

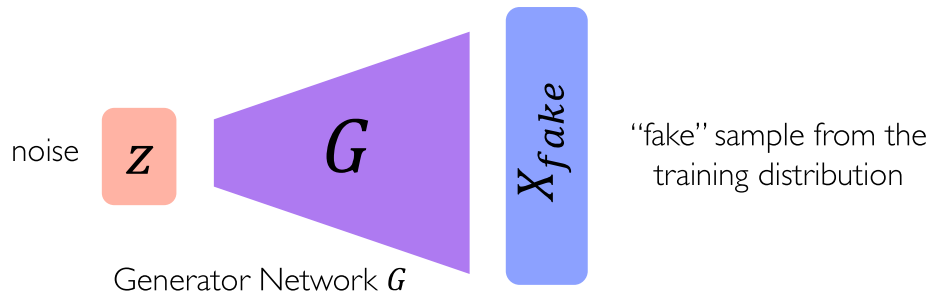
# Generative Adversarial Networks (GANs)

# What if we just want to sample?

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

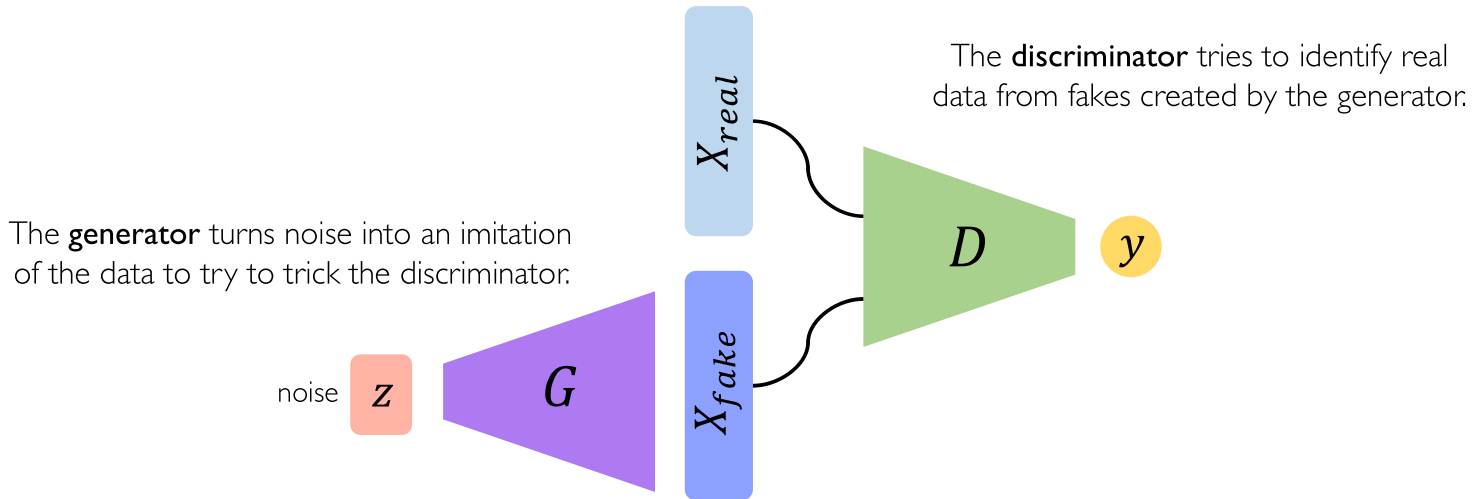
**Problem:** want to sample from complex distribution – can't do this directly!

**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:



# 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



 Fake data

# Intuition behind GANs

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

Discriminator

Generator



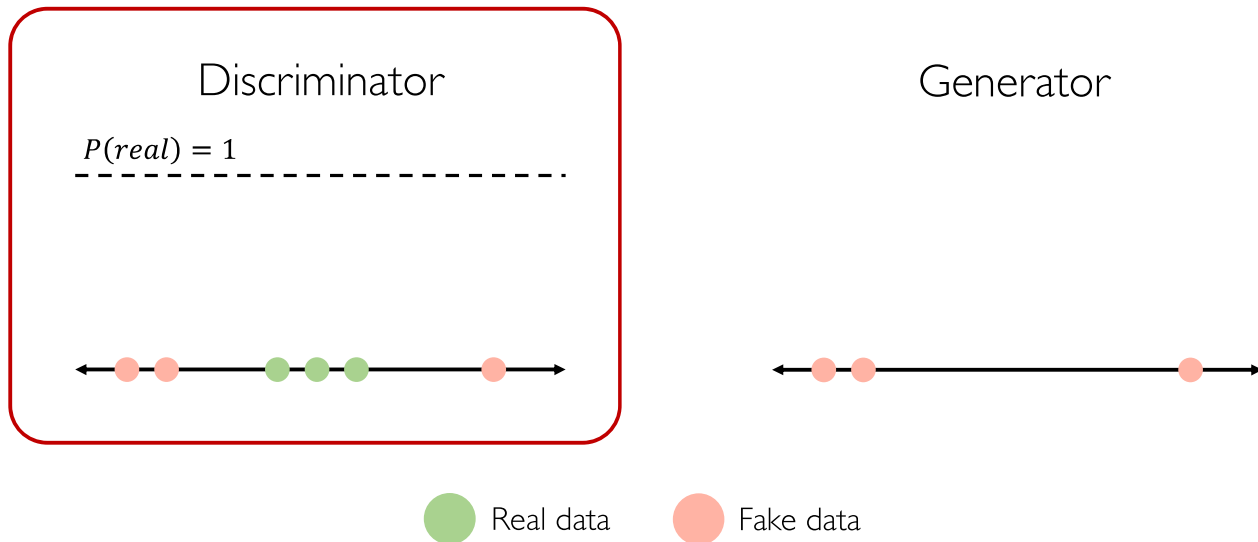
Real data



Fake data

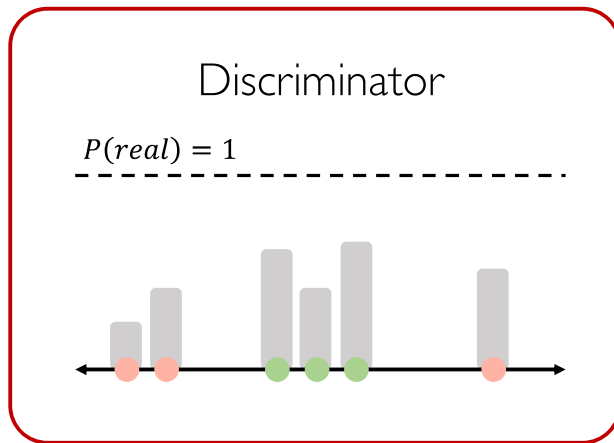
# Intuition behind GANs

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



# Intuition behind GANs

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



Generator



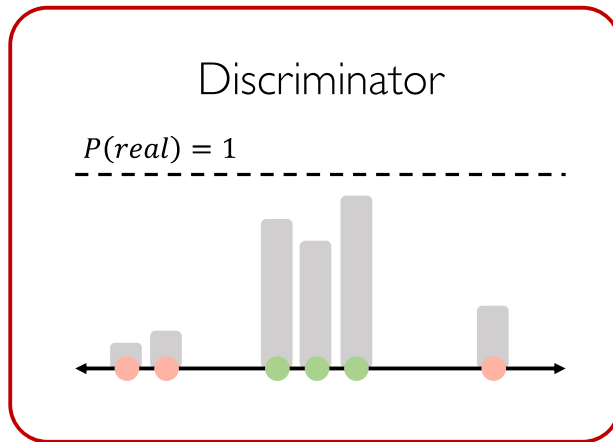
● Real data

● Fake data



# Intuition behind GANs

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Generator



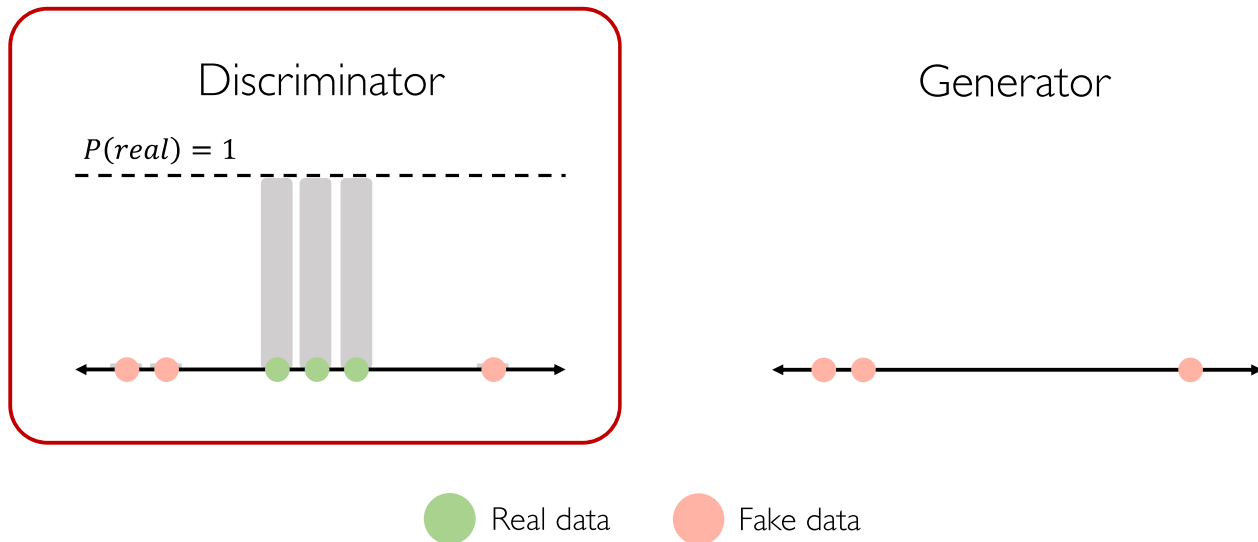
Real data



Fake data

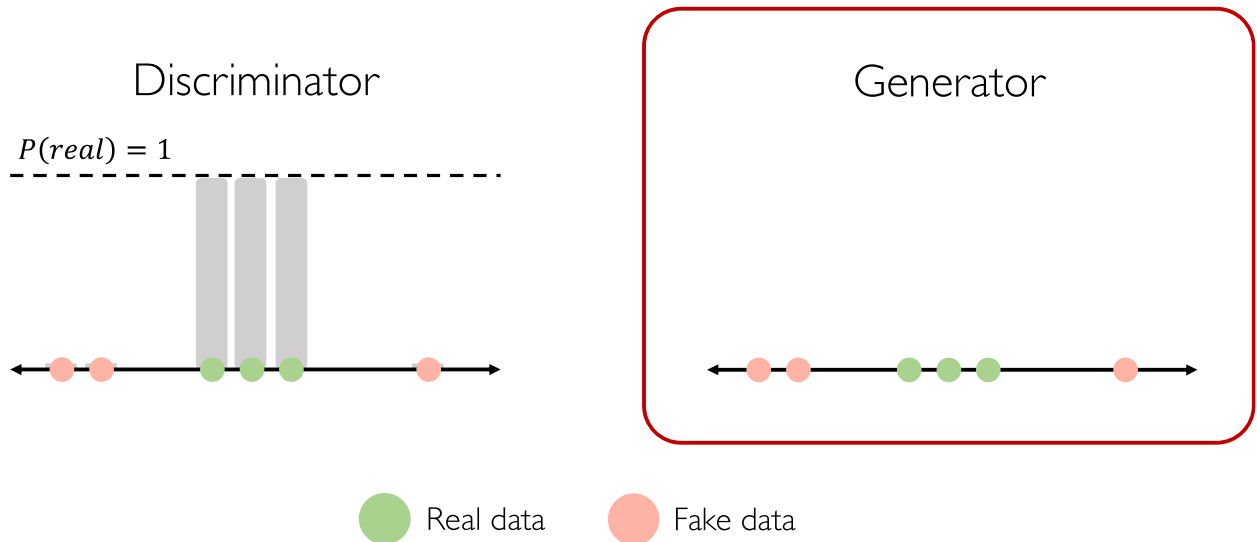
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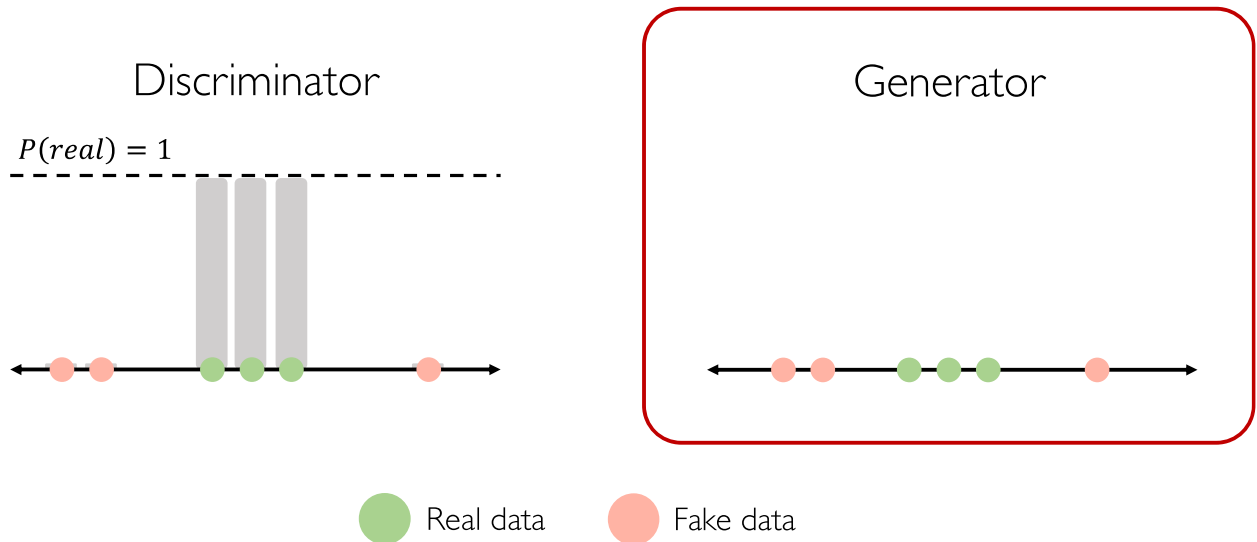
# Intuition behind GANs

**Generator** tries to improve its imitation of the data.



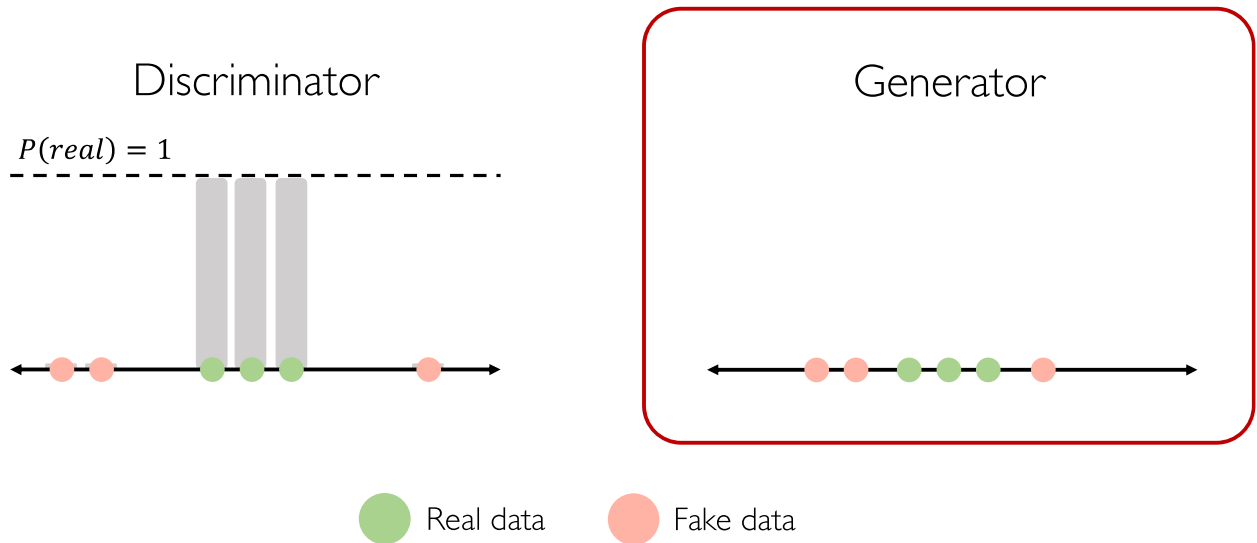
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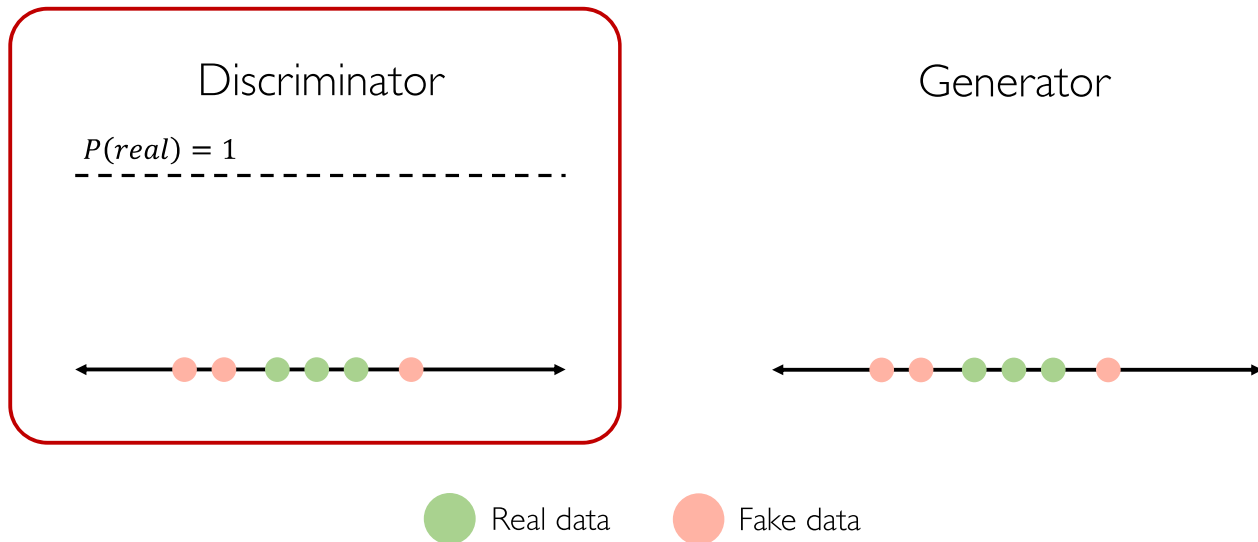
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**Generator** tries to improve its imitation of the data.



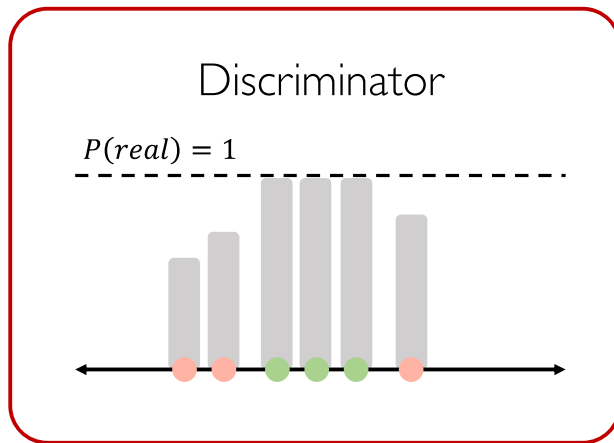
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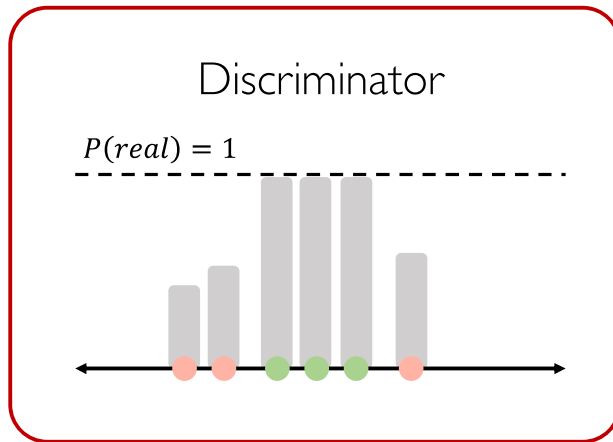
Generator



● Real data      ● Fake data

# Intuition behind GANs

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



Generator

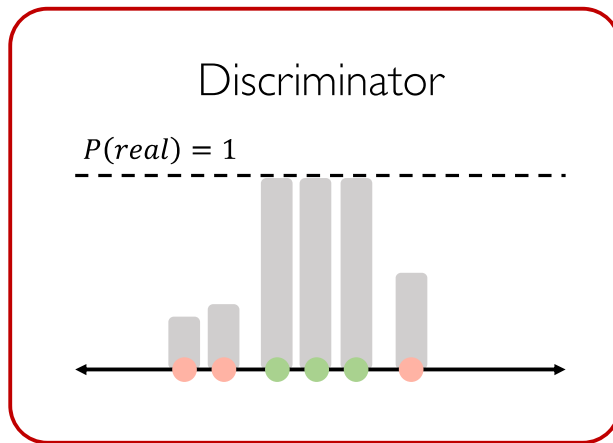


● Real data      ● Fake data



# Intuition behind GANs

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



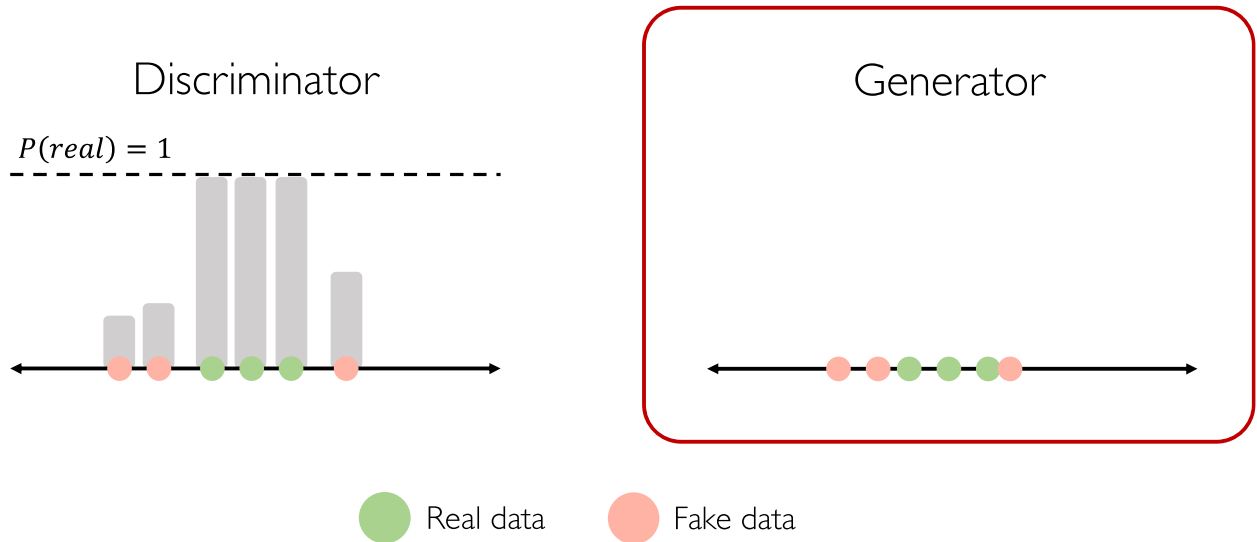
Generator



● Real data      ● Fake data

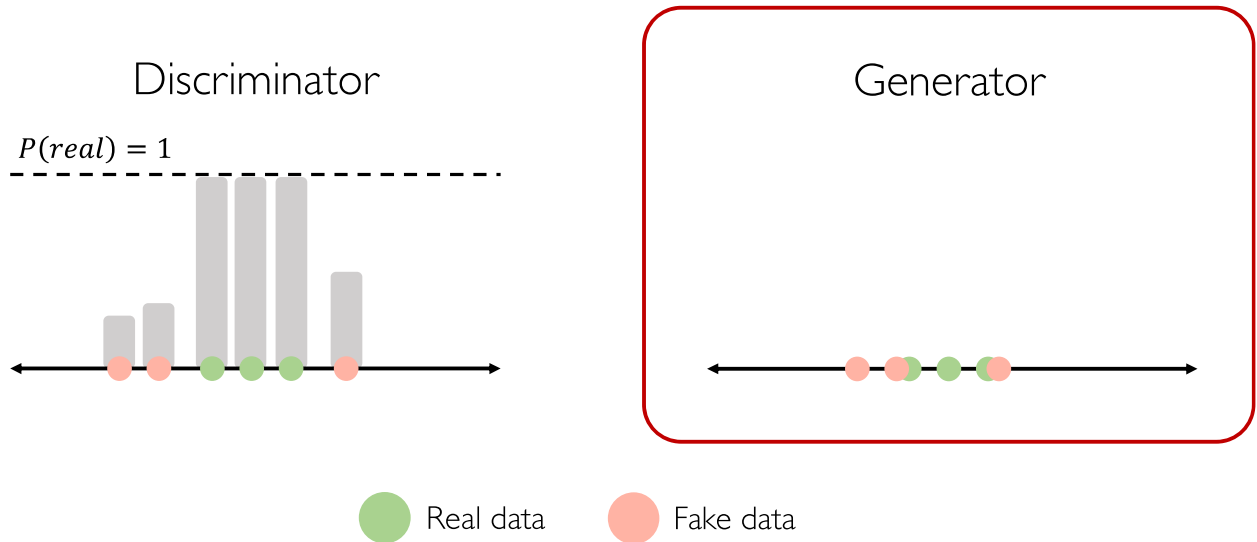
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**Generator** tries to improve its imitation of the data.



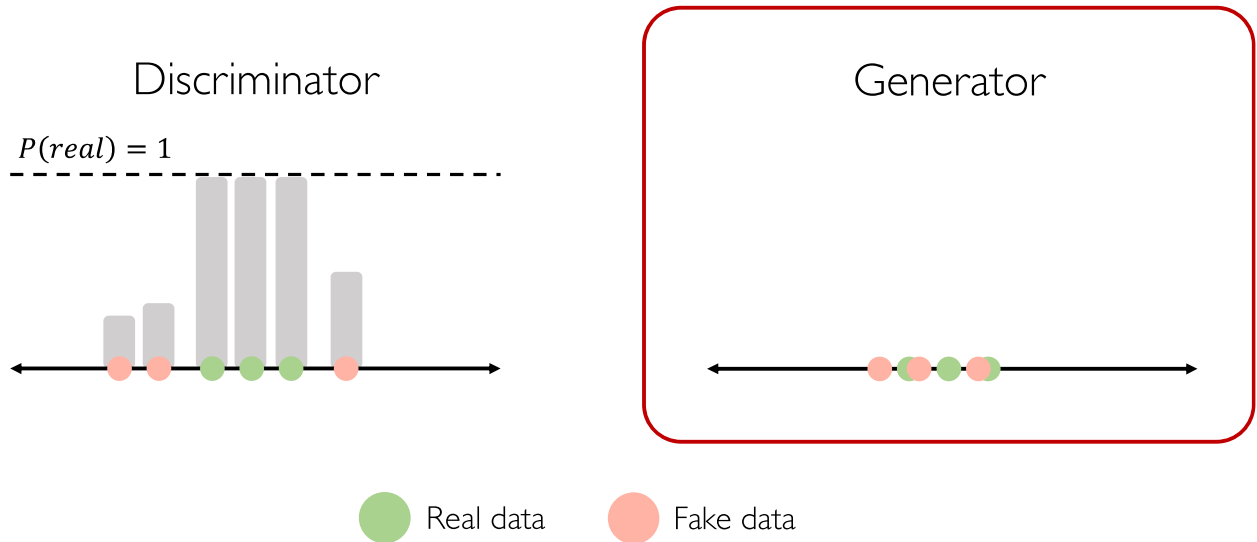
# Intuition behind GANs

**Generator** tries to improve its imitation of the data.



# Intuition behind GANs

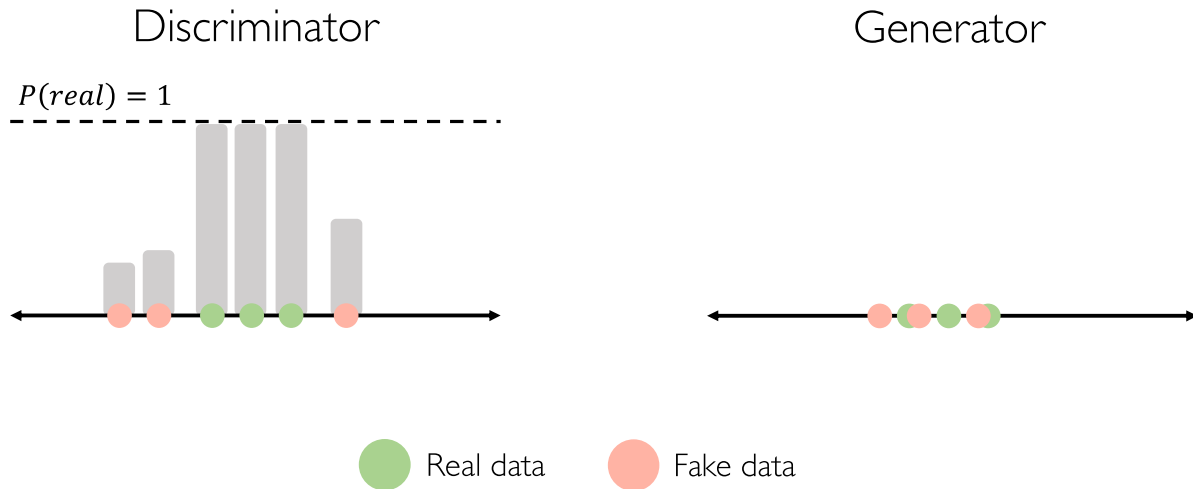
**Generator** tries to improve its imitation of the data.



# 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.



# 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.

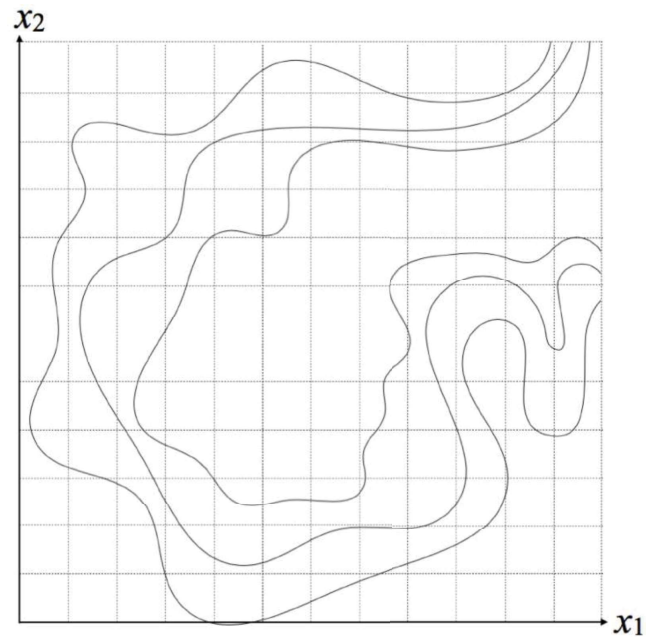
Train GAN jointly via **minimax** game:

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

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

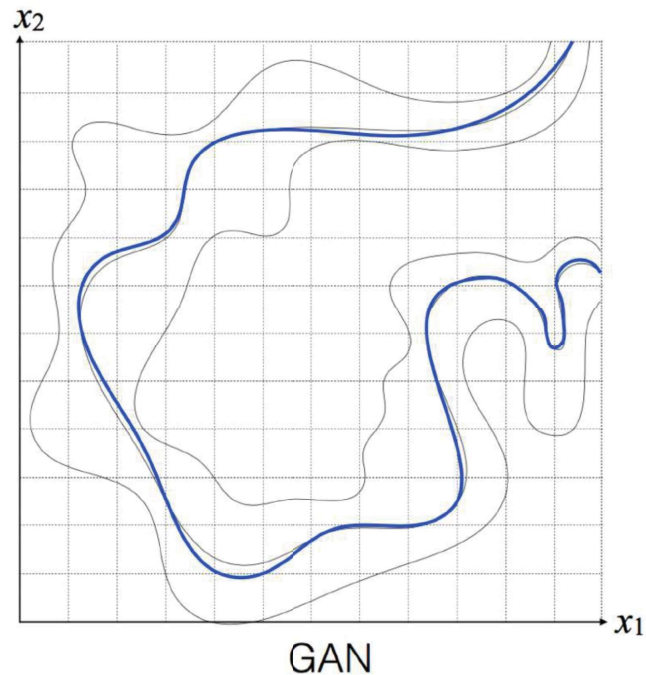
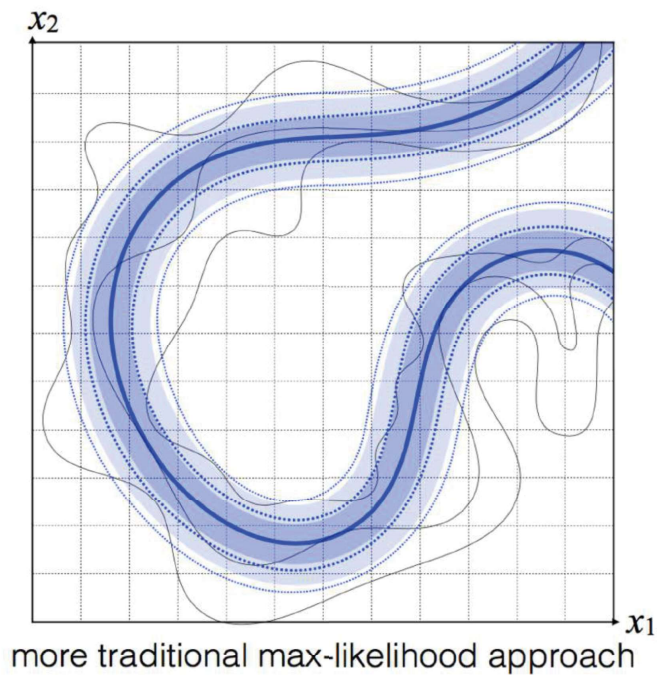
**Generator** wants to minimize objective s.t.  $D(G(z))$  close to 1.

# Why GANs?



A. Courville, 6S191 2018.

# Why GANs?

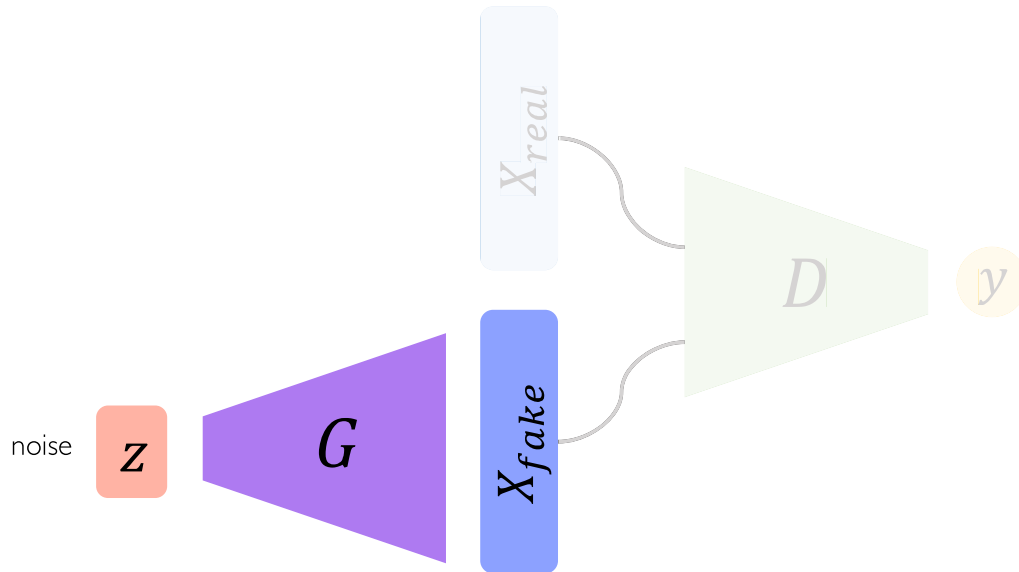


A. Courville, 6S191 2018.



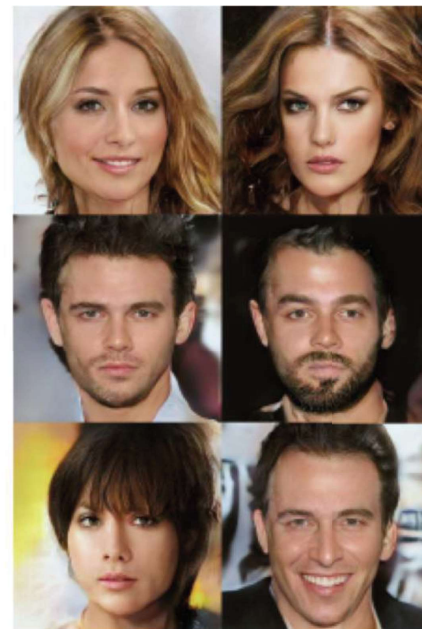
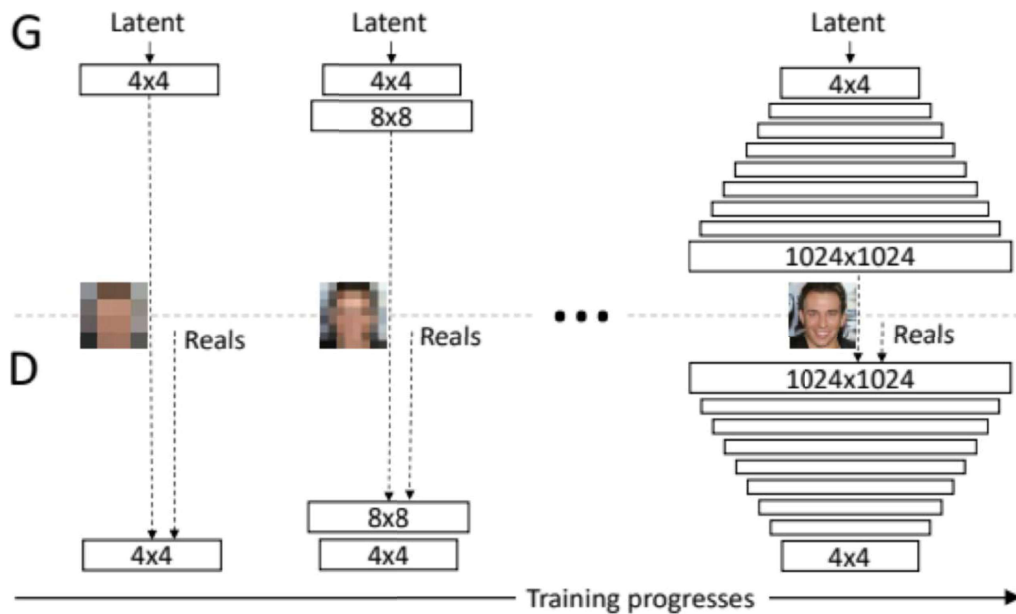
# Generating new data with GANs

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

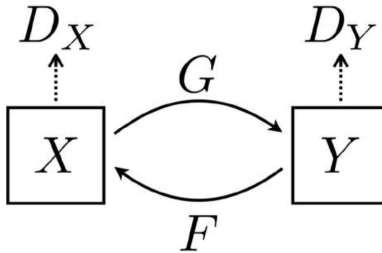


Karras et al., Arxiv 2018.



# CycleGAN: domain transformation

CycleGAN learns transformations across domains with unpaired data.

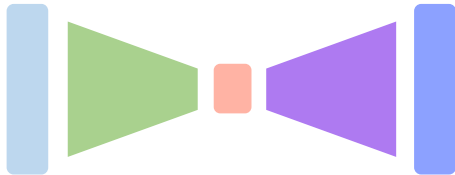


Zhu et al., ICCV 2017.

# Deep Generative Modeling: Summary

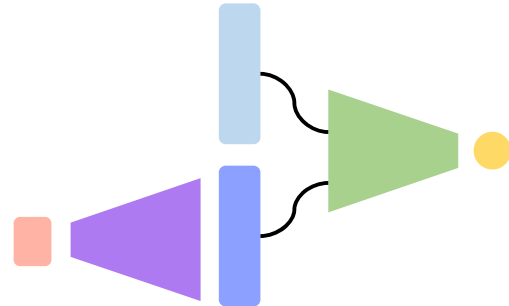
## Autoencoders and Variational Autoencoders (VAEs)

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>