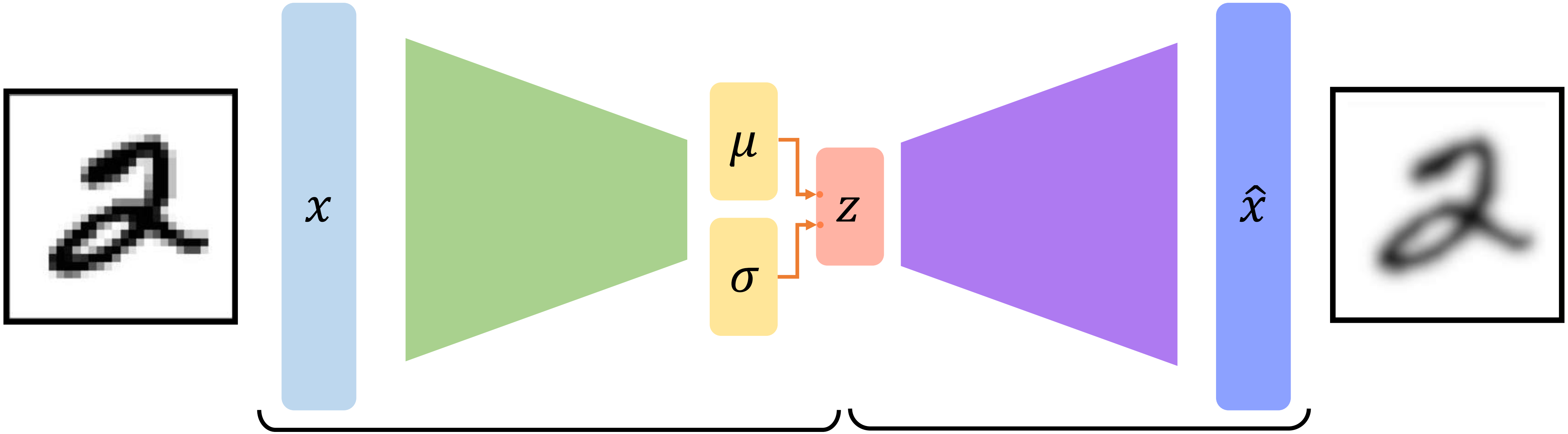
VAEs computation graph



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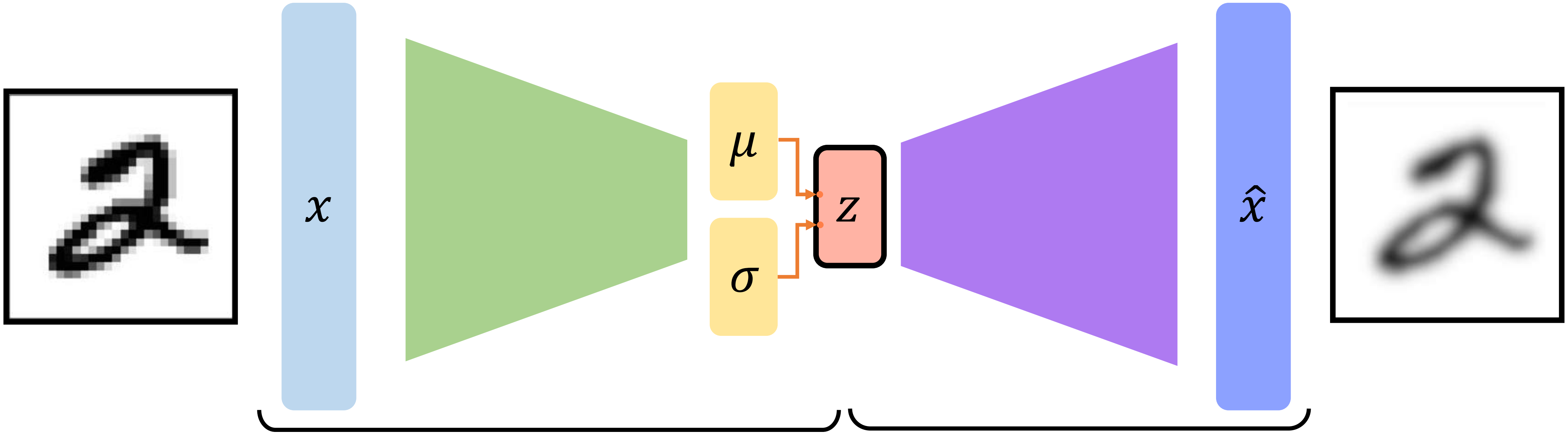
VAEs computation graph

Problem: We cannot backpropagate gradients through sampling layers!



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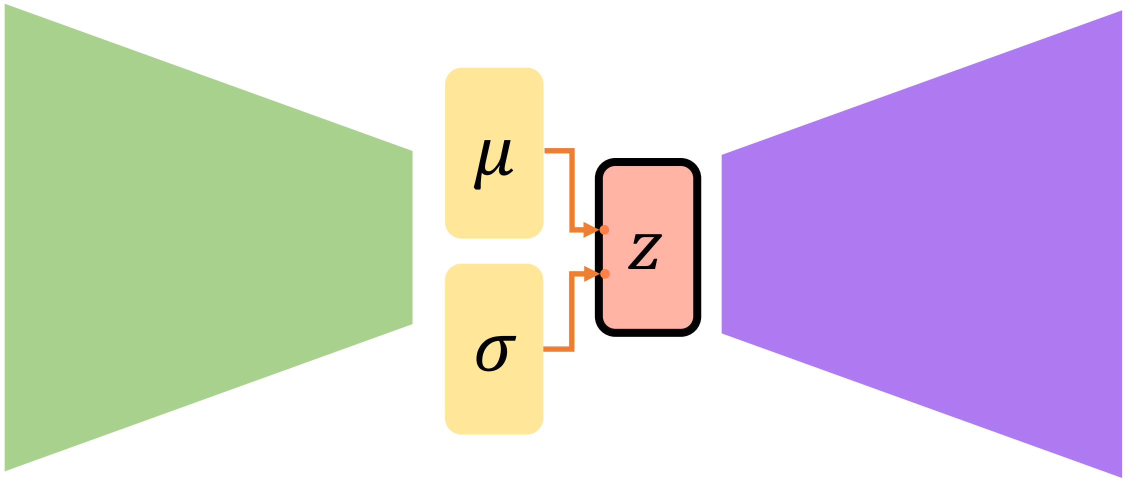
Reparametrizing the sampling layer



Key Idea:

$$\cancel{z \sim \mathcal{N}(\mu, \sigma^2)}$$

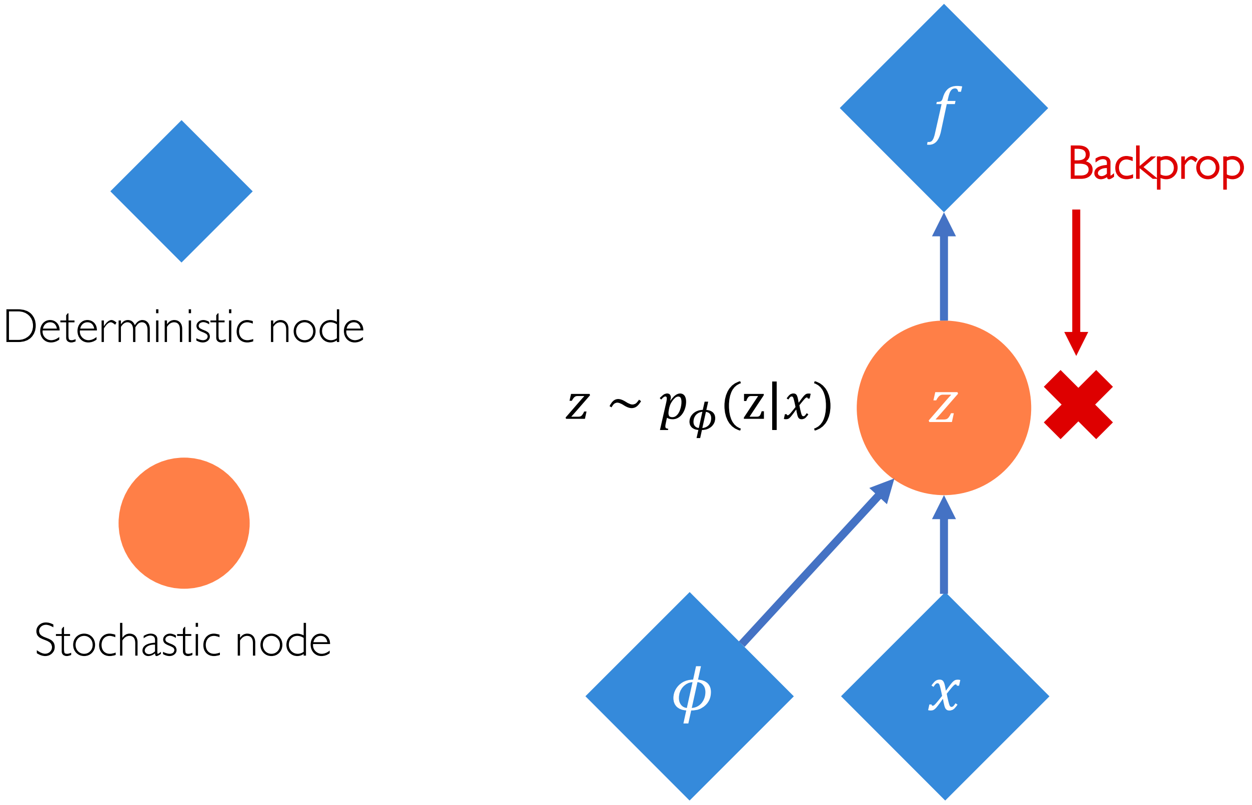
Consider the sampled latent vector as a sum of

- a fixed μ vector,
- and fixed σ vector, scaled by random constants drawn from the prior distribution

$$\Rightarrow z = \mu + \sigma \odot \varepsilon$$

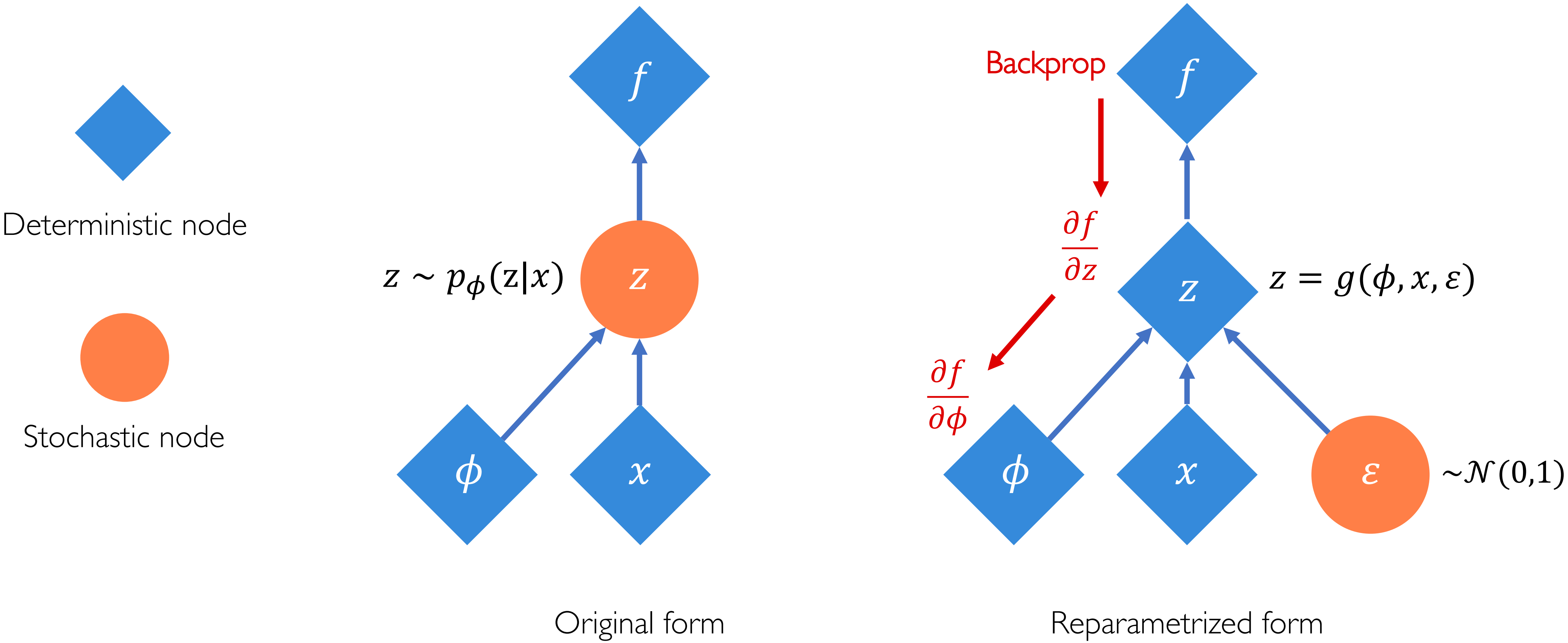
where $\varepsilon \sim \mathcal{N}(0,1)$

Reparametrizing the sampling layer



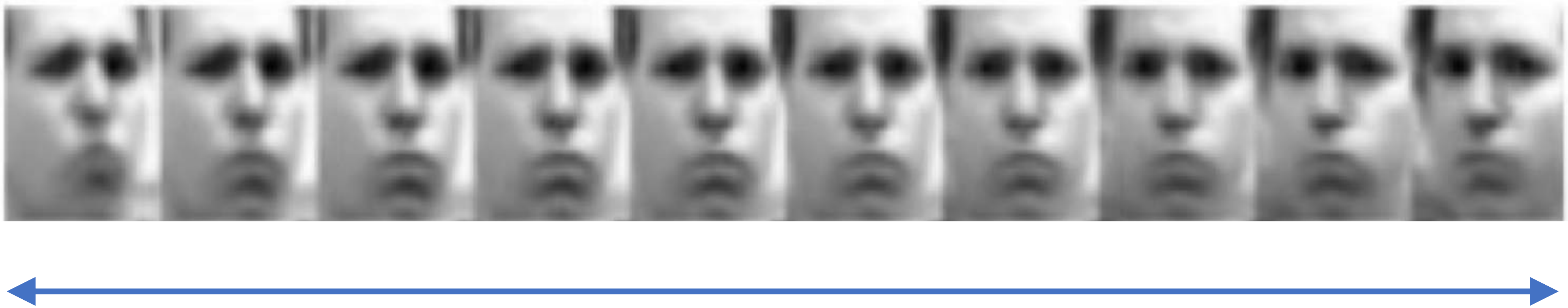
Original form

Reparametrizing the sampling layer



VAEs: Latent perturbation

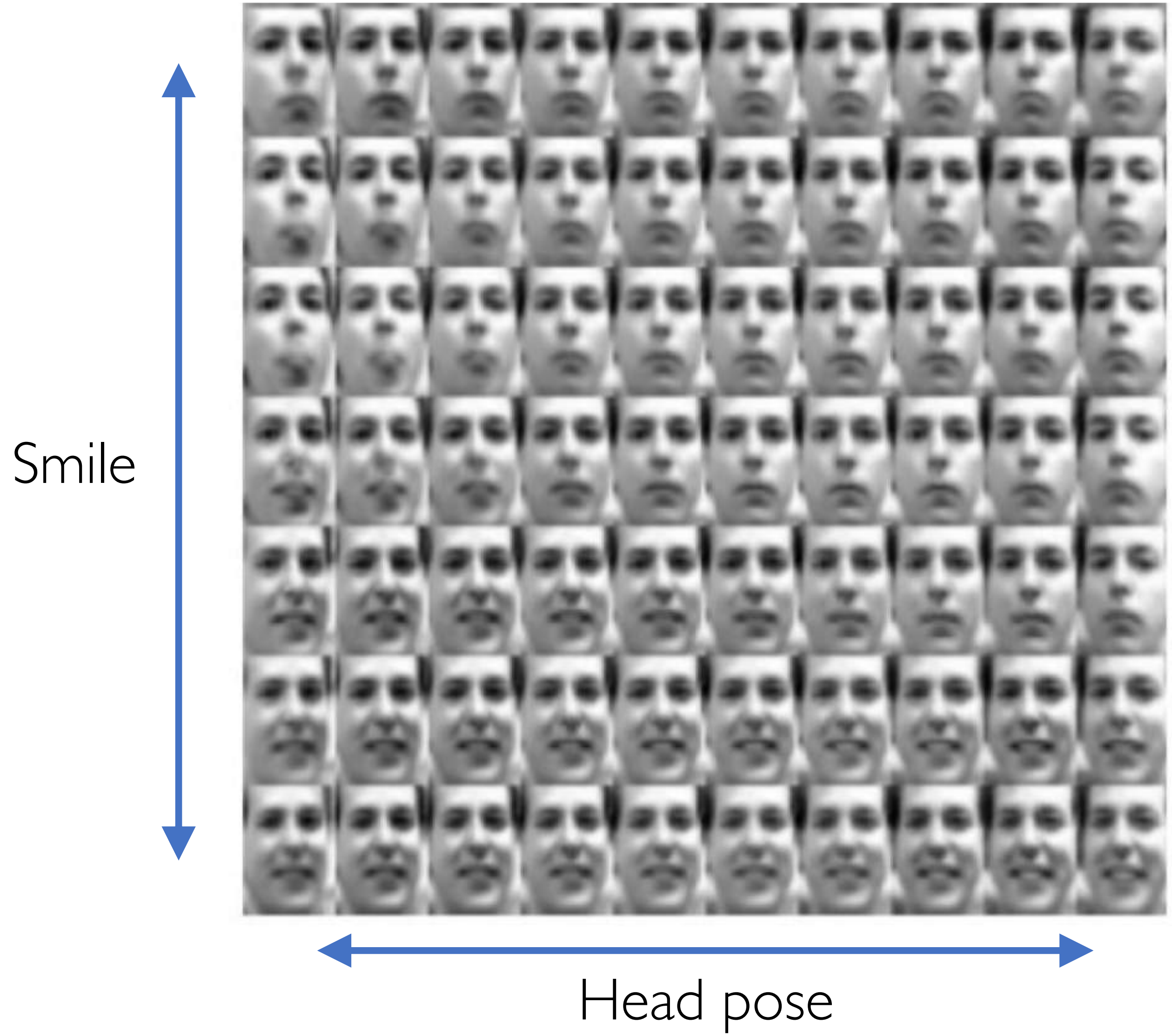
Slowly increase or decrease a **single latent variable**
Keep all other variables fixed



Head pose

Different dimensions of z encodes **different interpretable latent features**

VAEs: Latent perturbation

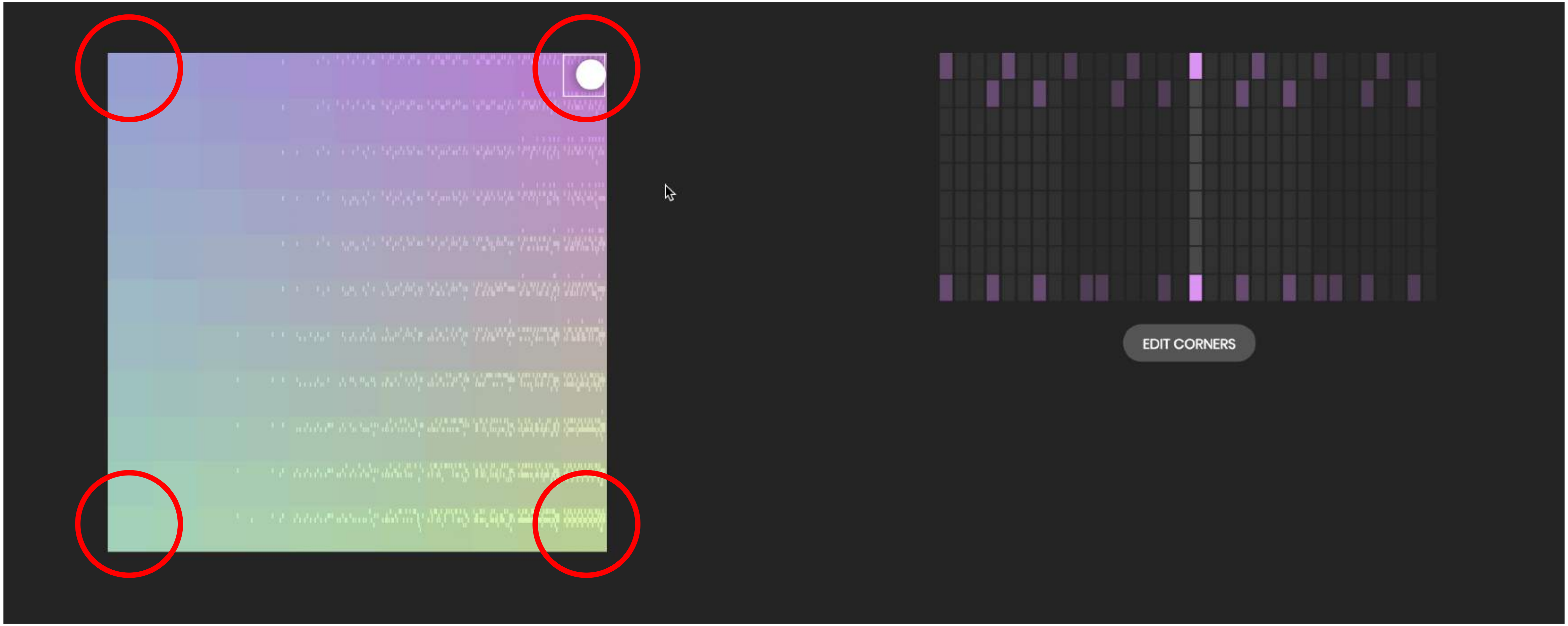


Ideally, we want latent variables that are uncorrelated with each other

Enforce diagonal prior on the latent variables to encourage independence

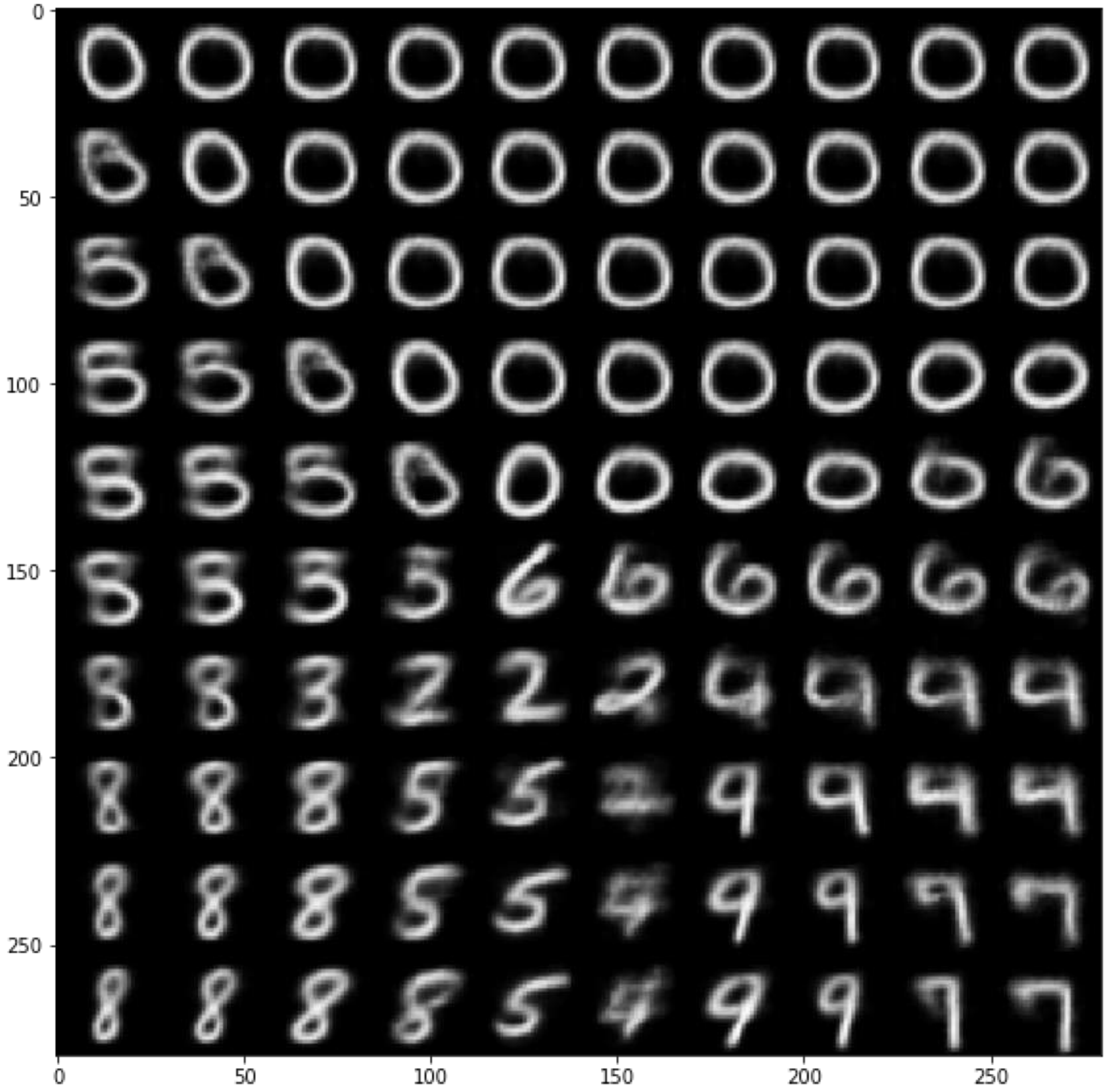
Disentanglement

VAEs: Latent perturbation



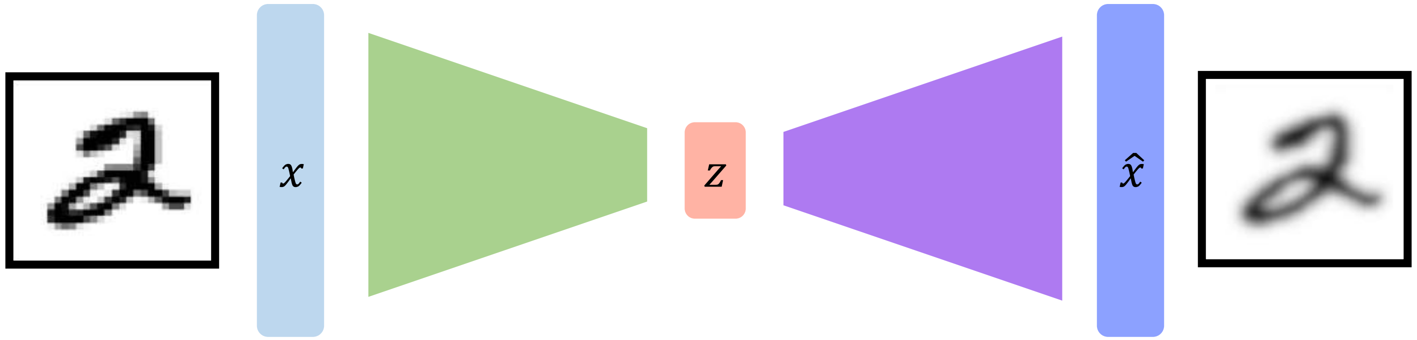
Google BeatBlender

VAEs: Latent perturbation



VAE summary

1. Compress representation of world to something we can use to learn



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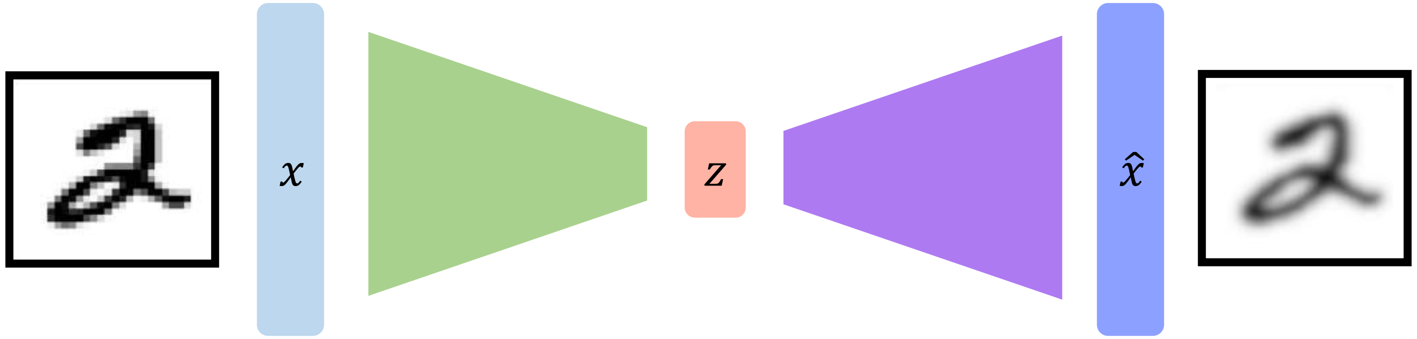

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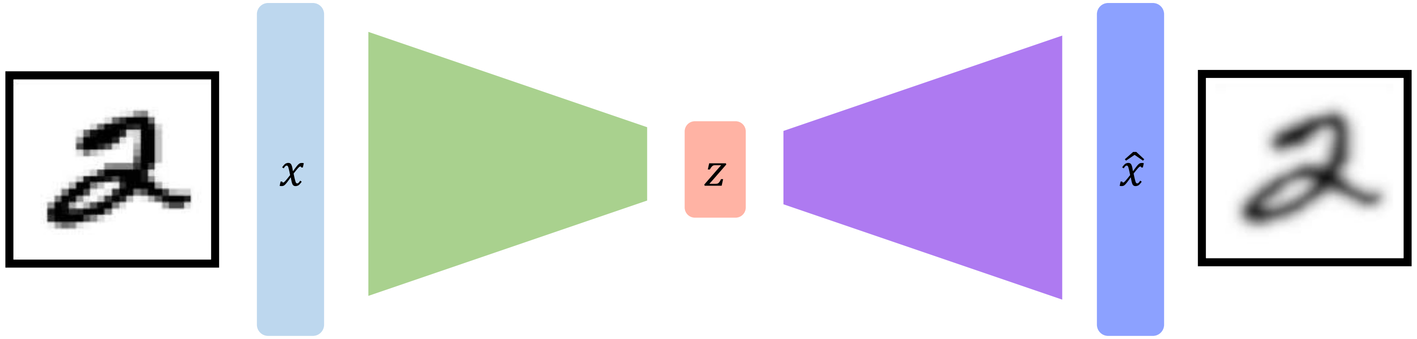

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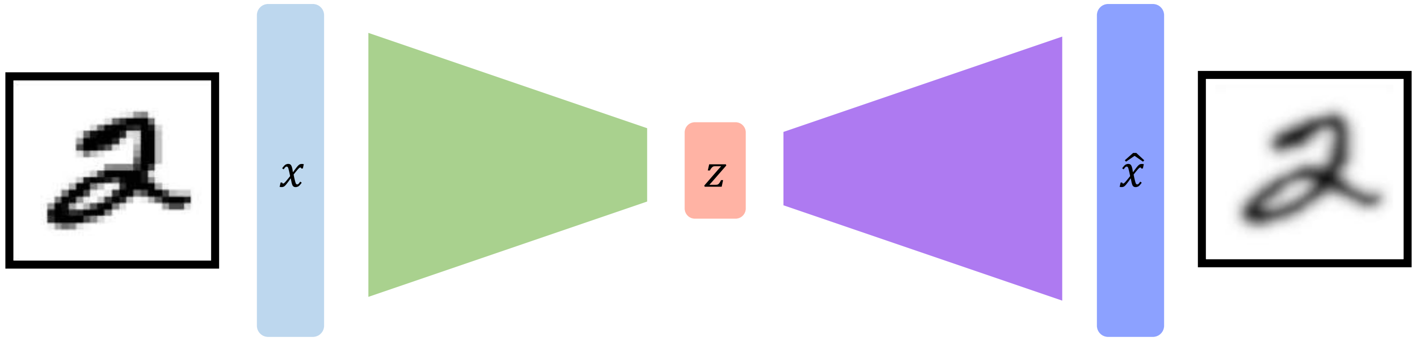

VAE summary

1. Compress representation of world to something we can use to learn
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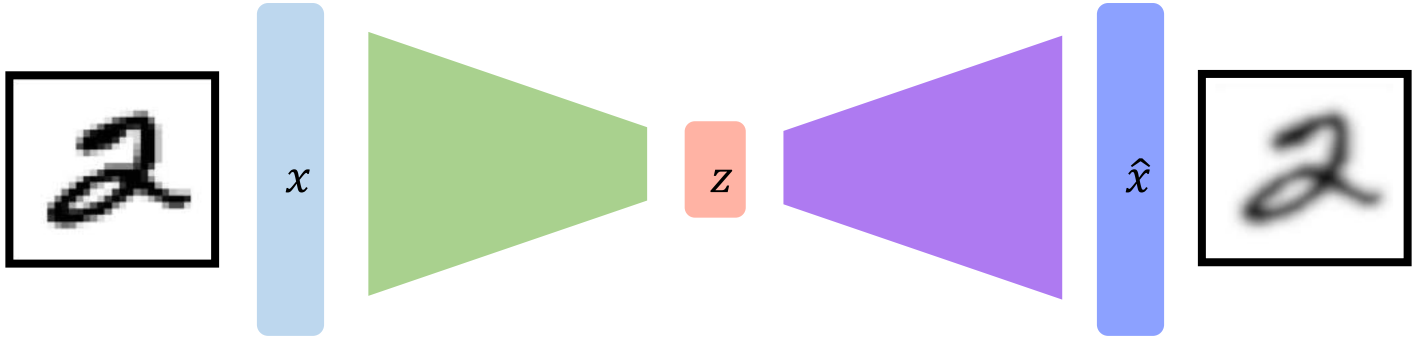
5. Generating new examples



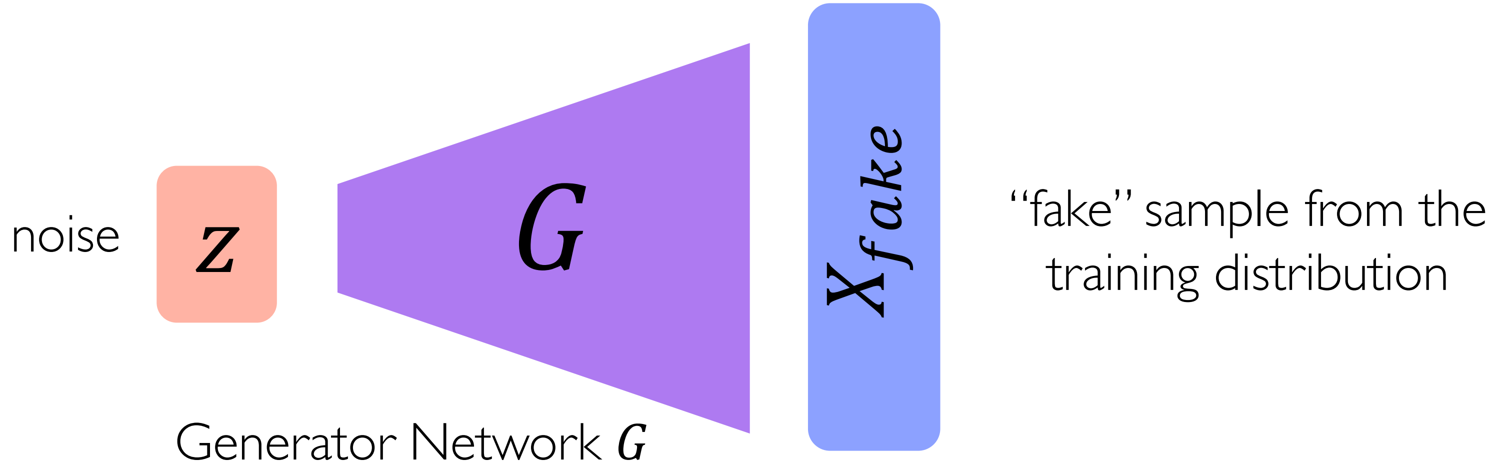
Generative Adversarial Networks (GANs)

What if we just want to sample?

Idea: don't explicitly model density, and instead just sample to generate new instances.

Problem: want to sample from complex distribution – can't do this directly!

Solution: sample from something simple (noise), learn a transformation to the training distribution.

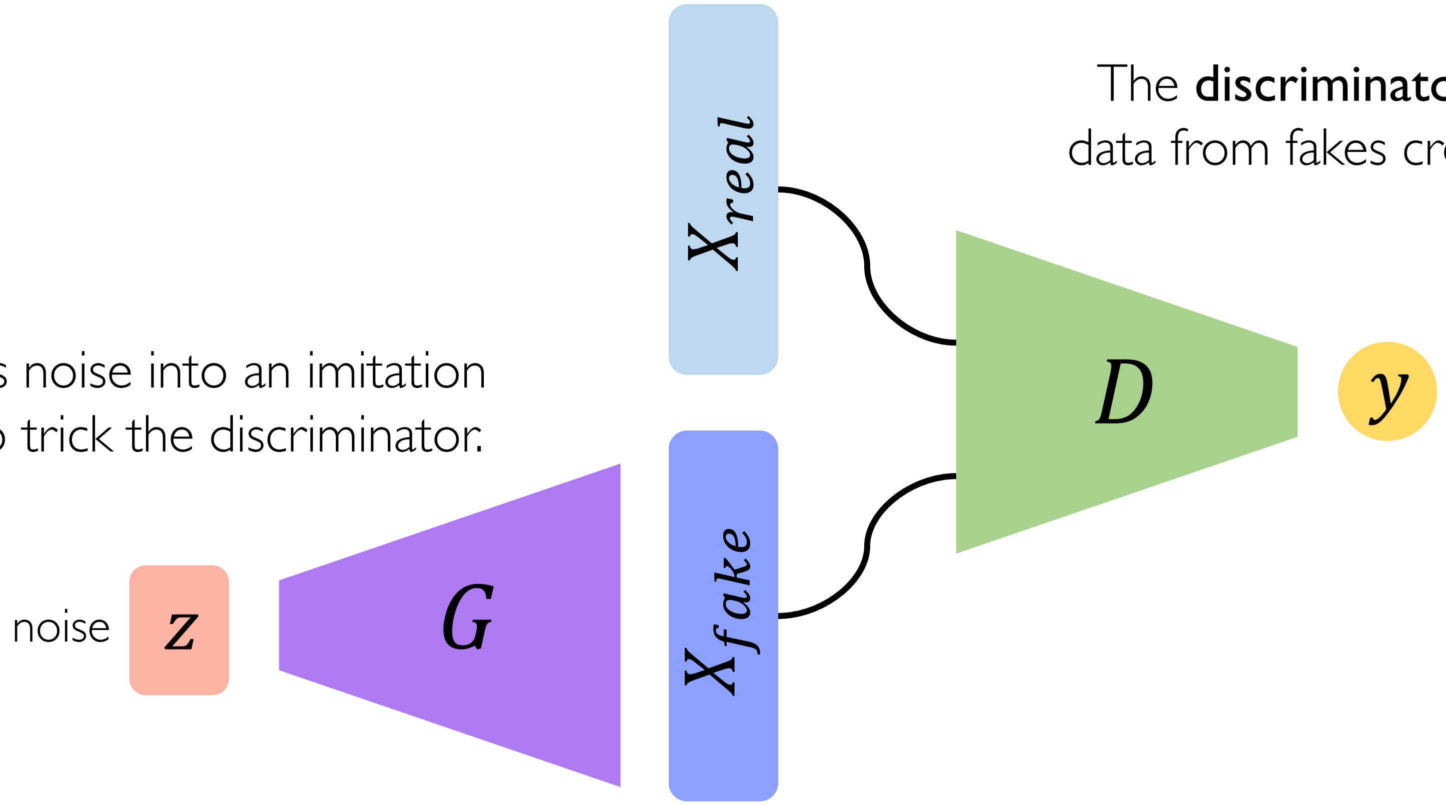


Generative Adversarial Networks (GANs)

Generative Adversarial Networks (GANs) are a way to make a generative model by having two neural networks compete with each other.

The **discriminator** tries to identify real data from fakes created by the generator.

The **generator** turns noise into an imitation of the data to try to trick the discriminator.



Intuition behind GANs

Generator starts from noise to try to create an imitation of the data.

Generator

Fake data

Intuition behind GANs

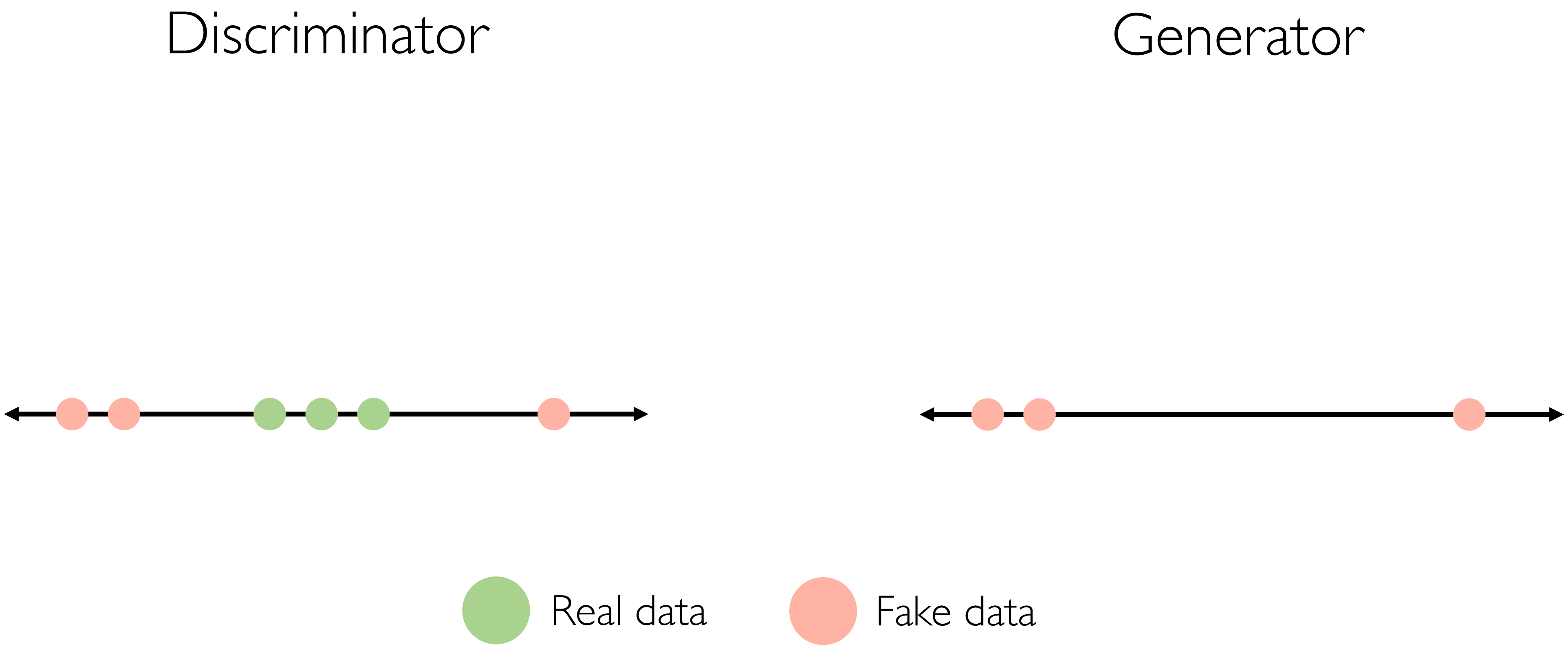
Discriminator looks at both real data and fake data created by the generator.

Discriminator

Generator

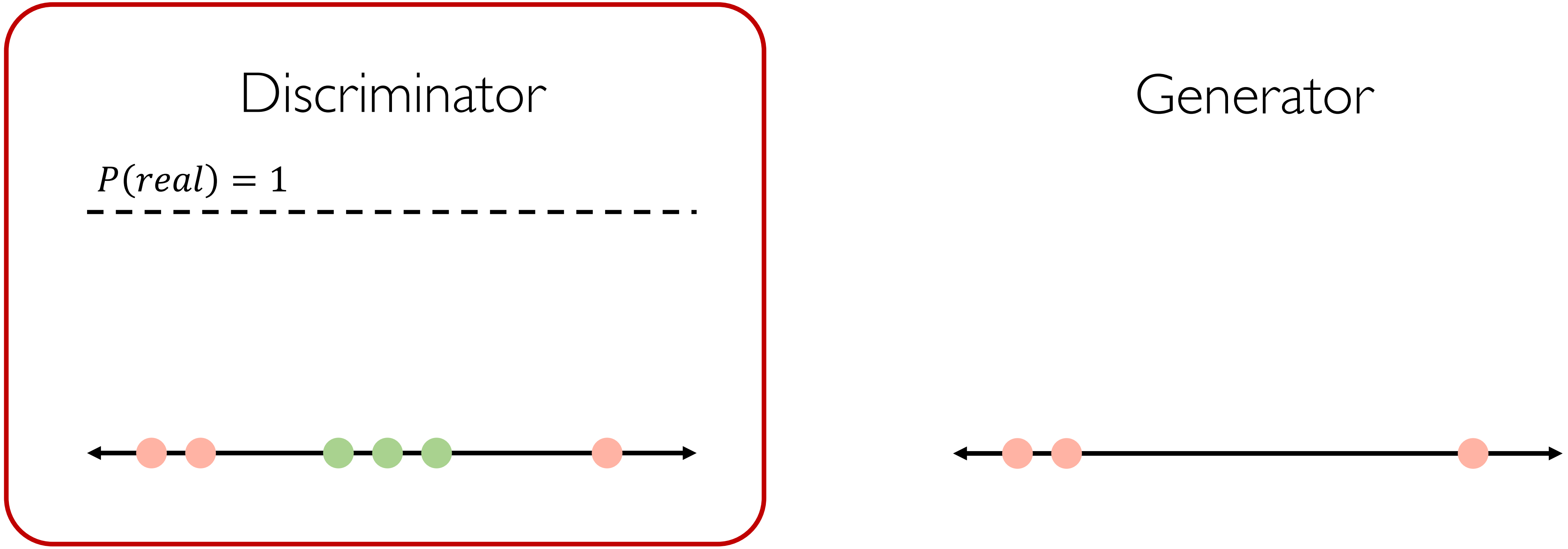
Intuition behind GANs

Discriminator looks at both real data and fake data created by the generator.



Intuition behind GANs

Discriminator tries to predict what's real and what's fake.



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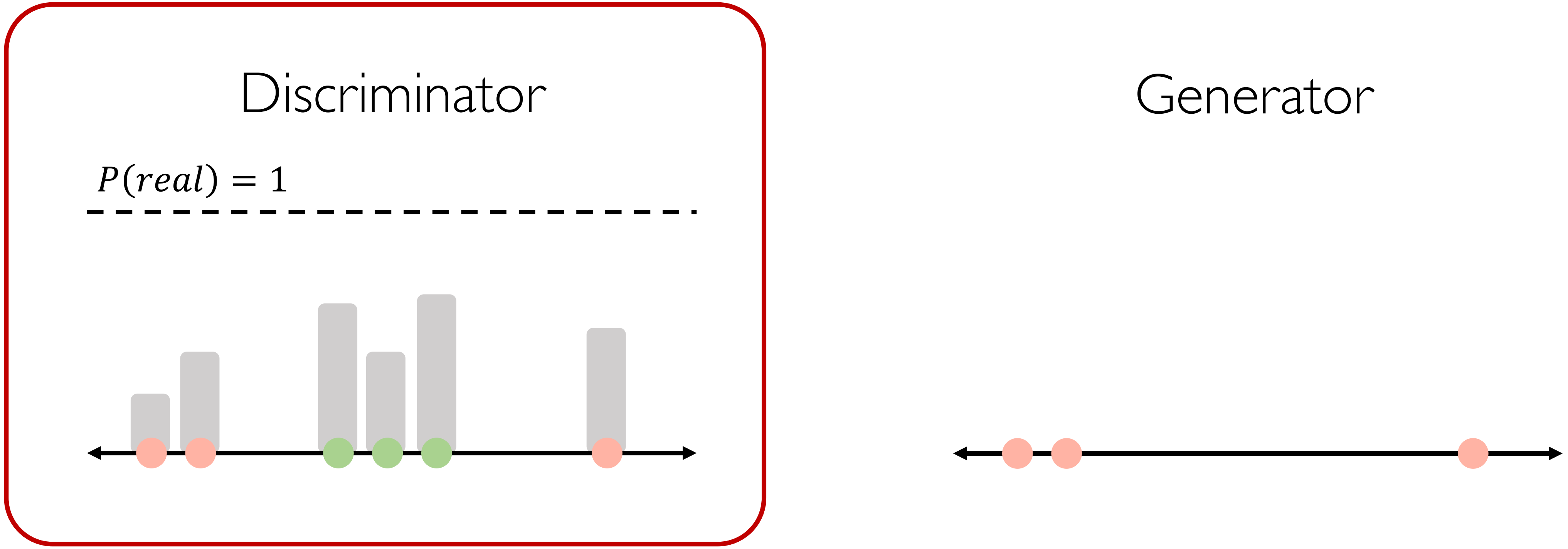

Real data   Fake data

Intuition behind GANs

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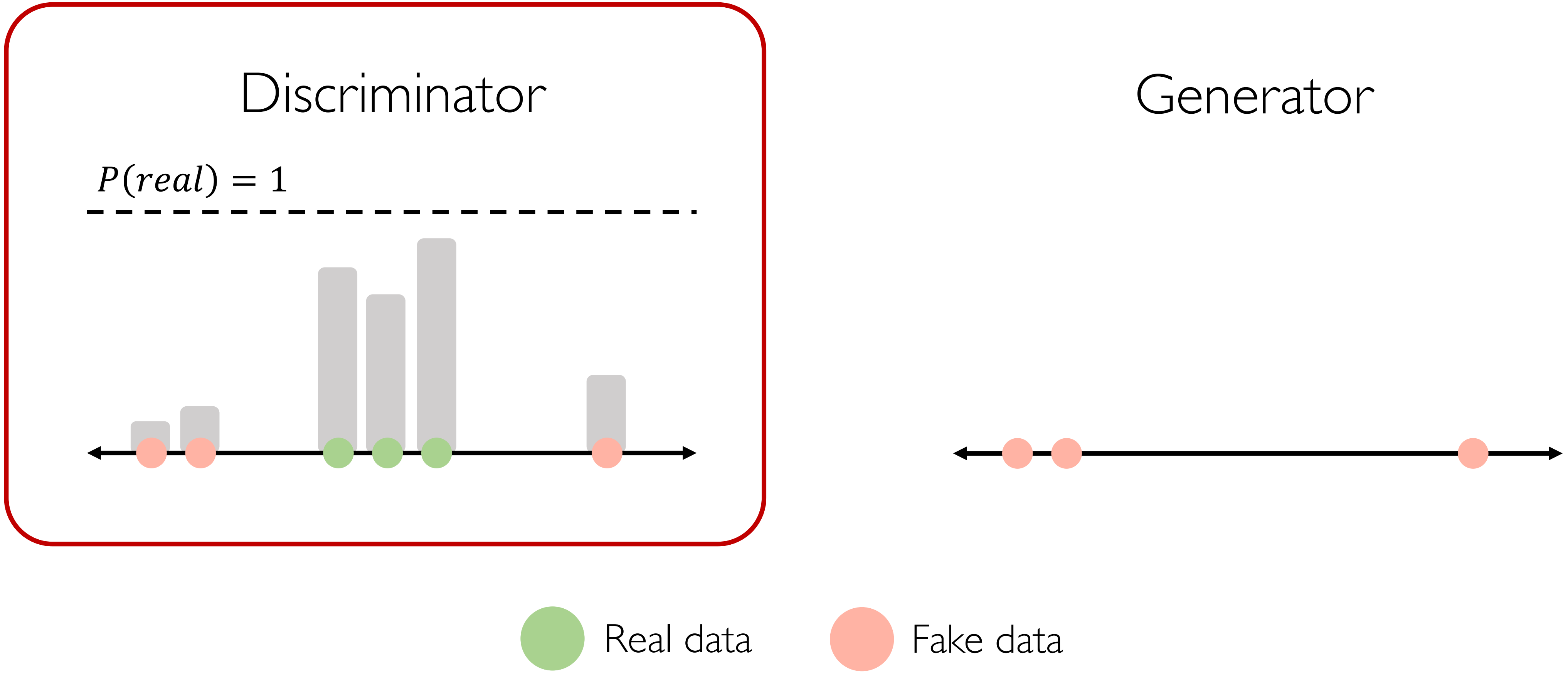

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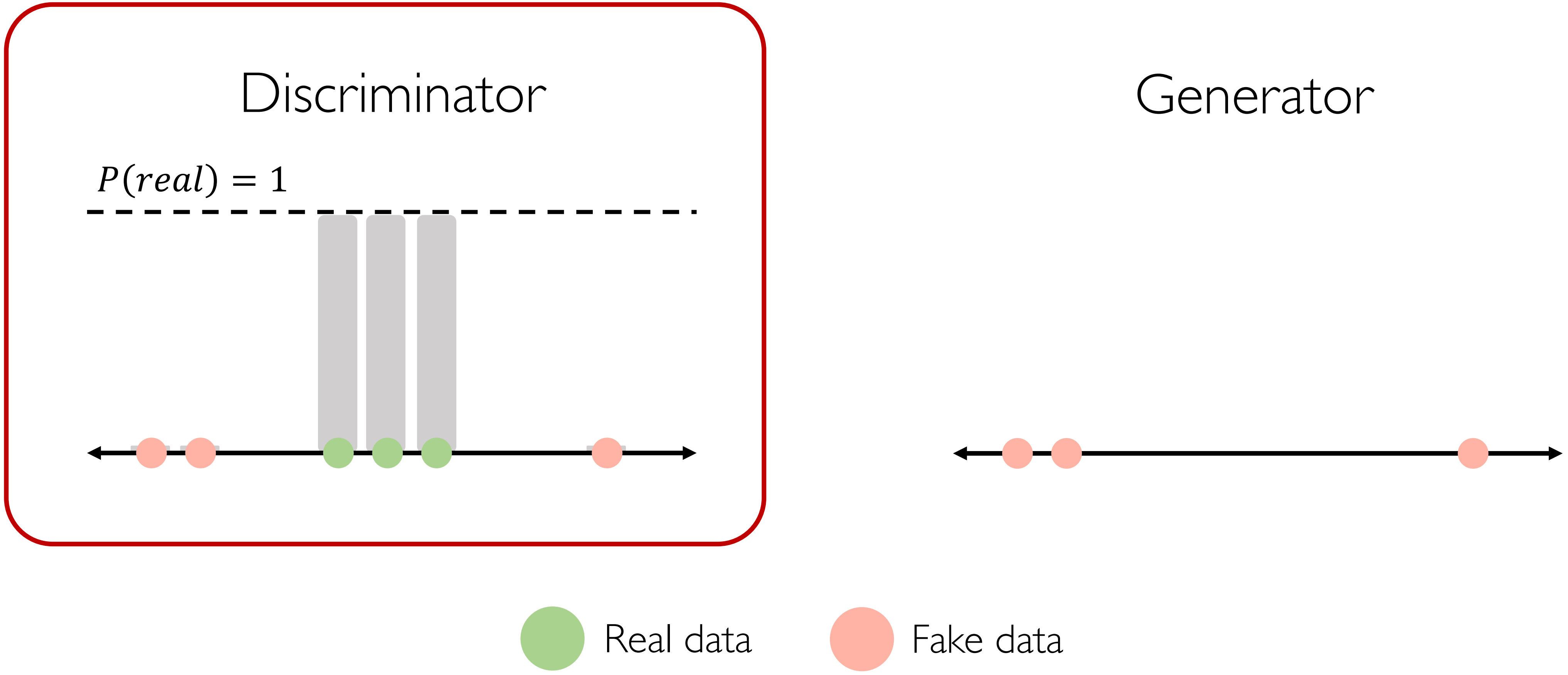
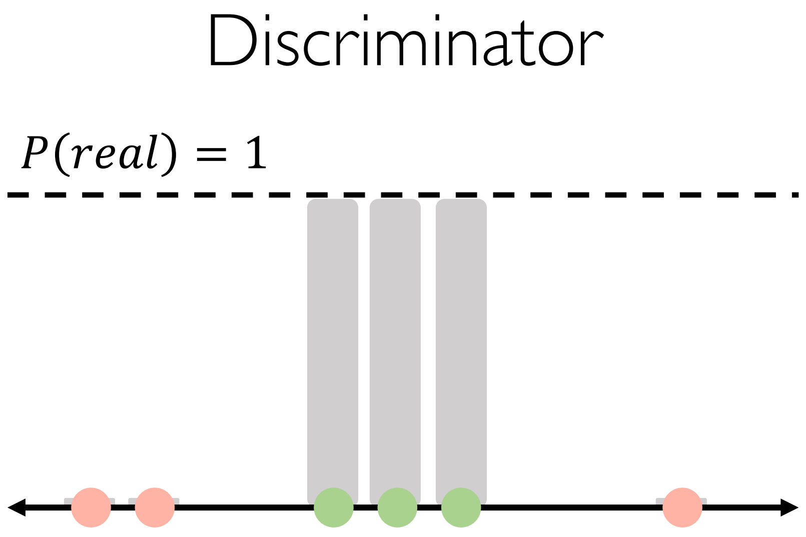
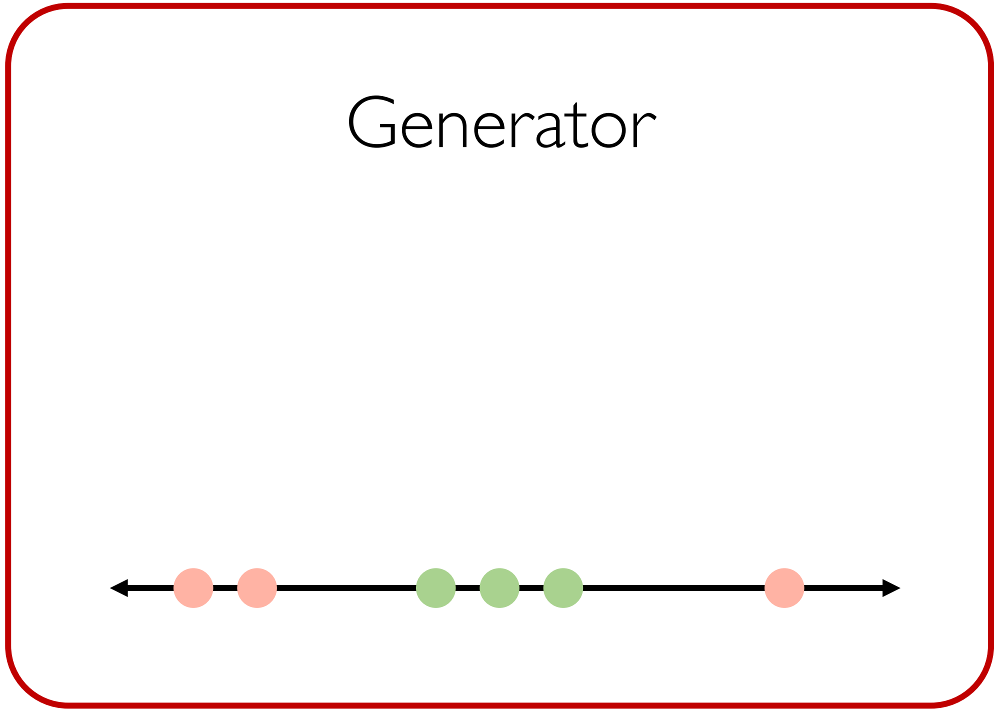


Intuition behind GANs

Generator tries to improve its imitation of the data.





Real data Fake data

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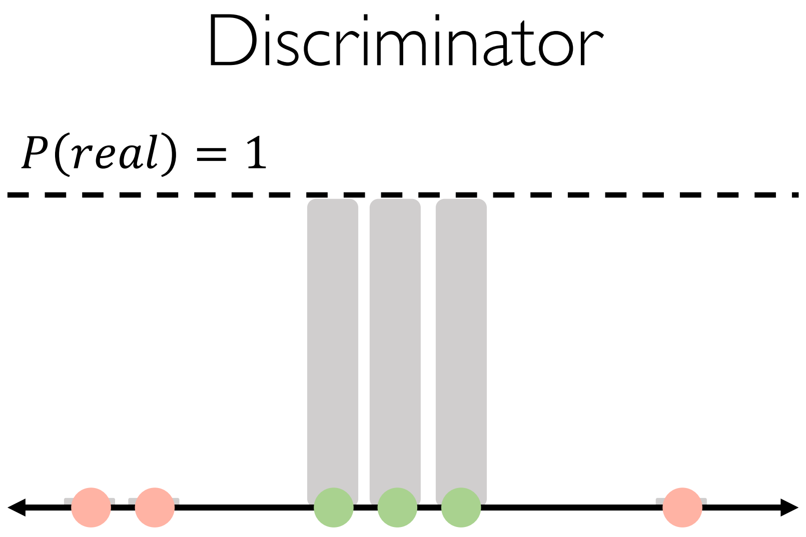

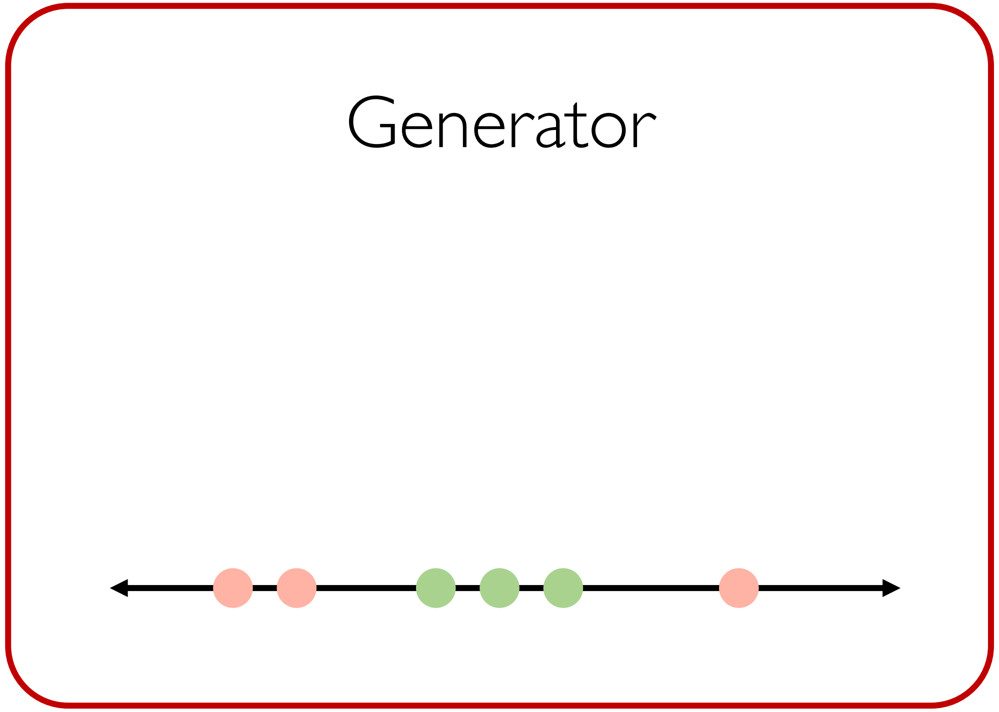

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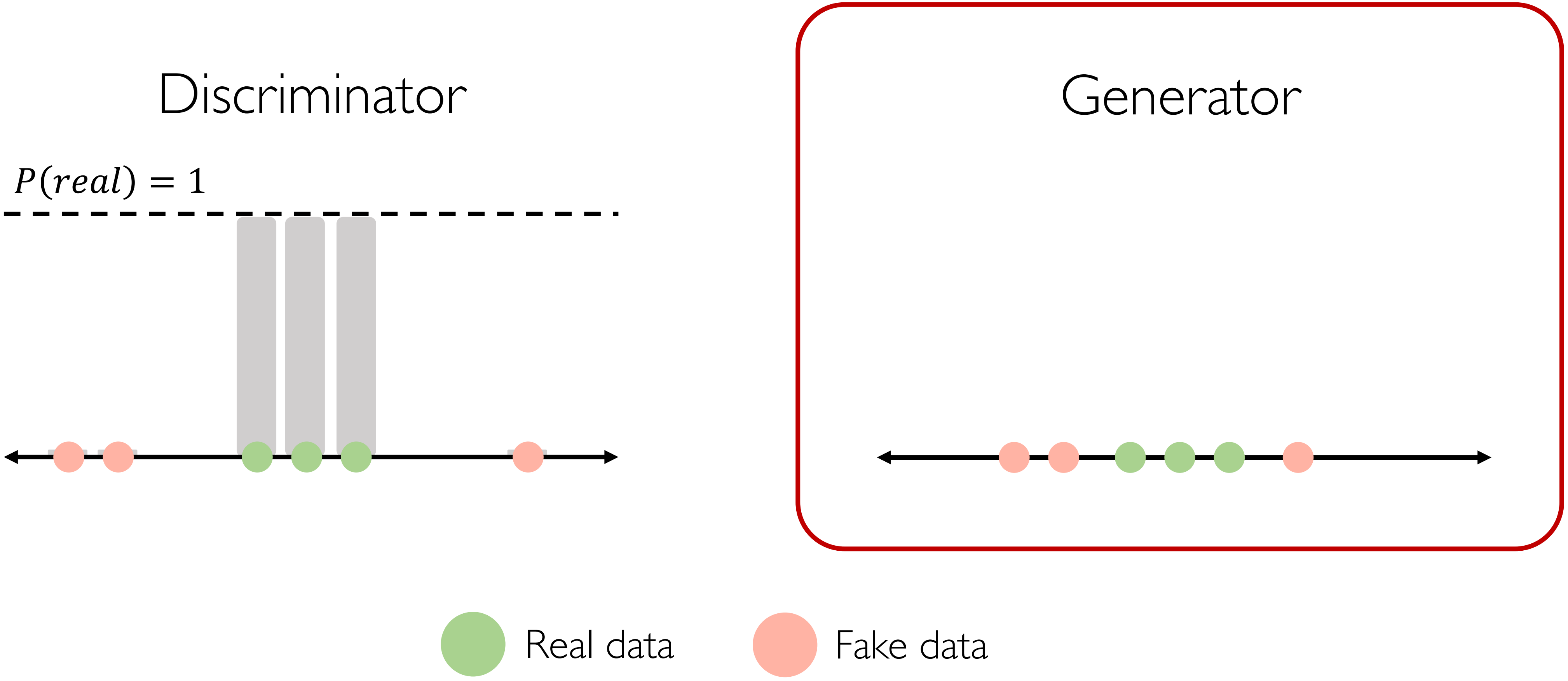

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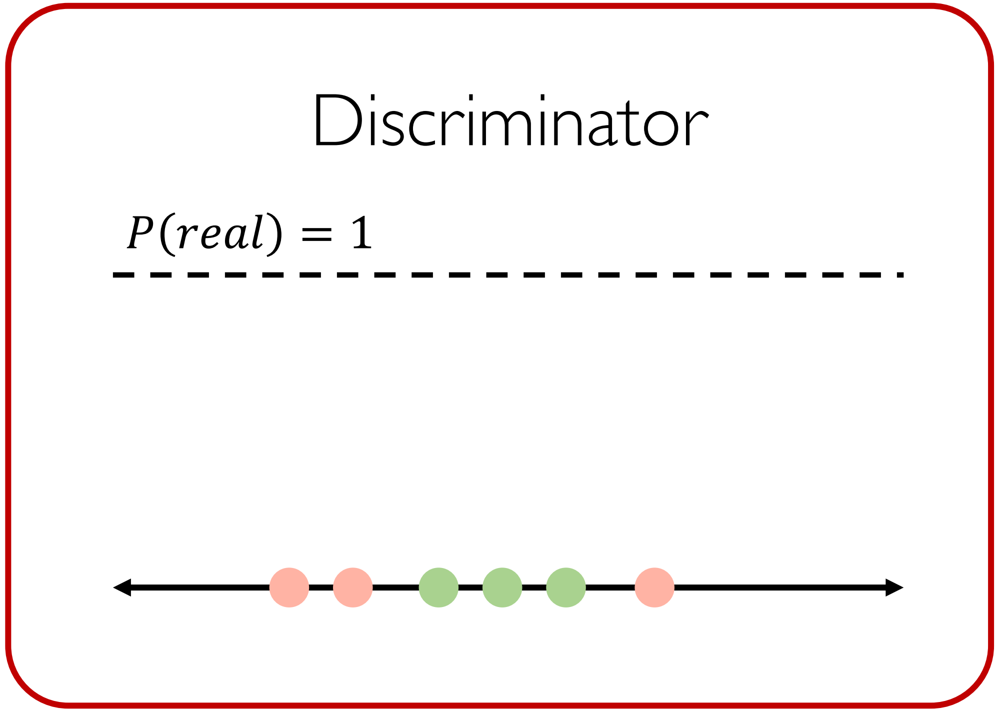

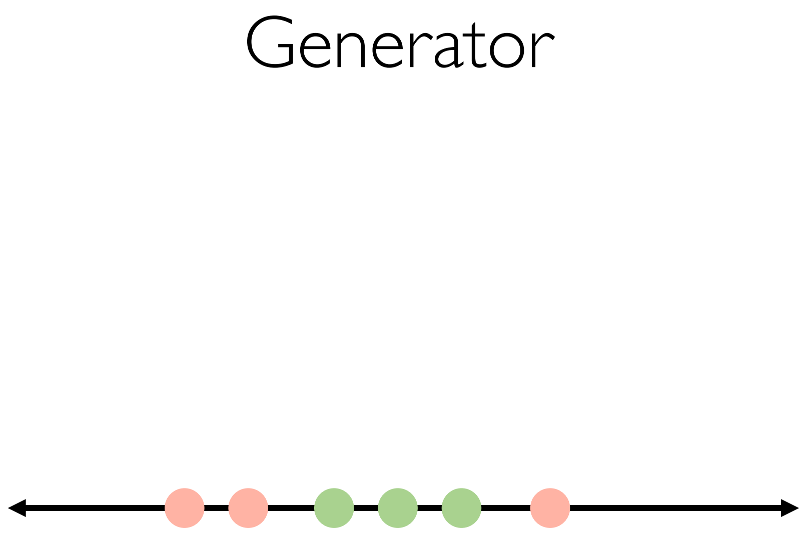

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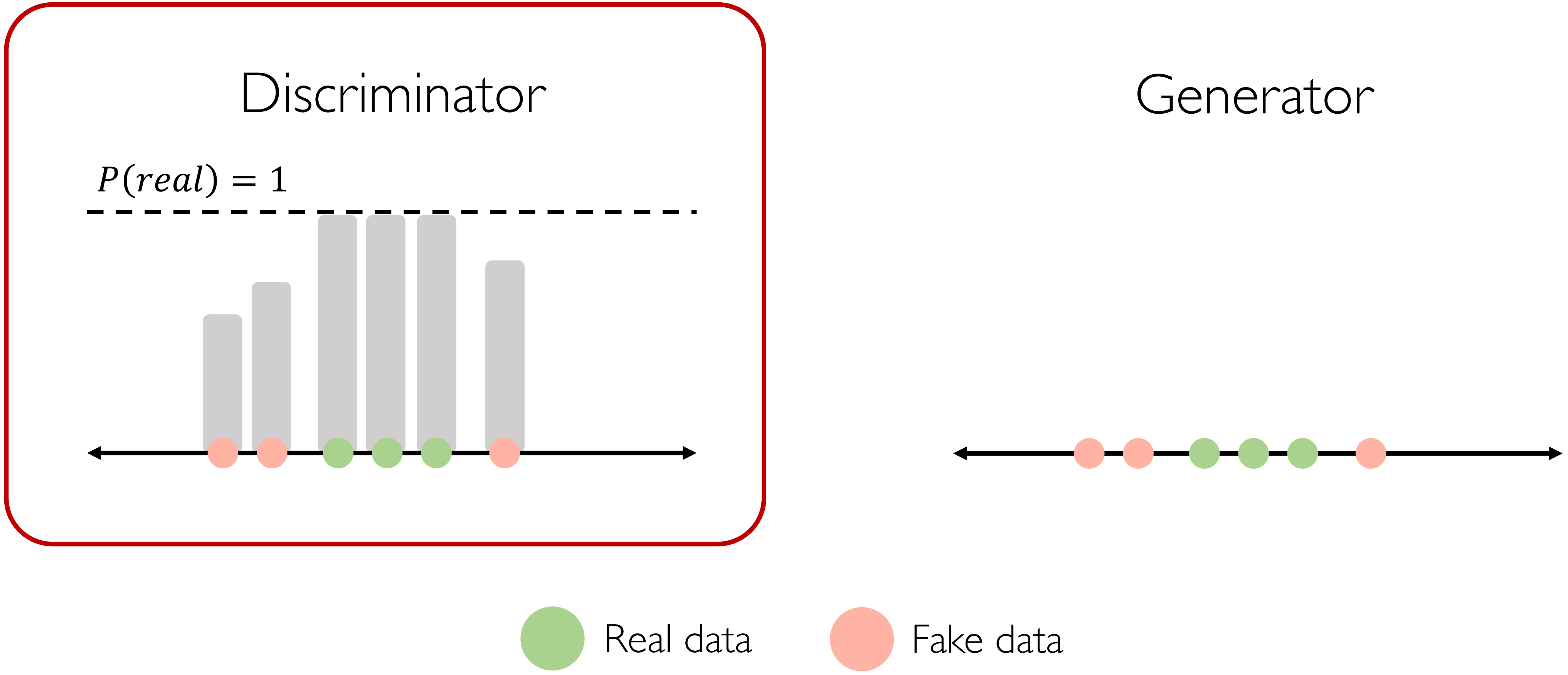
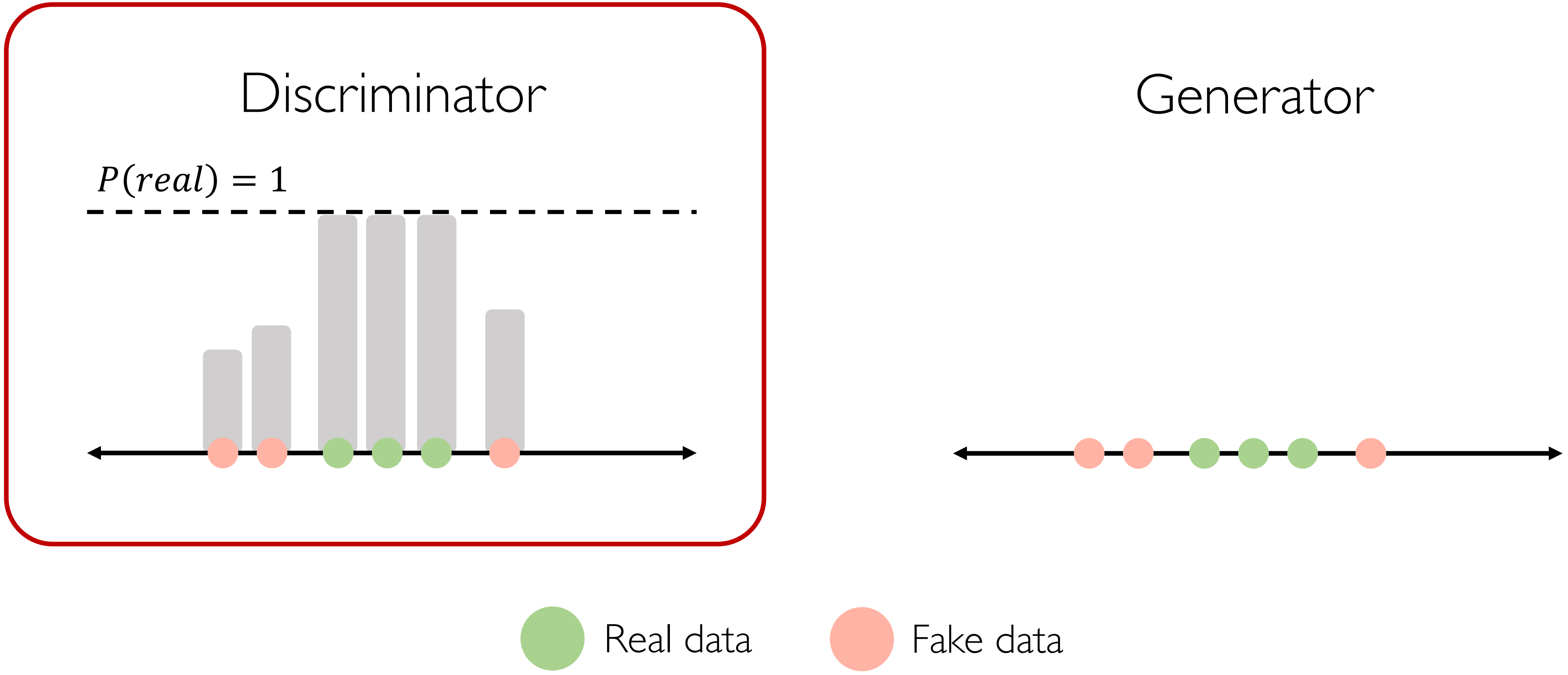


Intuition behind GANs

Discriminator tries to predict what's real and what's fake.



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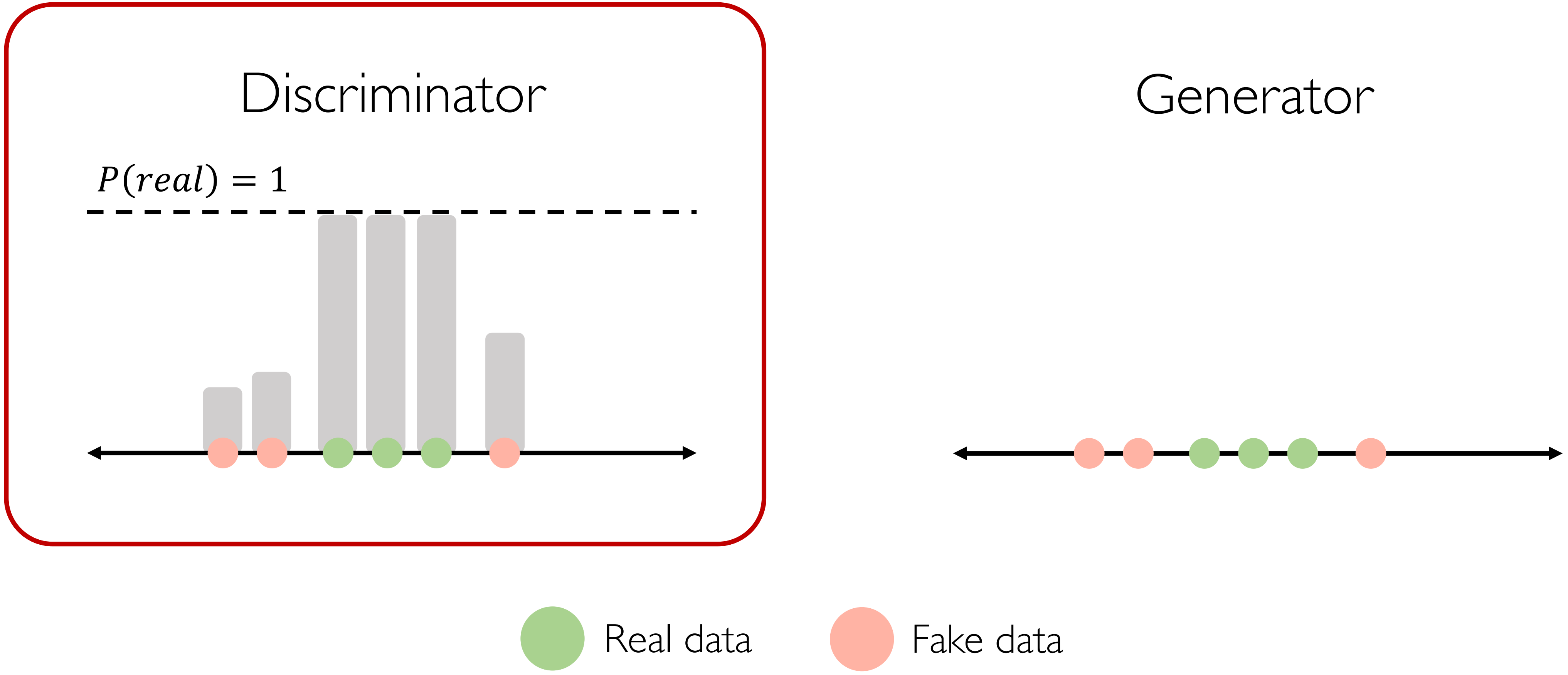
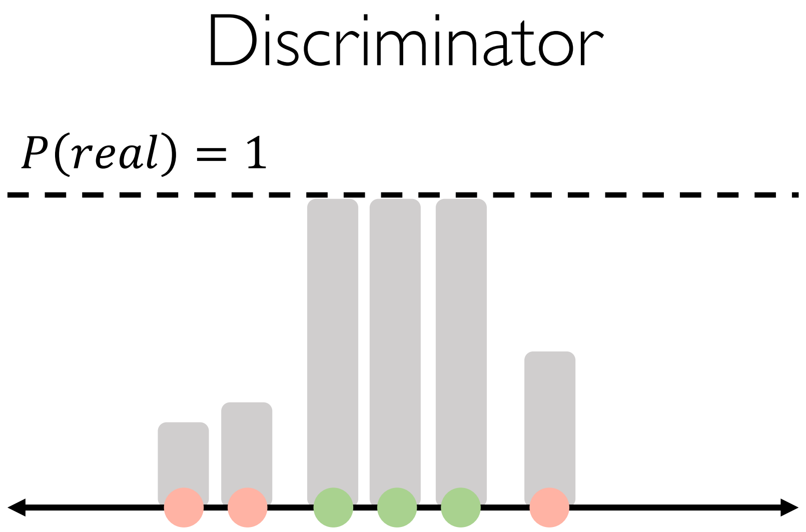
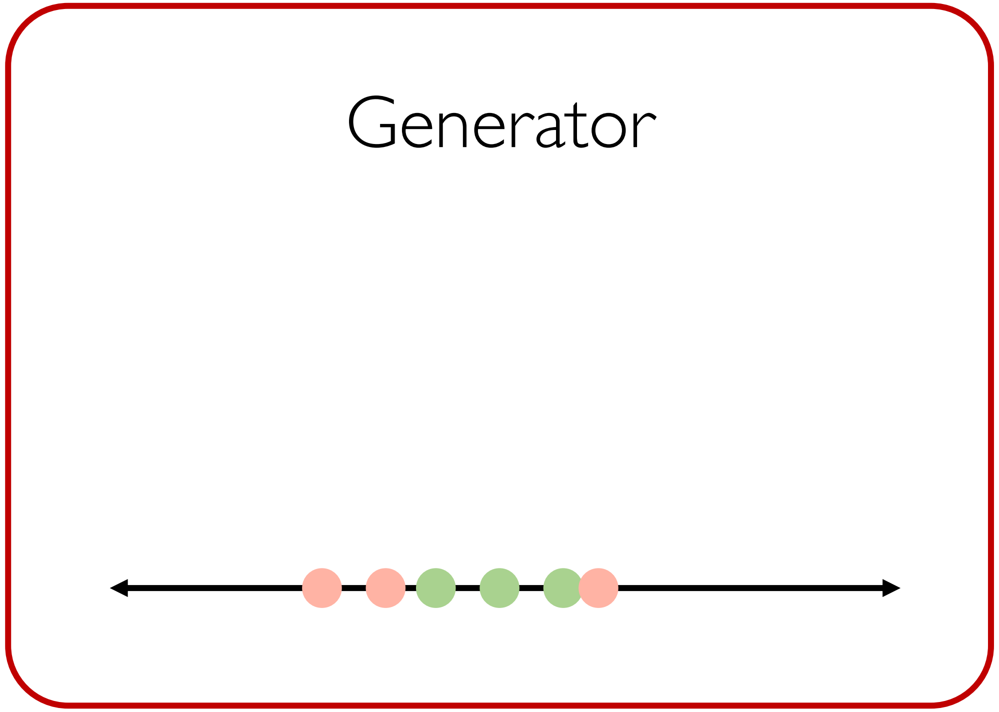


Intuition behind GANs

Generator tries to improve its imitation of the data.

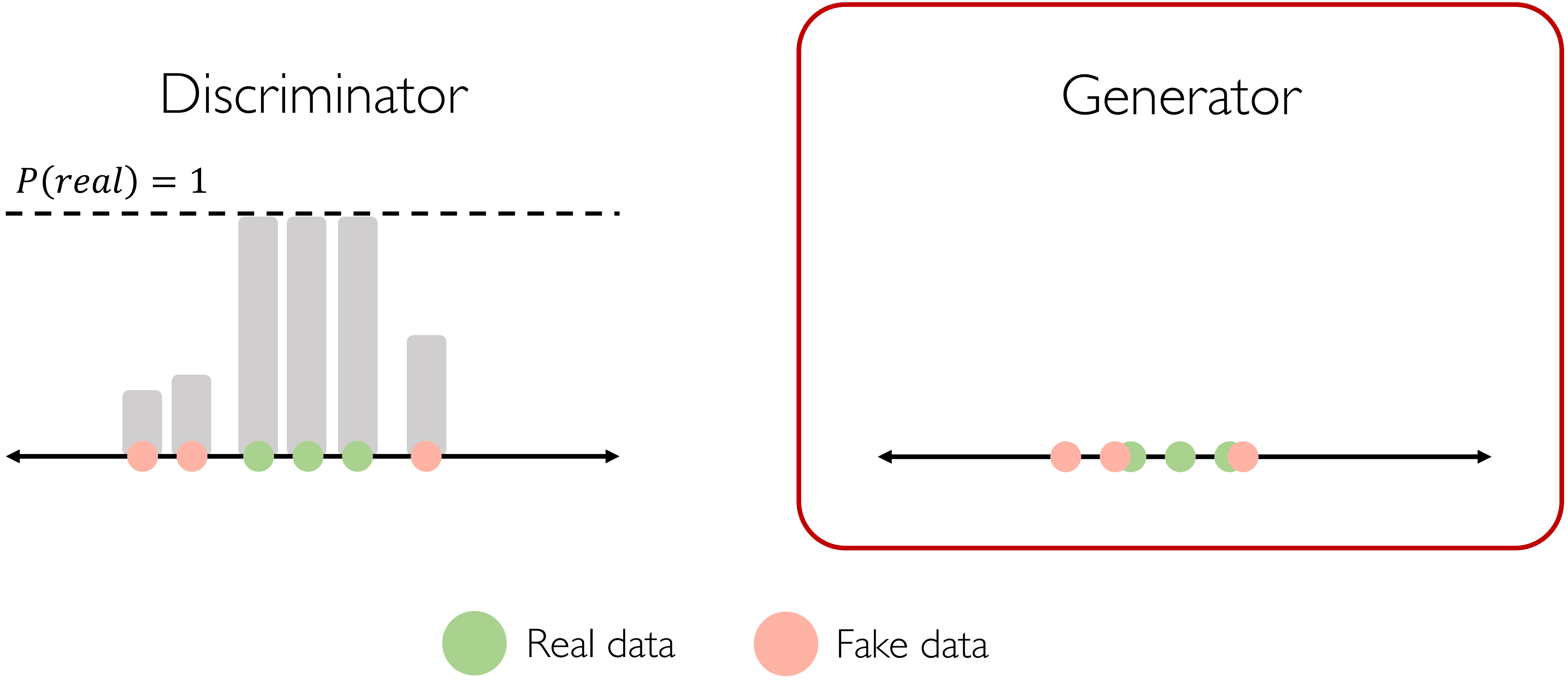




Real data Fake data

Intuition behind GANs

Generator tries to improve its imitation of the data.



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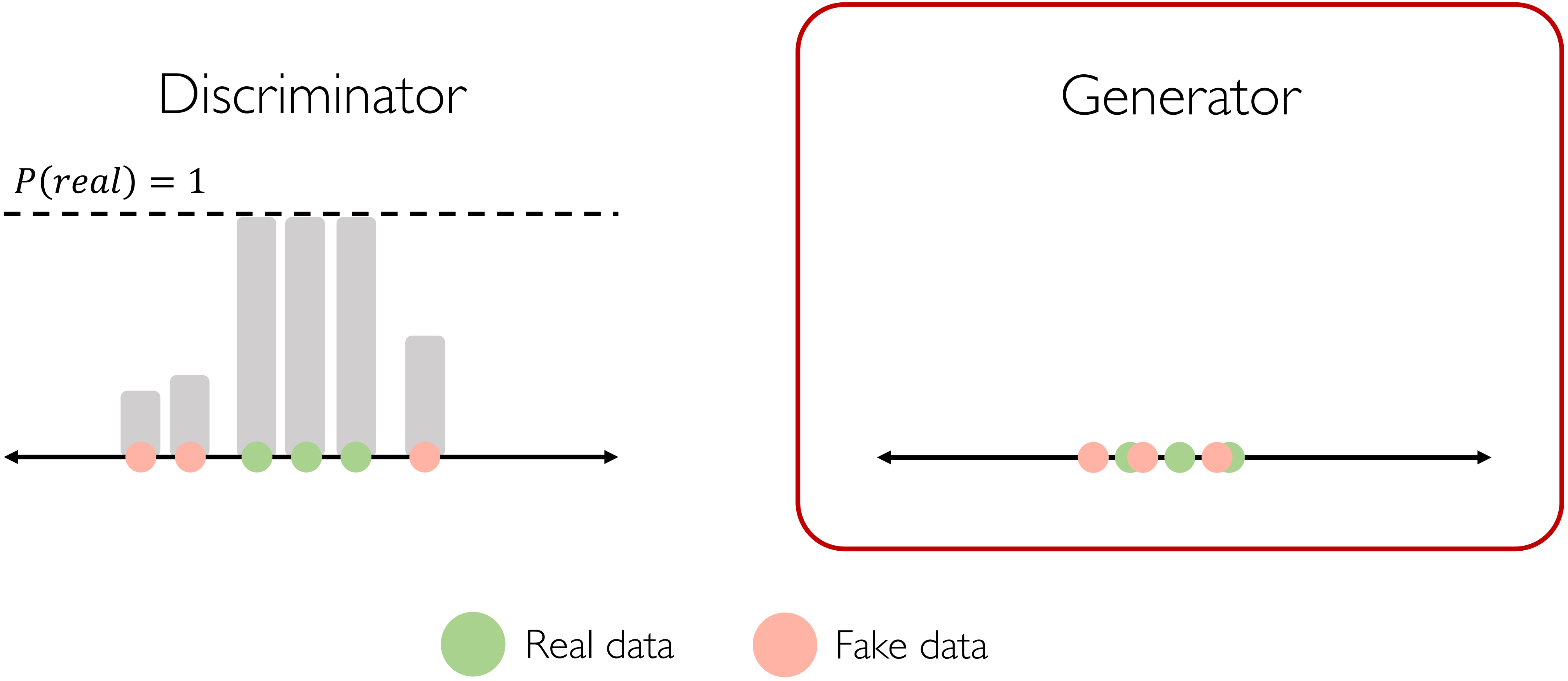
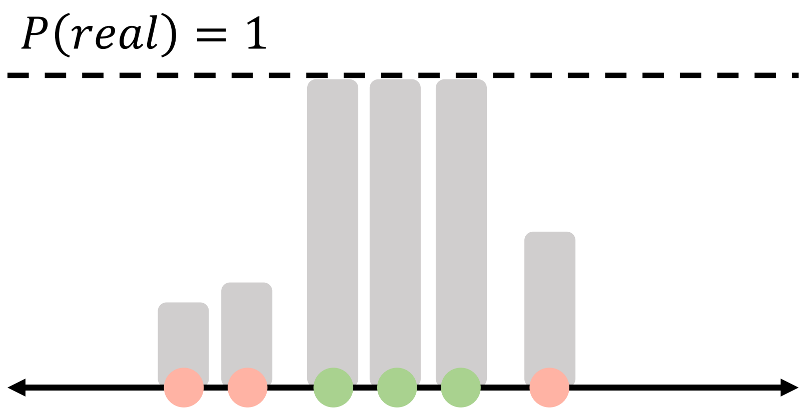


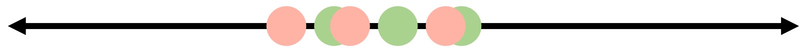
Intuition behind GANs

Discriminator tries to identify real data from fakes created by the generator.
Generator tries to create imitations of data to trick the discriminator.

Discriminator



Generator



Real data Fake data

Training GANs

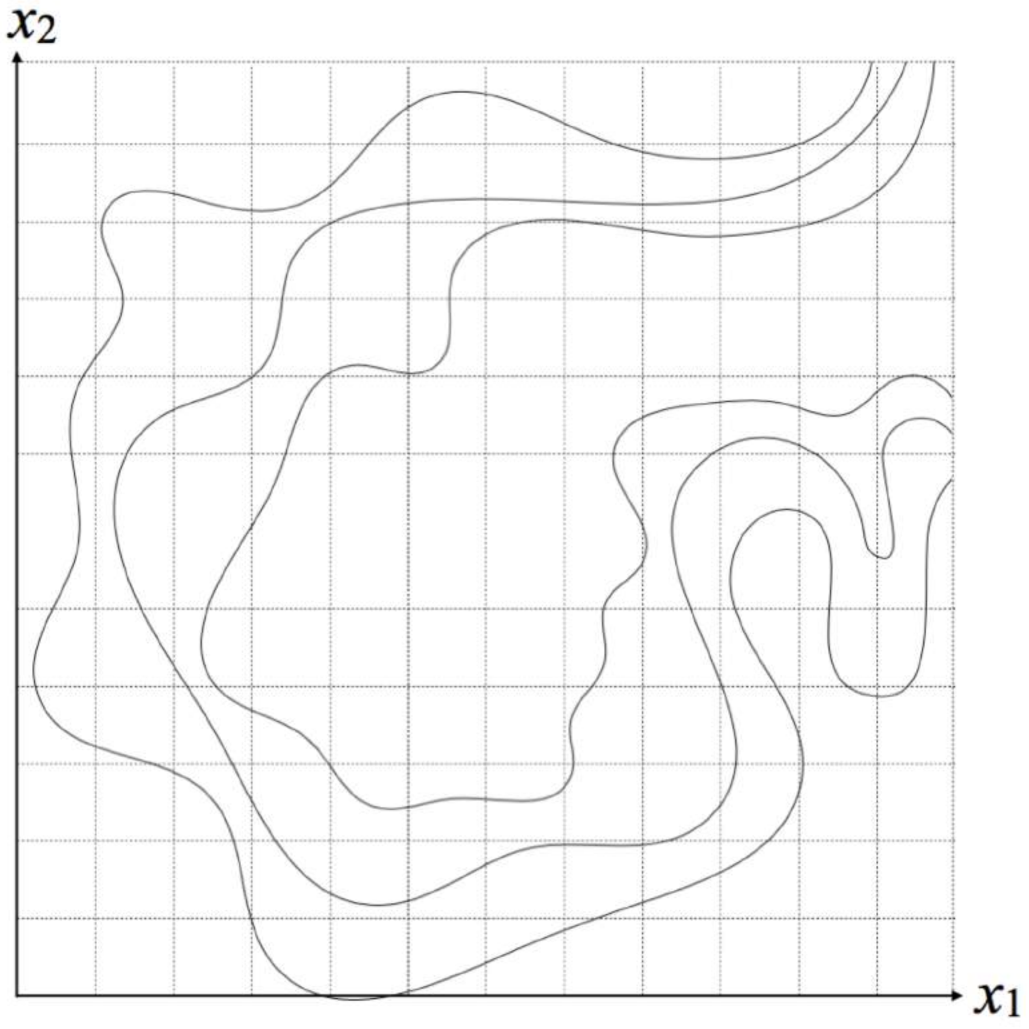
Discriminator tries to identify real data from fakes created by the generator.
Generator tries to create imitations of data to trick the discriminator.

Train GAN jointly via **minimax** game:

$$\min_{\theta_g} \max_{\theta_d} \left[\mathbb{E}_{x \sim p_{data}} \log D_{\theta_d}(x) + \mathbb{E}_{z \sim p(z)} \log \left(1 - D_{\theta_d}\left(G_{\theta_g}(z) \right) \right) \right]$$

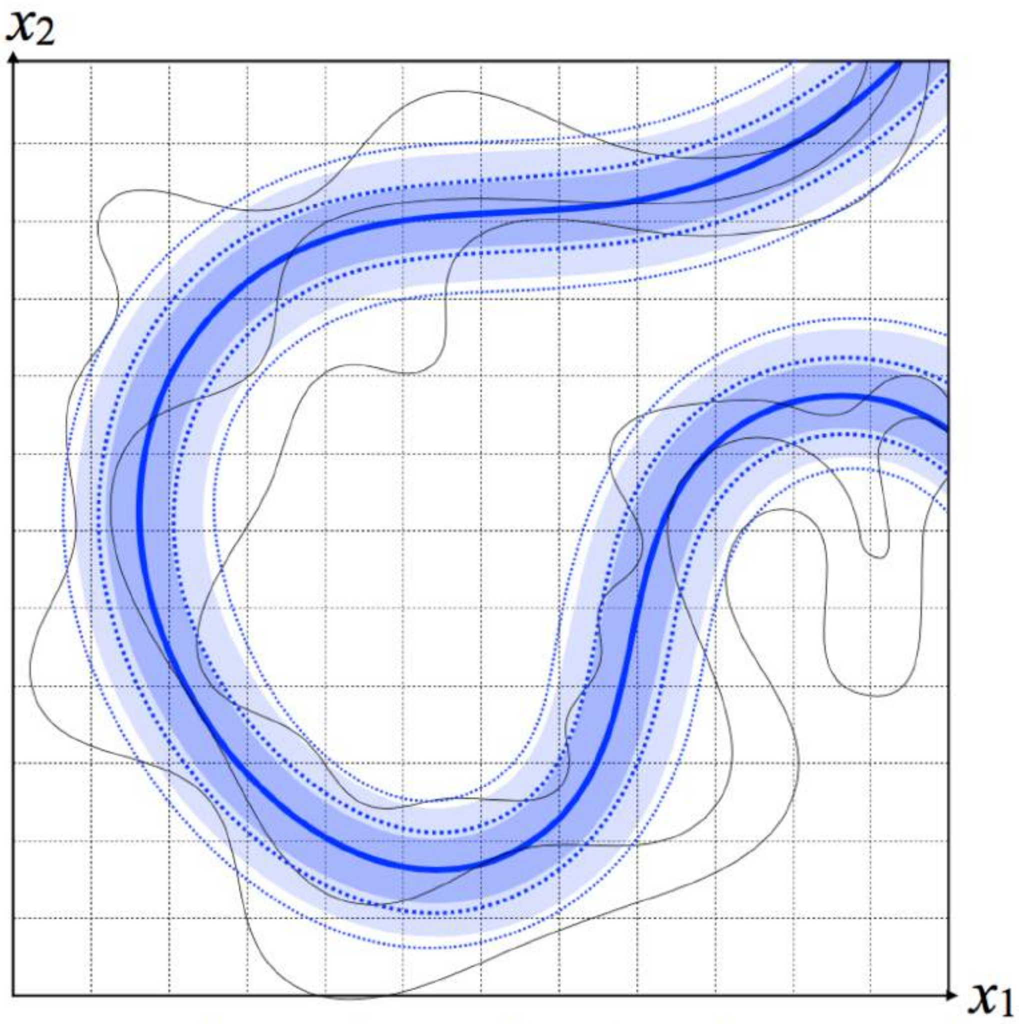
Discriminator wants to maximize objective s.t. $D(x)$ close to 1, $D(G(z))$ close to 0.
Generator wants to minimize objective s.t. $D(G(z))$ close to 1.

Why GANs?

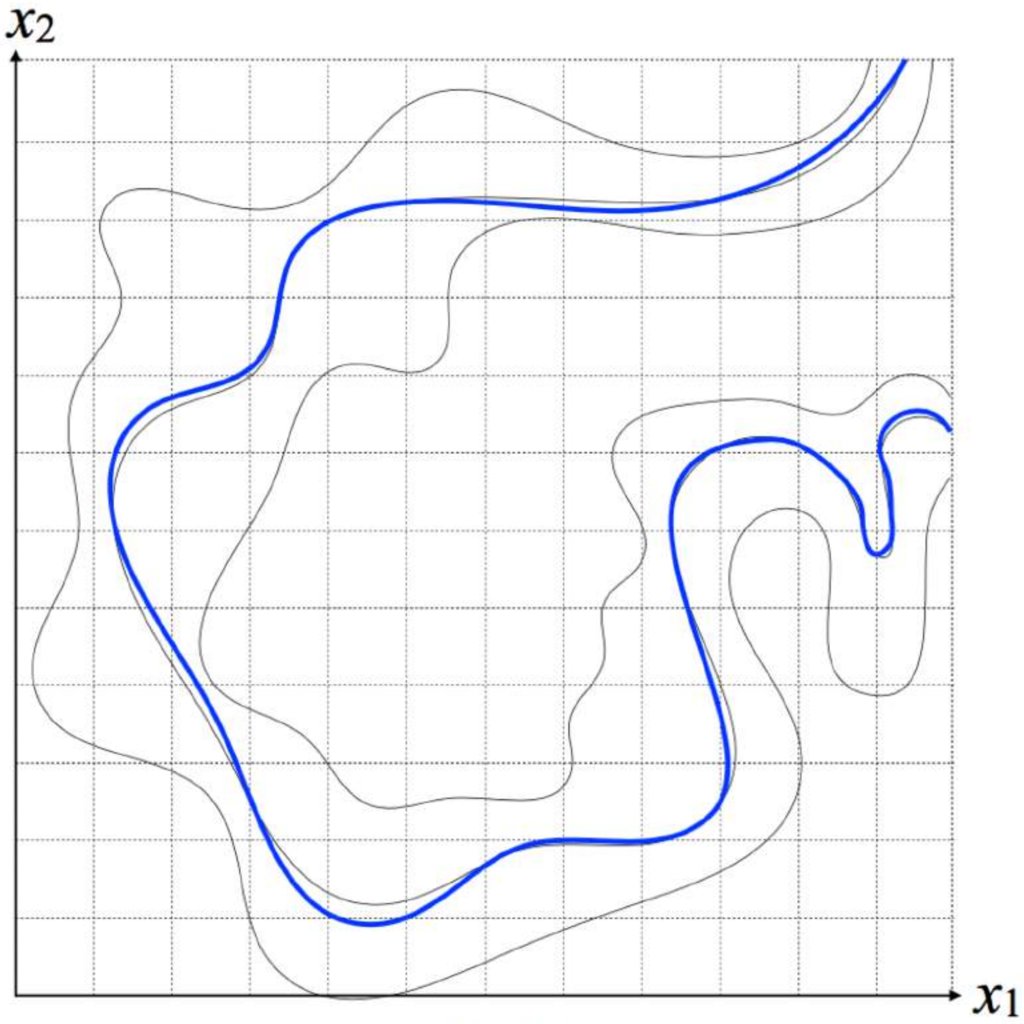


A. Courville, 6S191 2018.

Why GANs?



more traditional max-likelihood approach

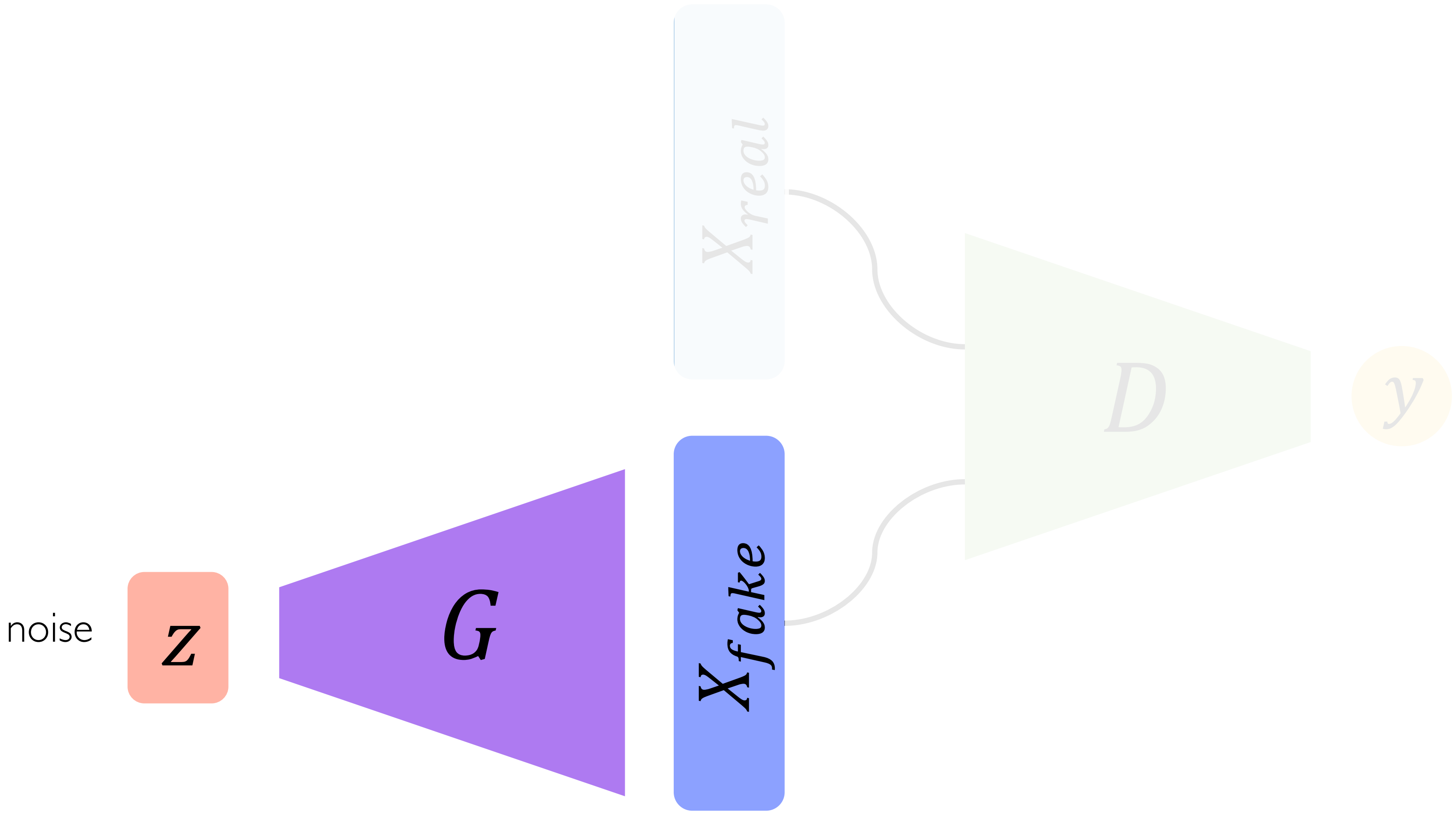


GAN

A. Courville, 6S191 2018.

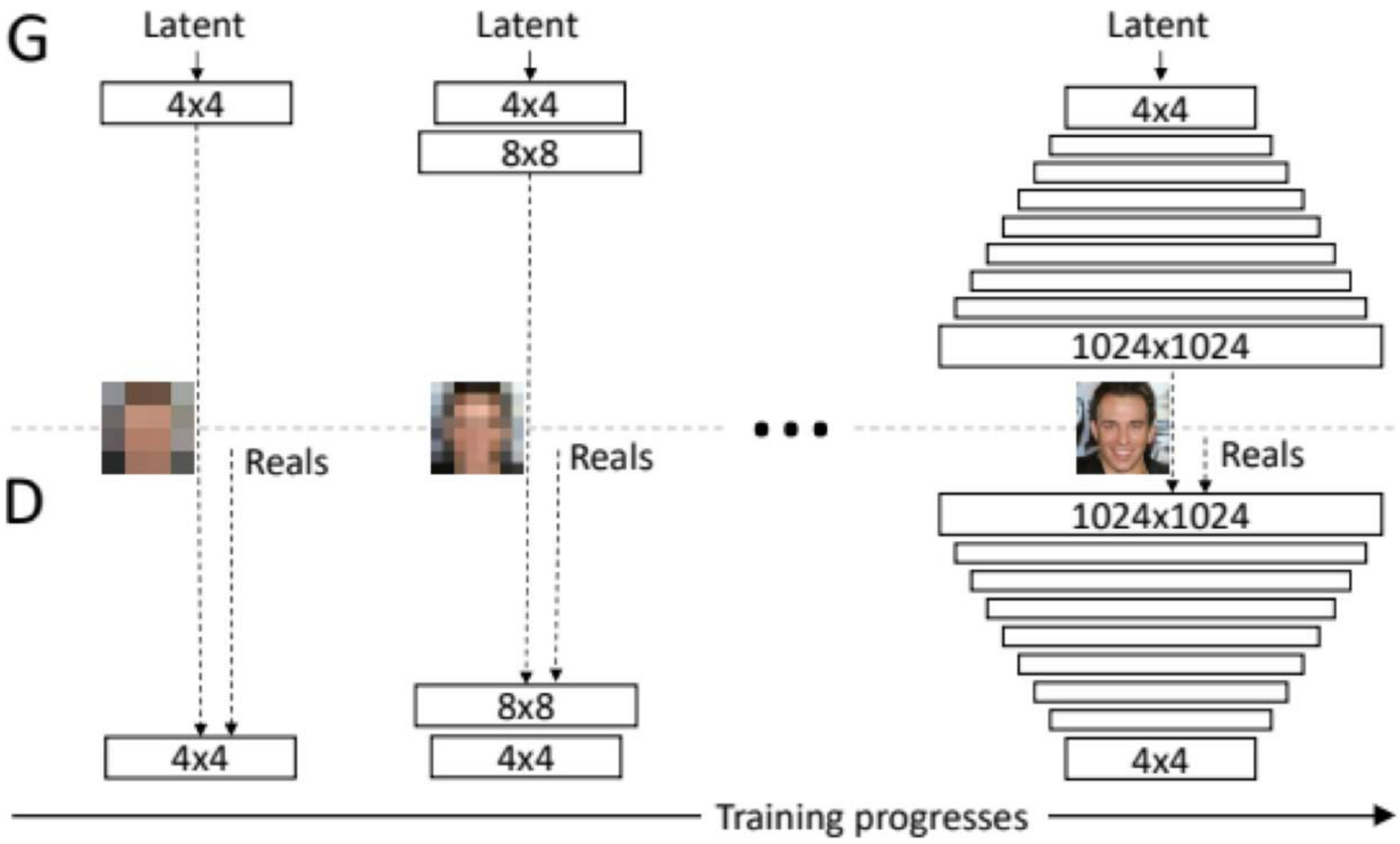
Generating new data with GANs

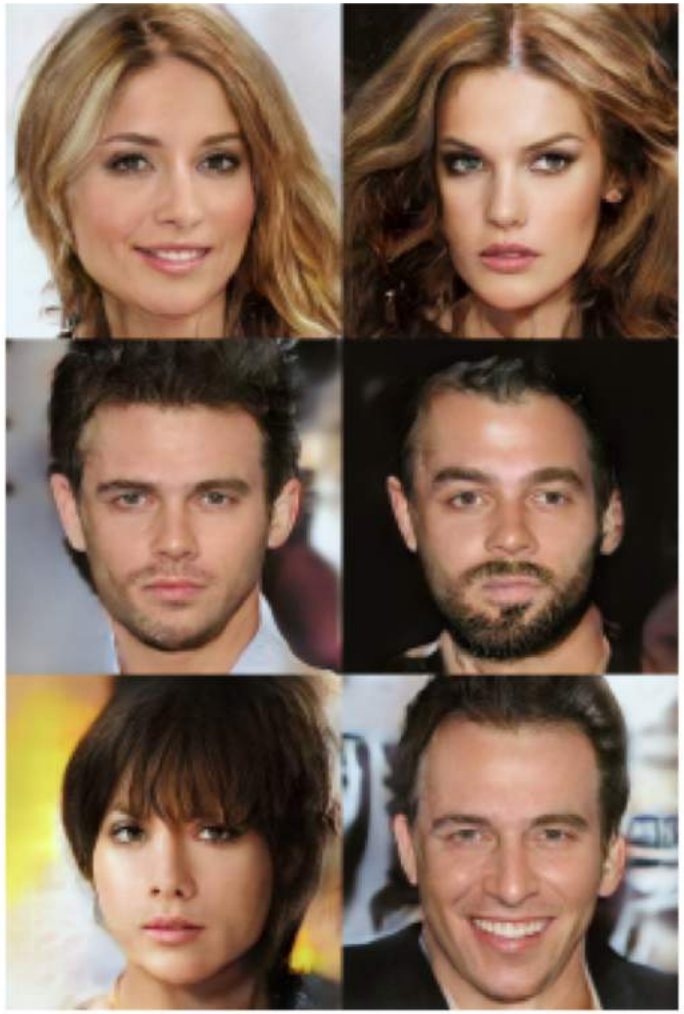
After training, use generator network to create **new data** that's never been seen before.



GANs: Recent Advances

Progressive growing of GANs (NVIDIA)





Karras et al., ICLR 2018.

Progressive growing of GANs: results

Karras et al., ICLR 2018.

Style-based generator: results

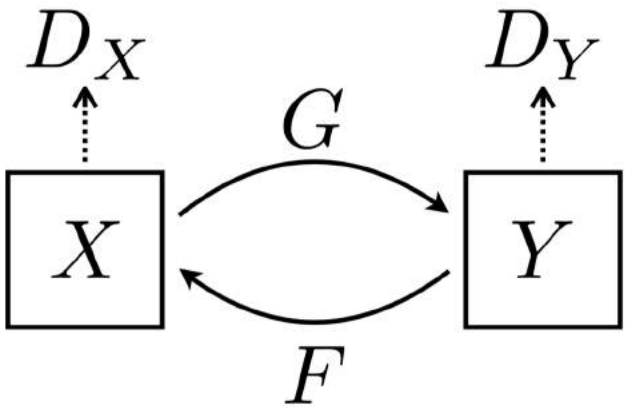
Karras et al., Arxiv 2018.

Style-based transfer: results

Karras et al., Arxiv 2018.

CycleGAN: domain transformation

CycleGAN learns transformations across domains with unpaired data.

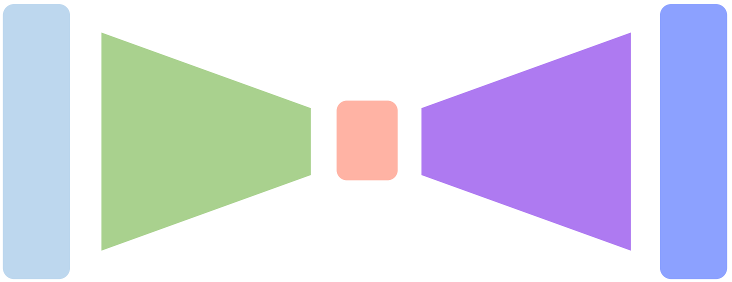


Zhu et al., ICCV 2017.

Deep Generative Modeling: Summary

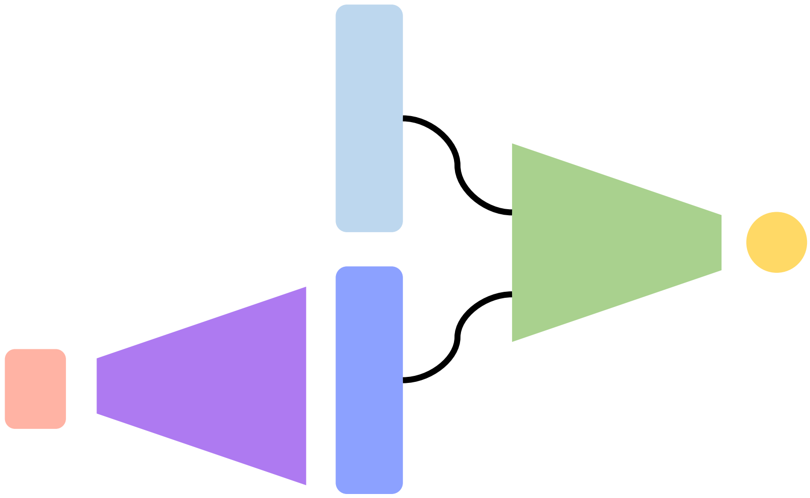
Autoencoders and Variational Autoencoders (VAEs)

Learn **lower-dimensional** latent space and **sample** to generate input reconstructions



Generative Adversarial Networks (GANs)

Competing **generator** and **discriminator** networks



References:

https://goo.gl/ZuBkGx9