Deep Generative Modeling

Ava Amini

MIT Introduction to Deep Learning

January 10, 2023

Which face is real?

A

B

C

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.

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Supervised vs unsupervised learning

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Examples: Clustering, feature or dimensionality reduction, etc.

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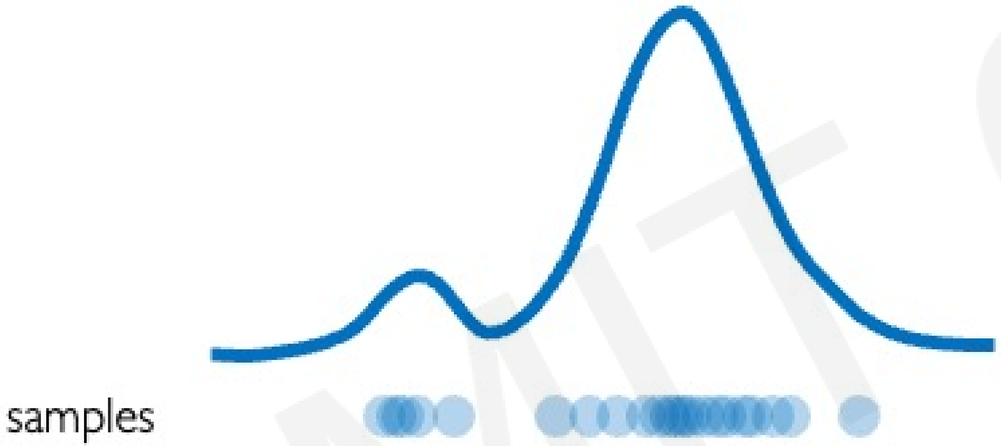
Generative modeling

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

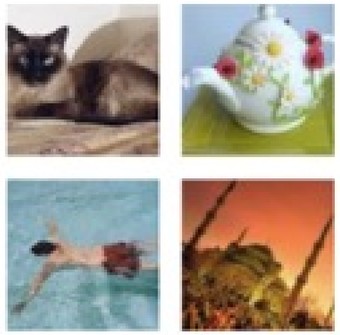
Density Estimation



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 $P_{data}(x)$?

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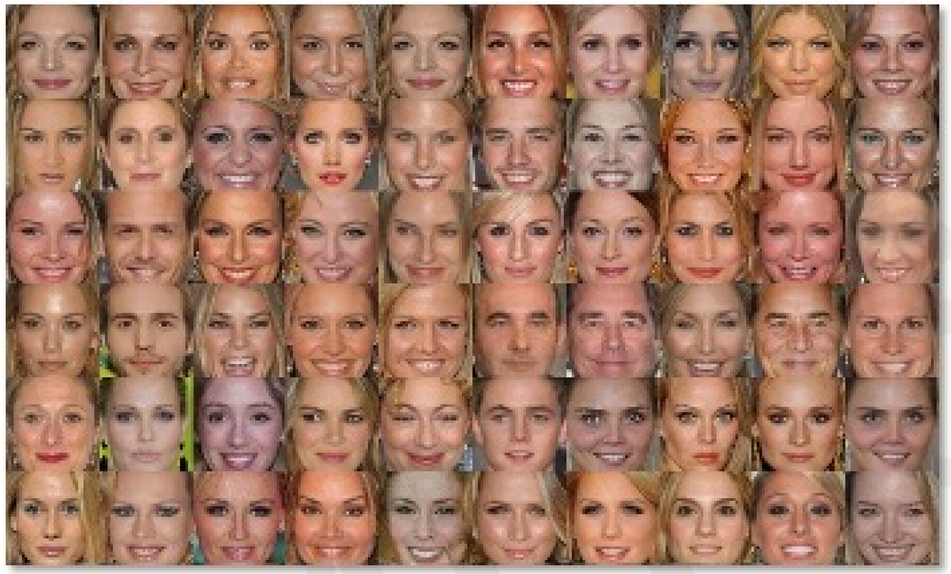
Why generative models? Debiasing

Capable of uncovering **underlying features** in a dataset



Homogeneous skin color, pose

VS

Diverse skin color, pose, illumination

How can we use this information to create fair and representative datasets?

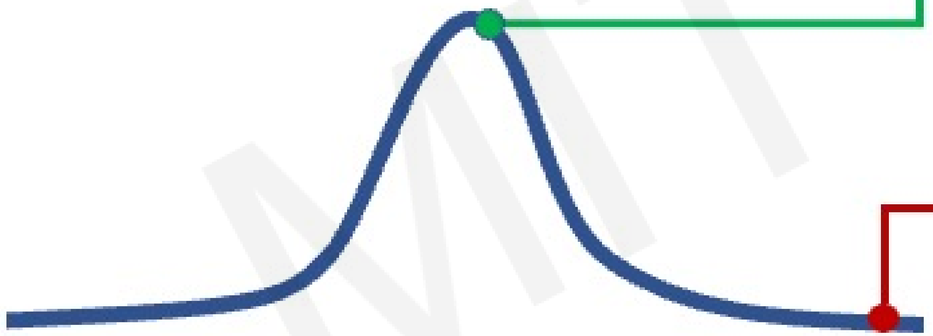
Software Lab!

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!

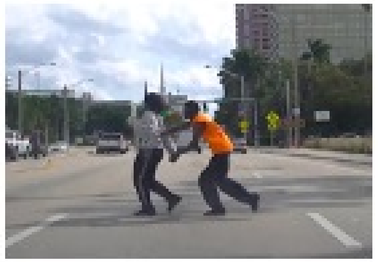
95% of Driving Data:
(1) sunny, (2) highway, (3) straight road

Detect outliers to avoid unpredictable behavior when training



Edge Cases

Harsh Weather



Pedestrians

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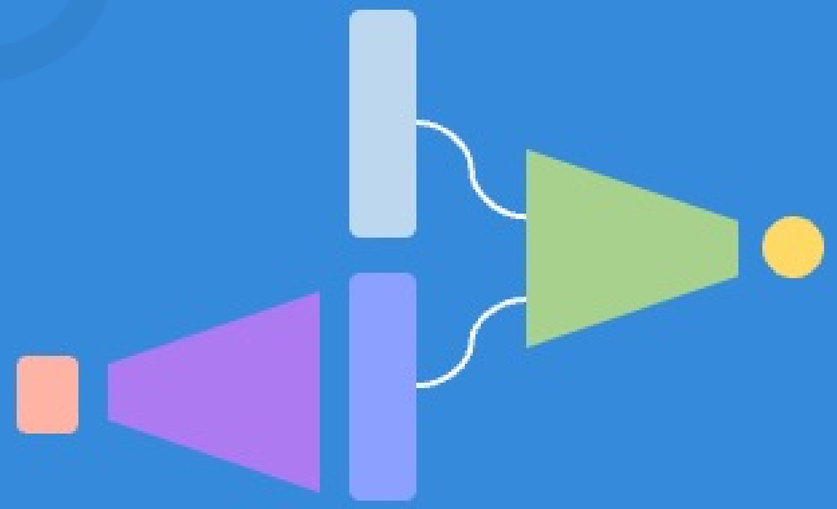
Latent variable models

Autoencoders and Variational Autoencoders (VAEs)

Generative Adversarial Networks (GANs)



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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

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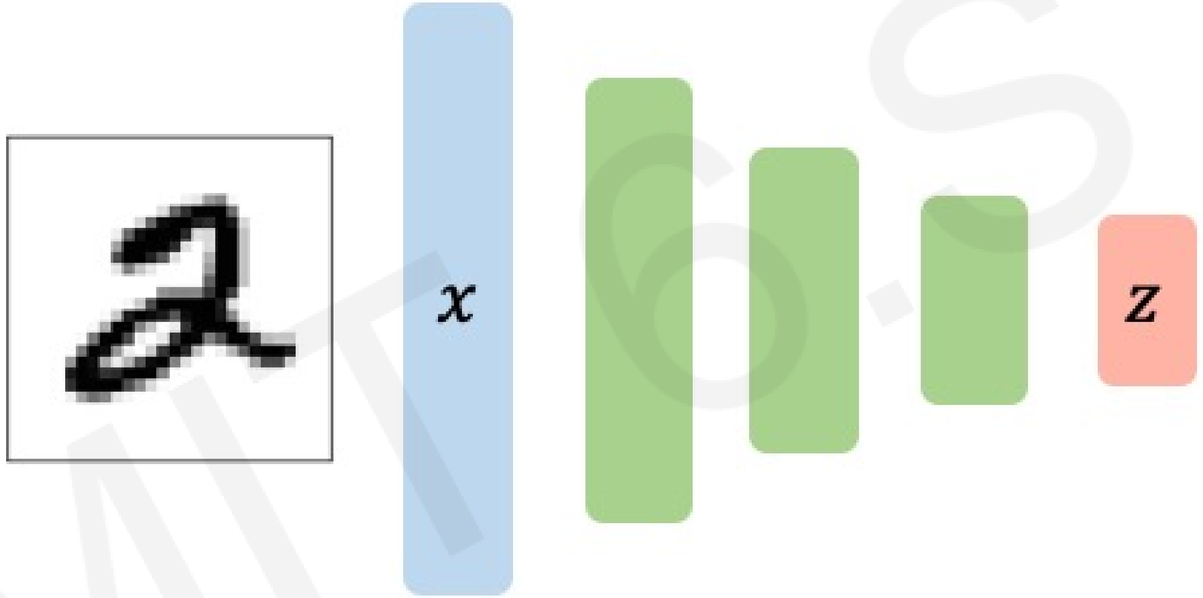
Autoencoders: background

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

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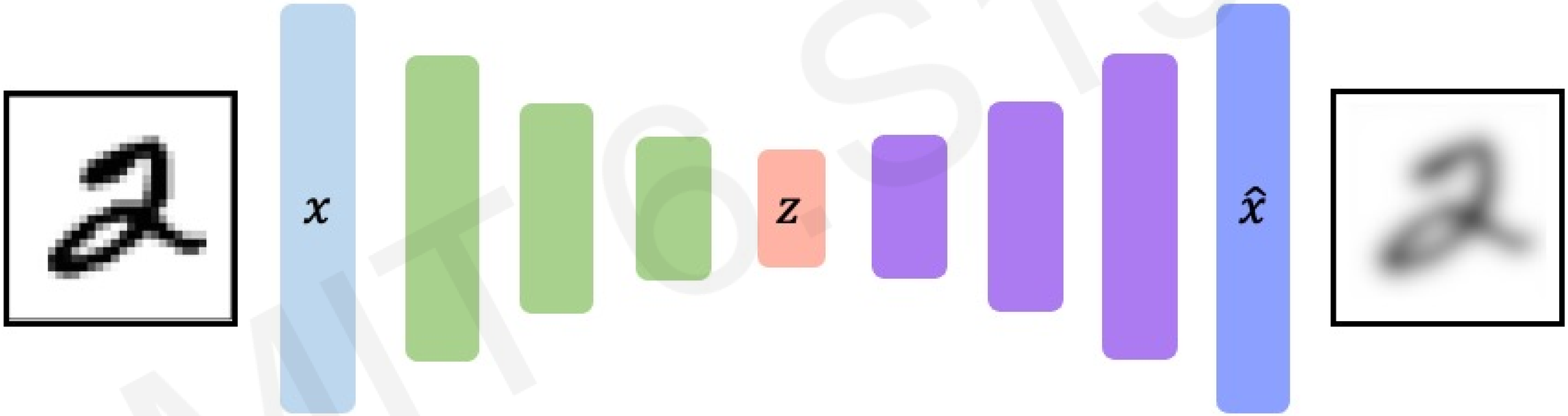
Autoencoders: background

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 space, z,
to a reconstructed observation, $\hat{x}$

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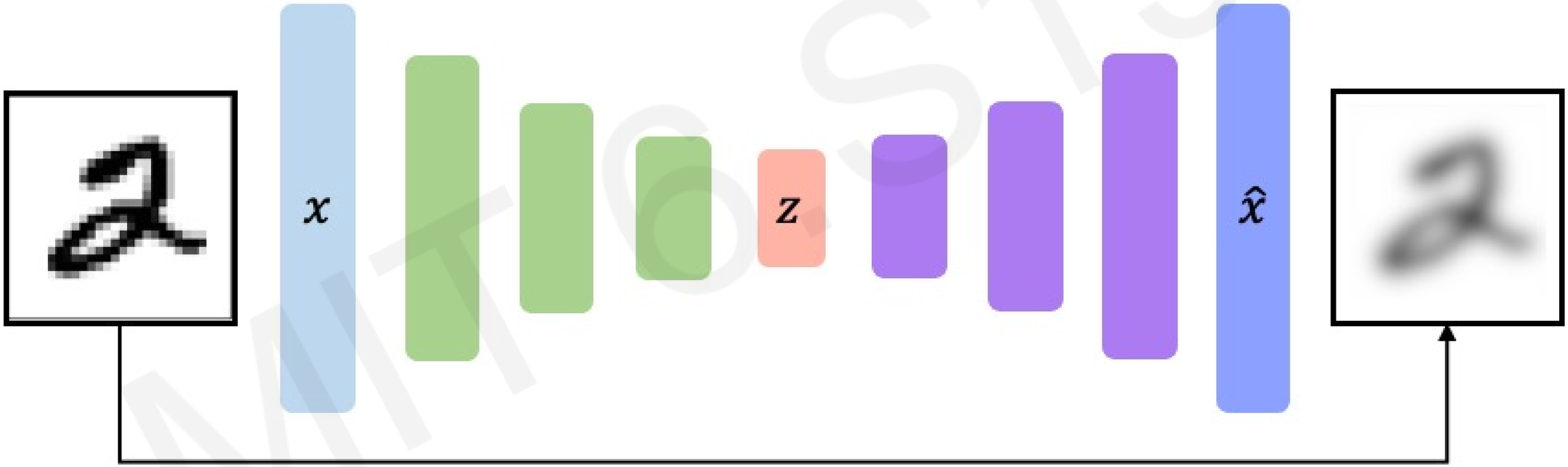
Autoencoders: background

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!!

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Autoencoders: background

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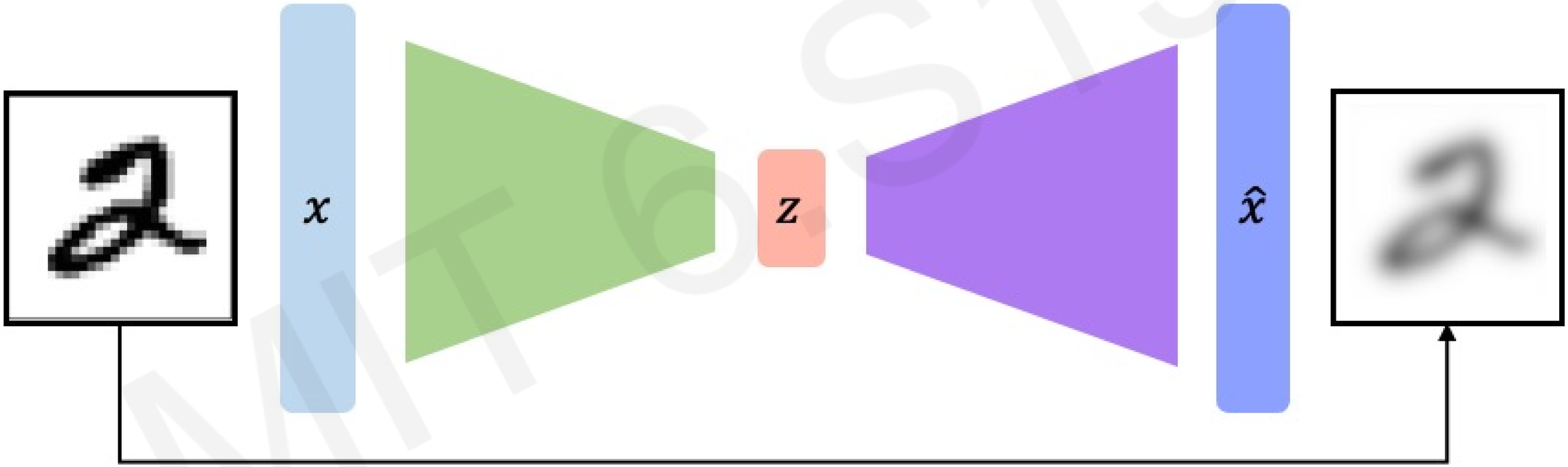
Train the model to use these features to **reconstruct the original data**



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

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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; "Auto" = **self**-encoding

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Variational Autoencoders (VAEs)

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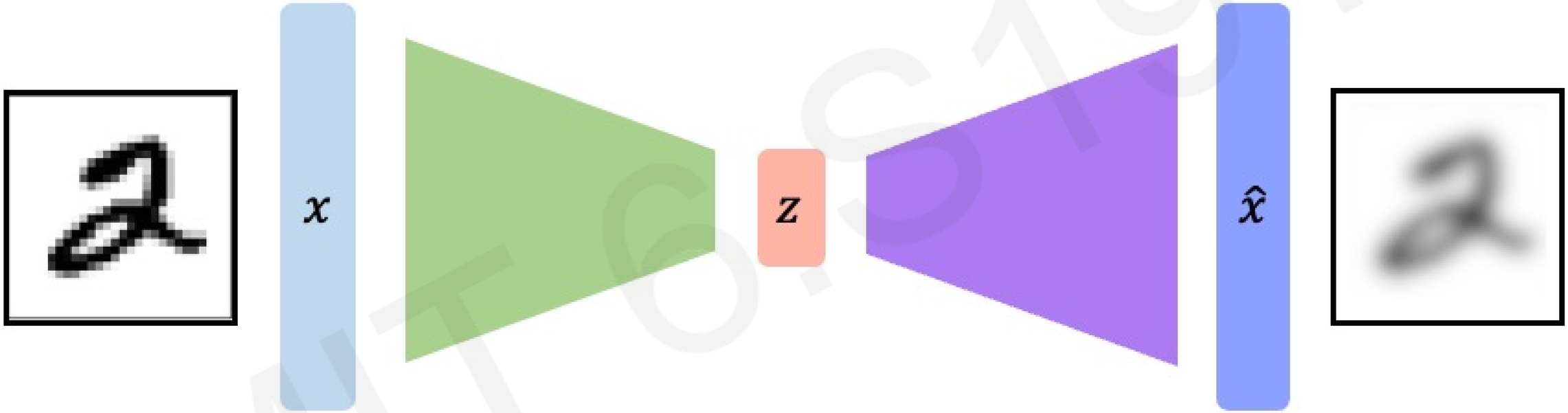
Traditional autoencoders



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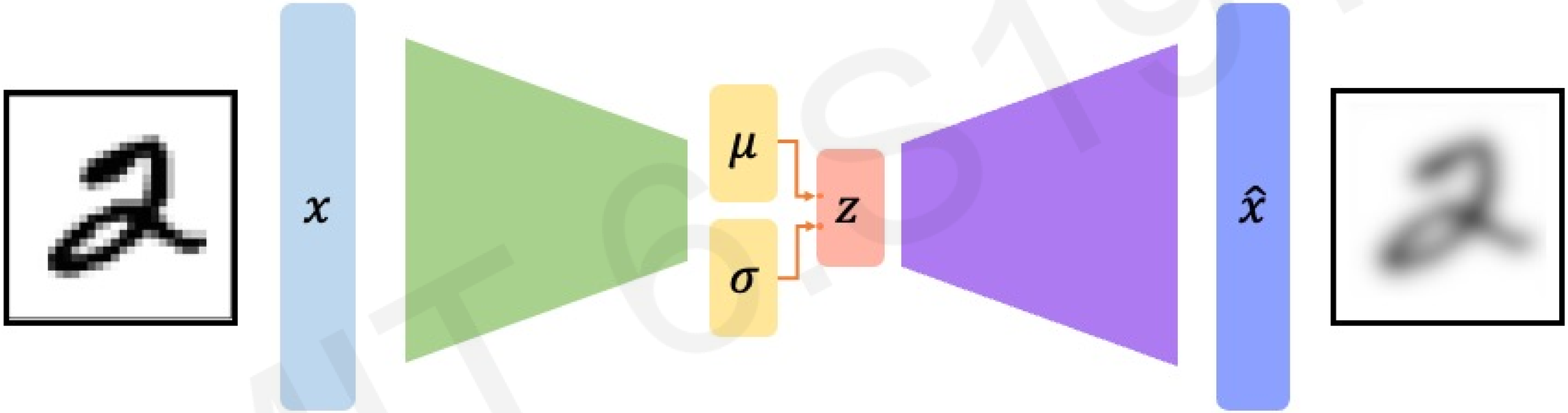
VAEs: key difference with traditional autoencoder



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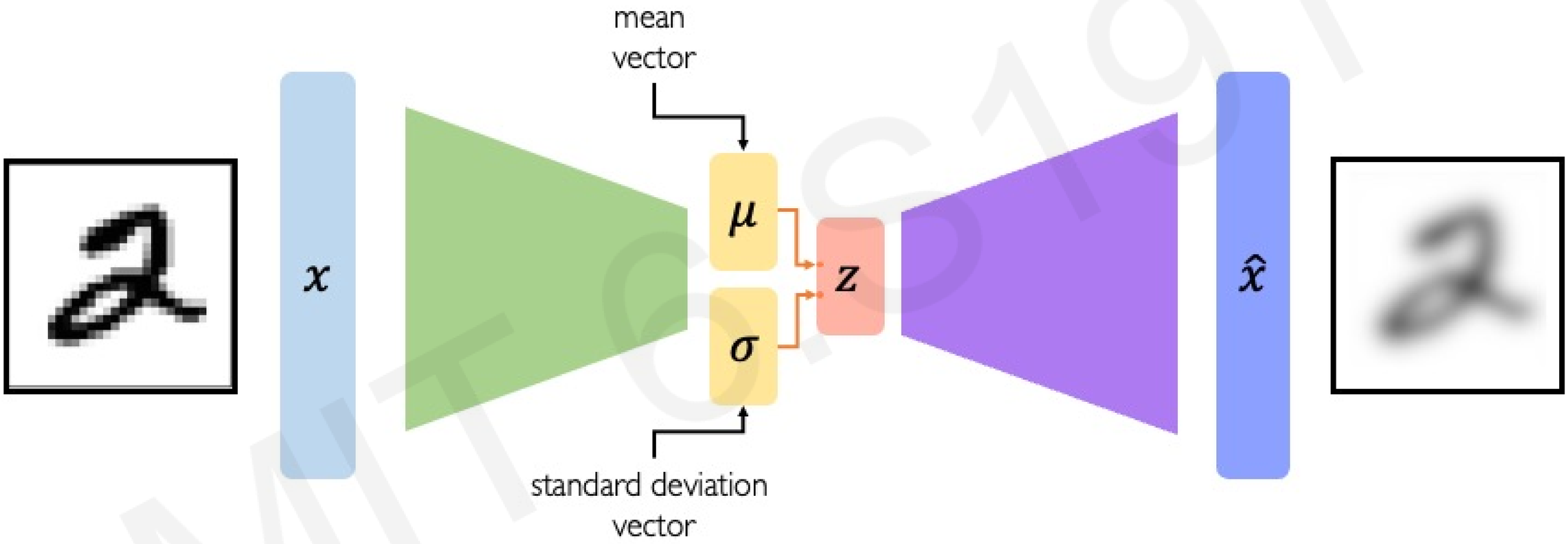

Variational autoencoders are a probabilistic twist on autoencoders!

Sample from the mean and standard deviation to compute latent sample

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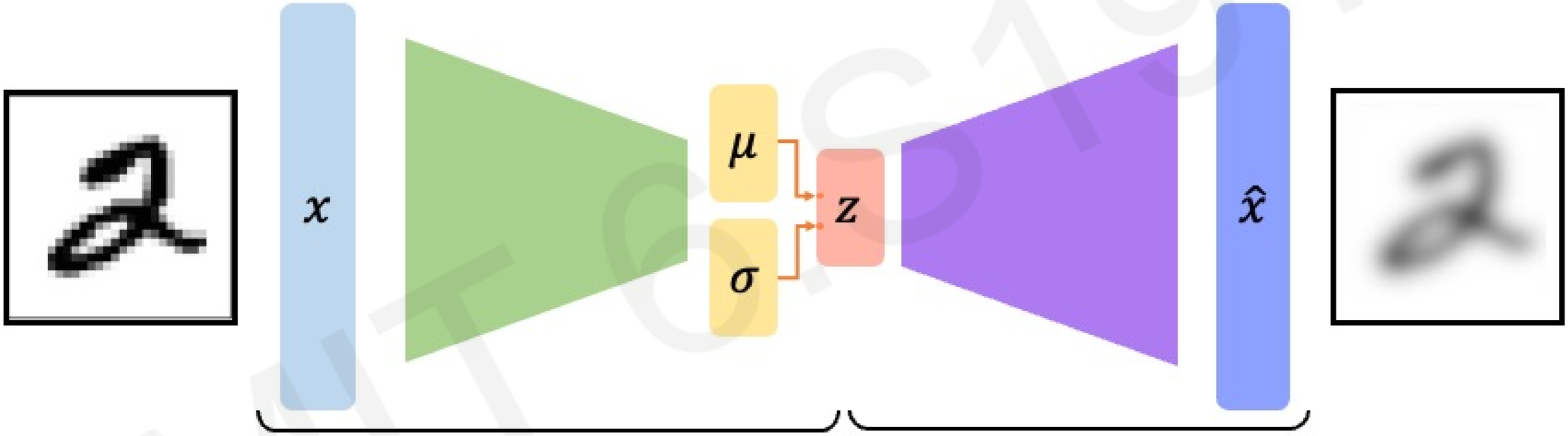
VAE optimization



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

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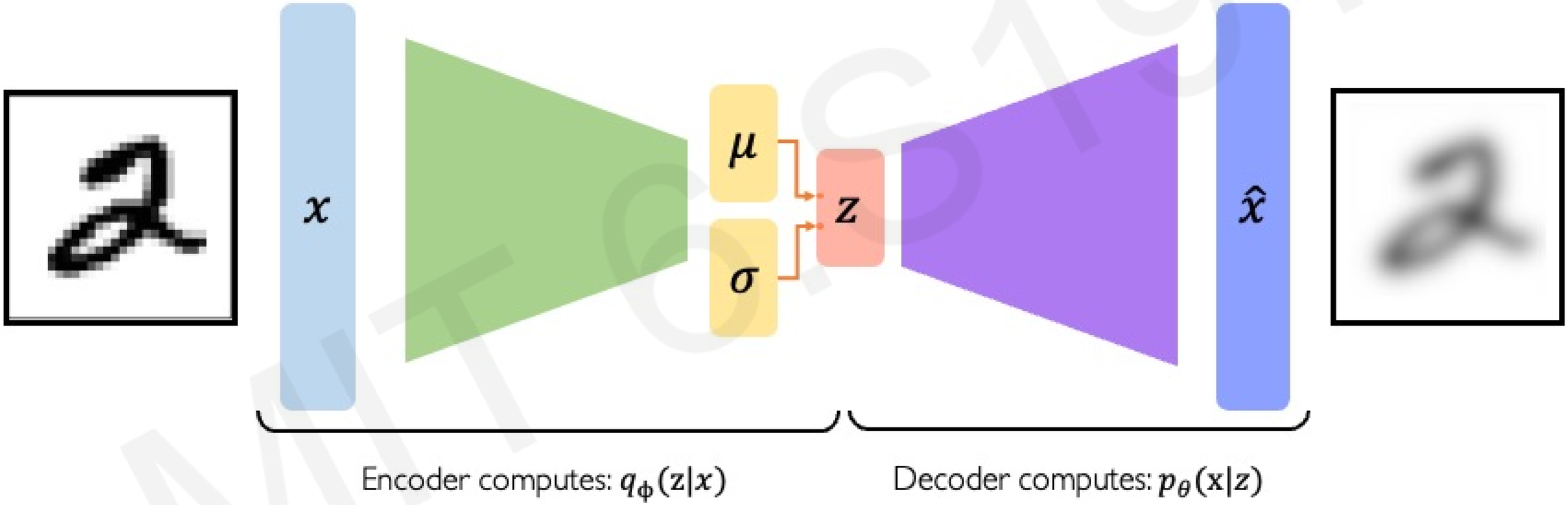
VAE optimization



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

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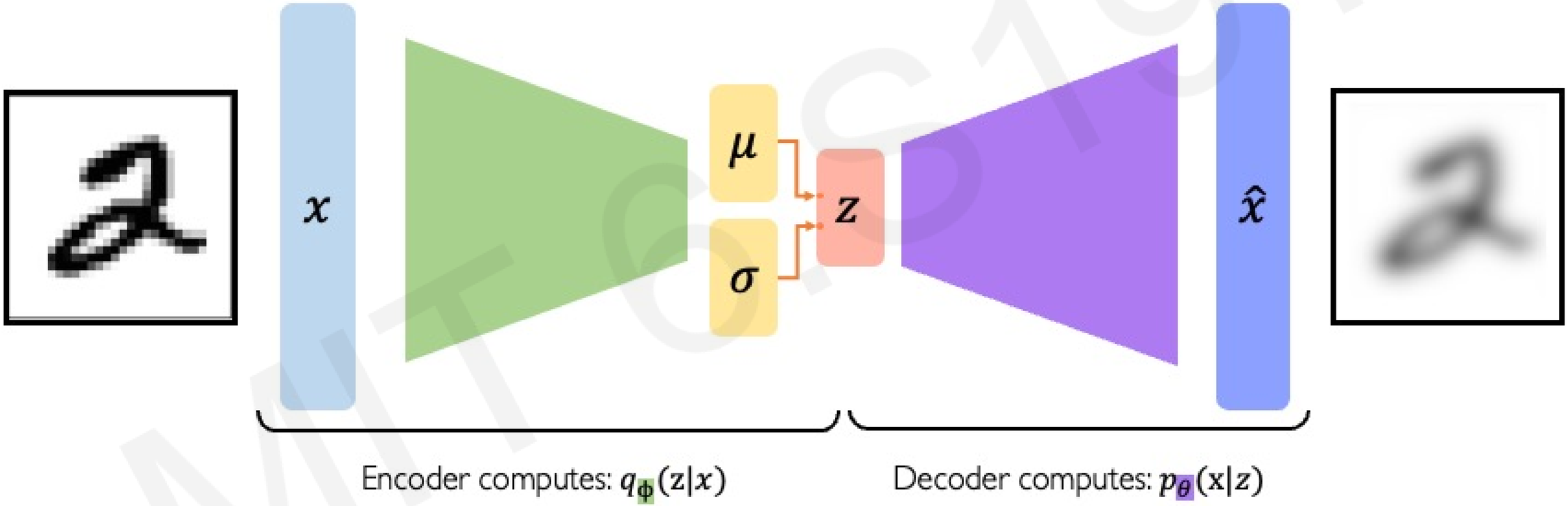
VAE optimization



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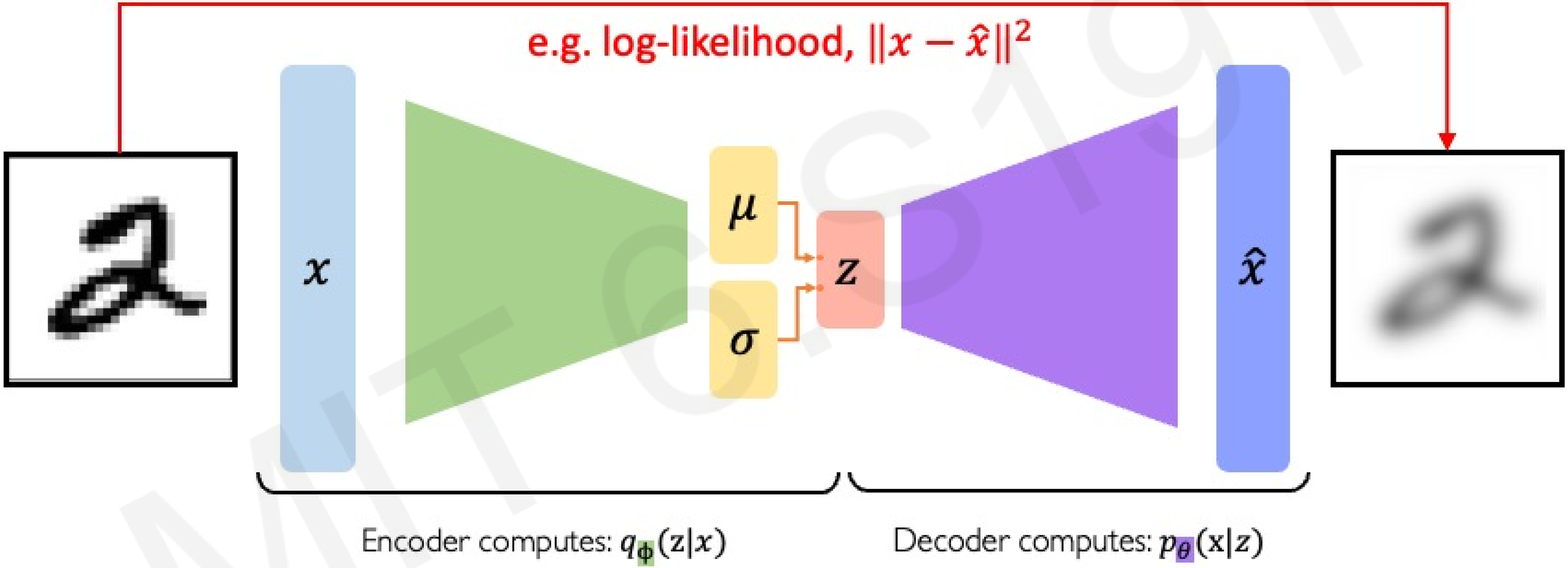

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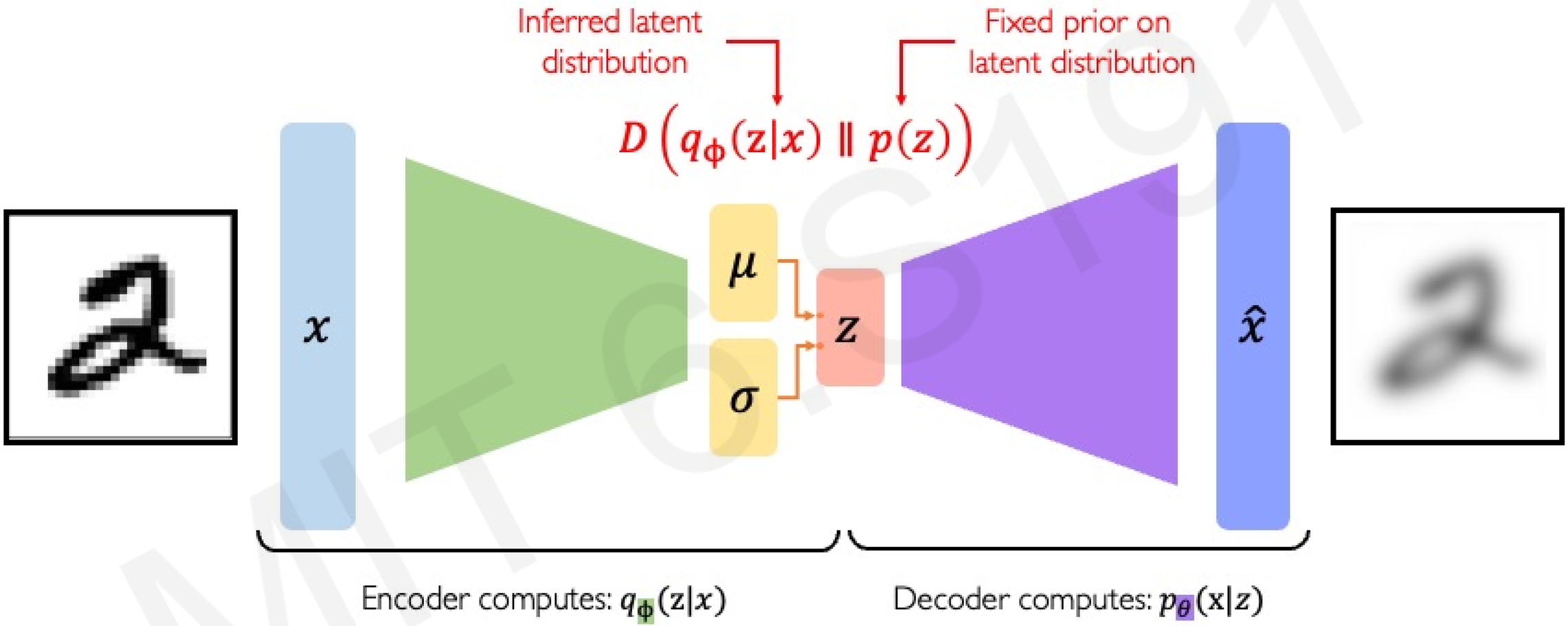

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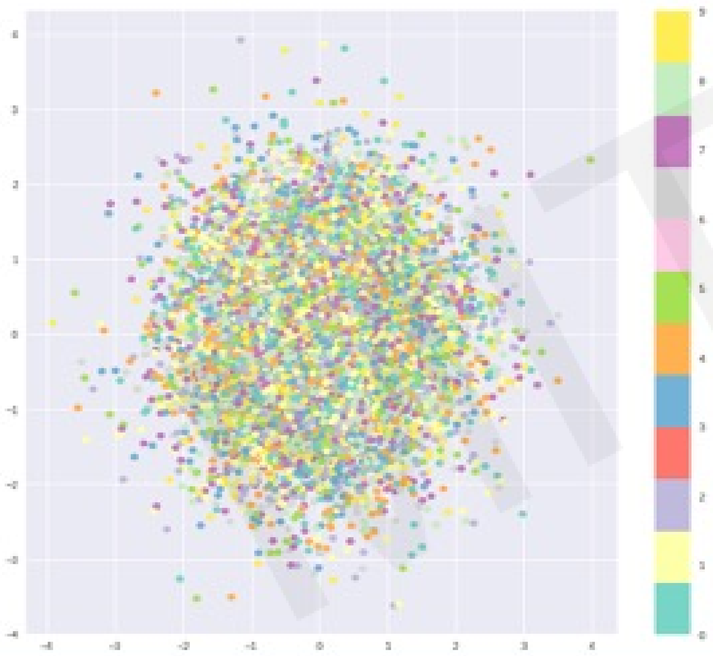
Priors on the latent distribution

$$D\left(q_\phi(z|x) \parallel p(z)\right)$$

Inferred latent distribution

Fixed prior on latent distribution



Common choice of prior – Normal Gaussian:

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

- 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 (i.e., by memorizing the data)

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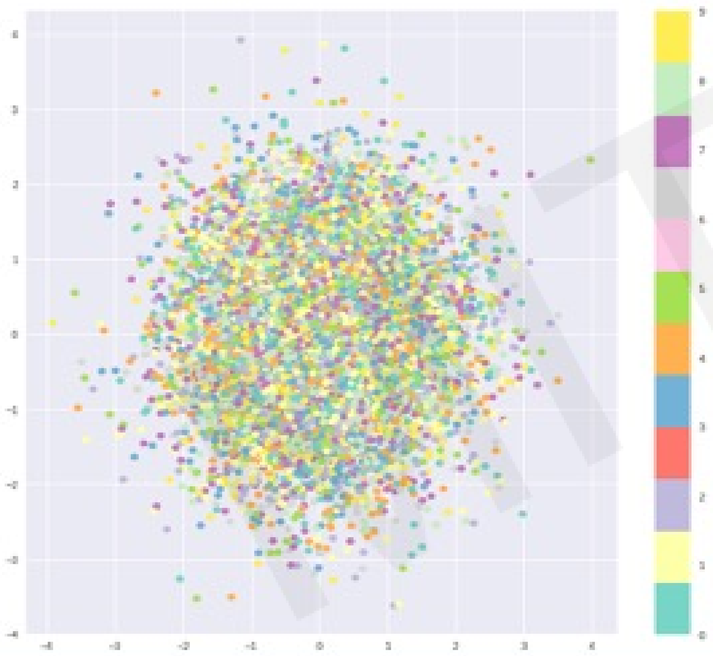
Priors on the latent distribution

$$D\left(q_\phi(z|x) \parallel p(z)\right)$$

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

KL-divergence between the two distributions



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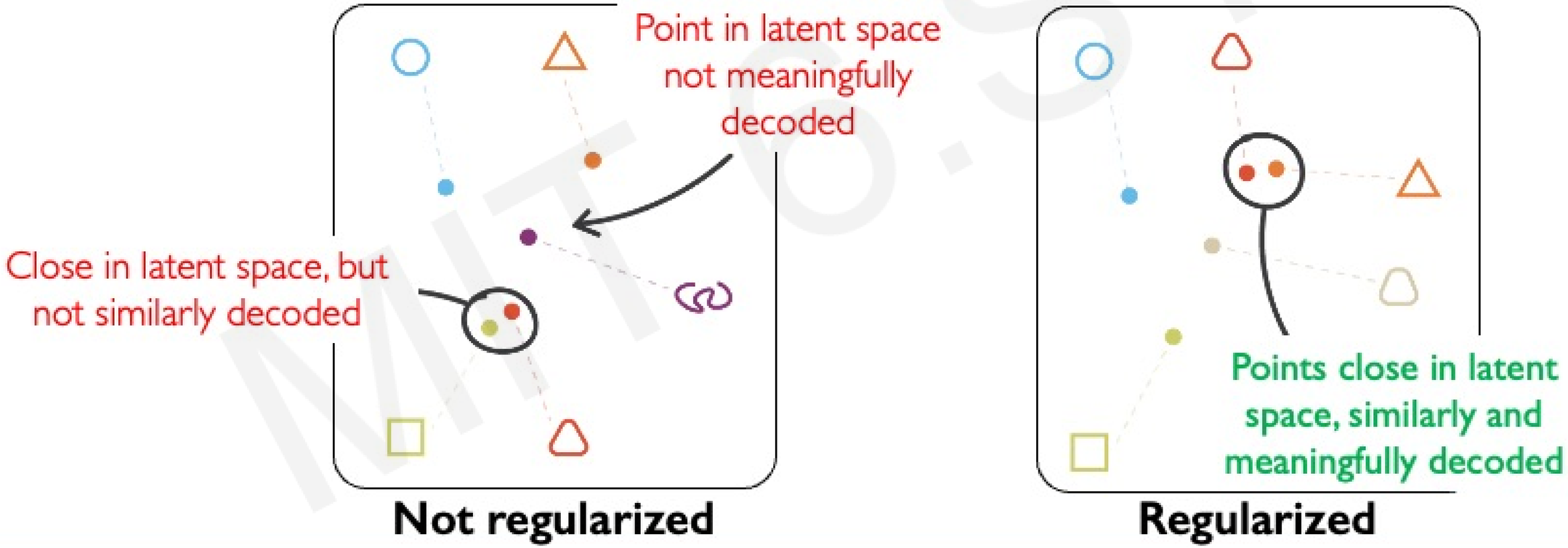
Intuition on regularization and the Normal prior

What properties do we want to achieve from regularization?

1. **Continuity:** points that are close in latent space → similar content after decoding
2. **Completeness:** sampling from latent space → "meaningful" content after decoding



Intuition on regularization and the Normal prior

1. **Continuity**: points that are close in latent space → similar content after decoding
2. **Completeness:** sampling from latent space → "meaningful" content after decoding

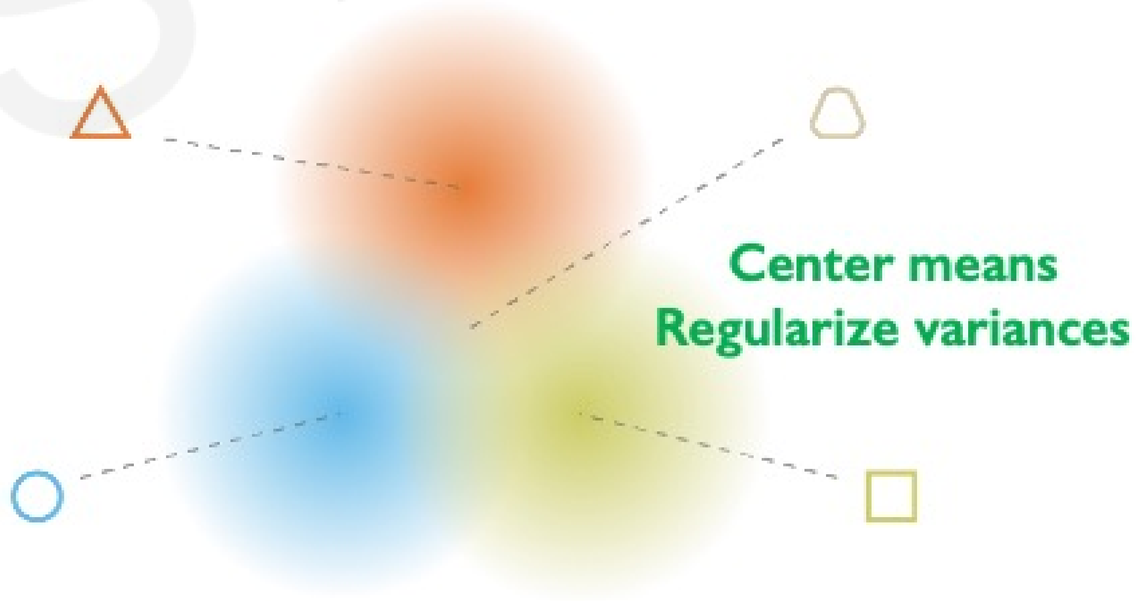
Encoding as a distribution does not guarantee these properties!

Normal prior →
continuity + completeness

Small variances →
Pointed distributions

Different means →
Discontinuities

Not regularized



Regularized

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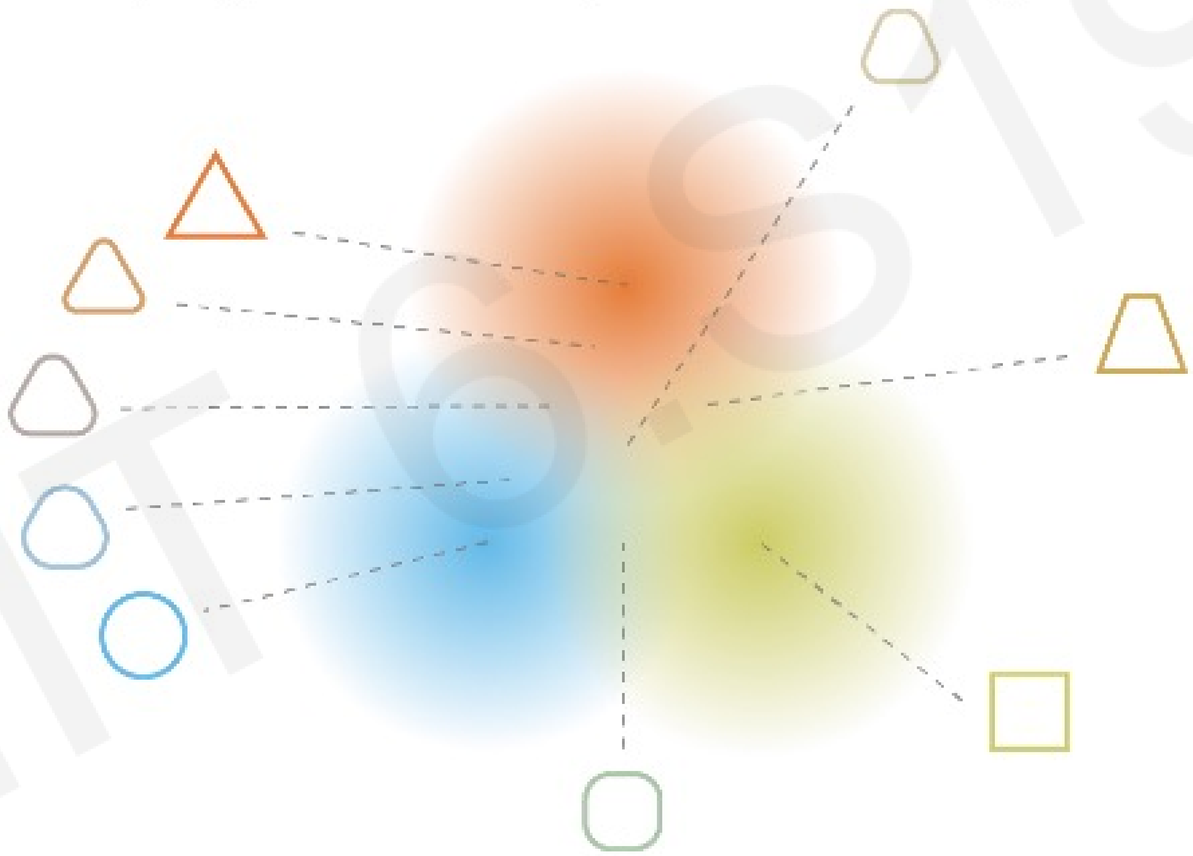

Regularization with Normal prior helps enforce **information gradient** in the latent space.

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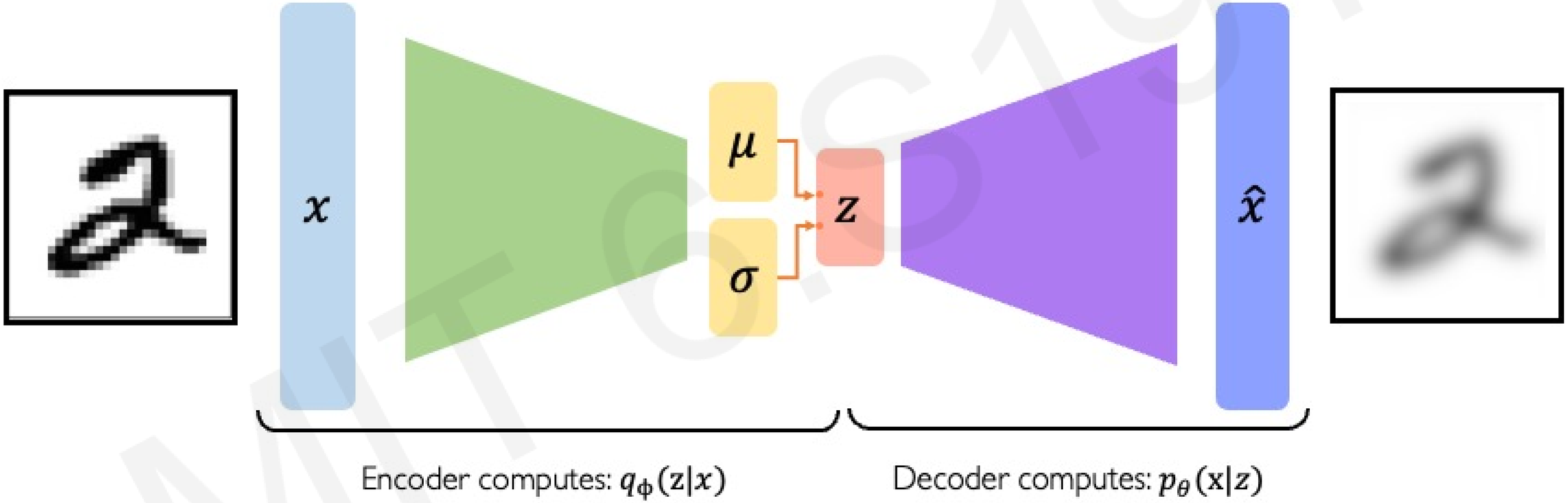
VAE computation graph



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

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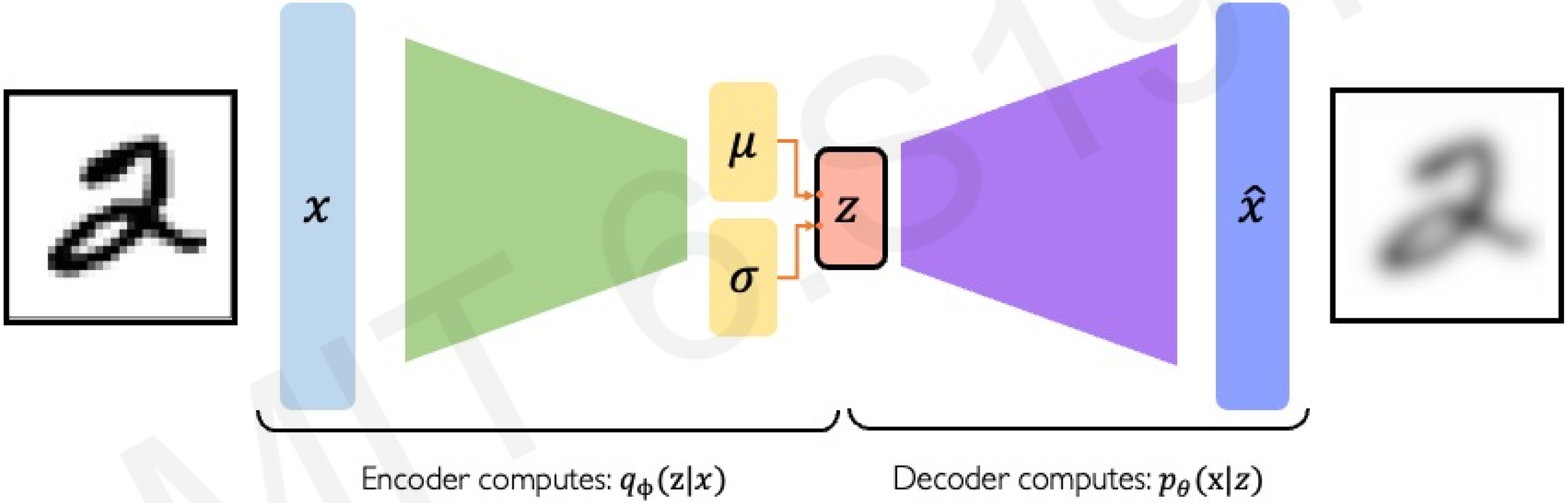
VAE computation graph

Problem: We cannot backpropagate gradients through sampling layers!



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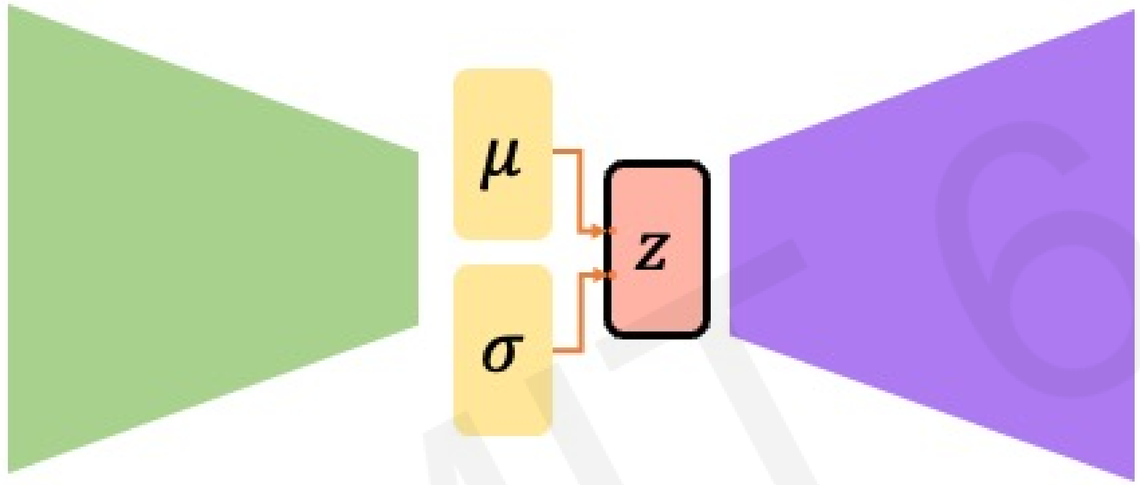
Reparametrizing the sampling layer



Key Idea:

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

Consider the sampled latent vector z 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 $\varepsilon \sim \mathcal{N}(0,1)$

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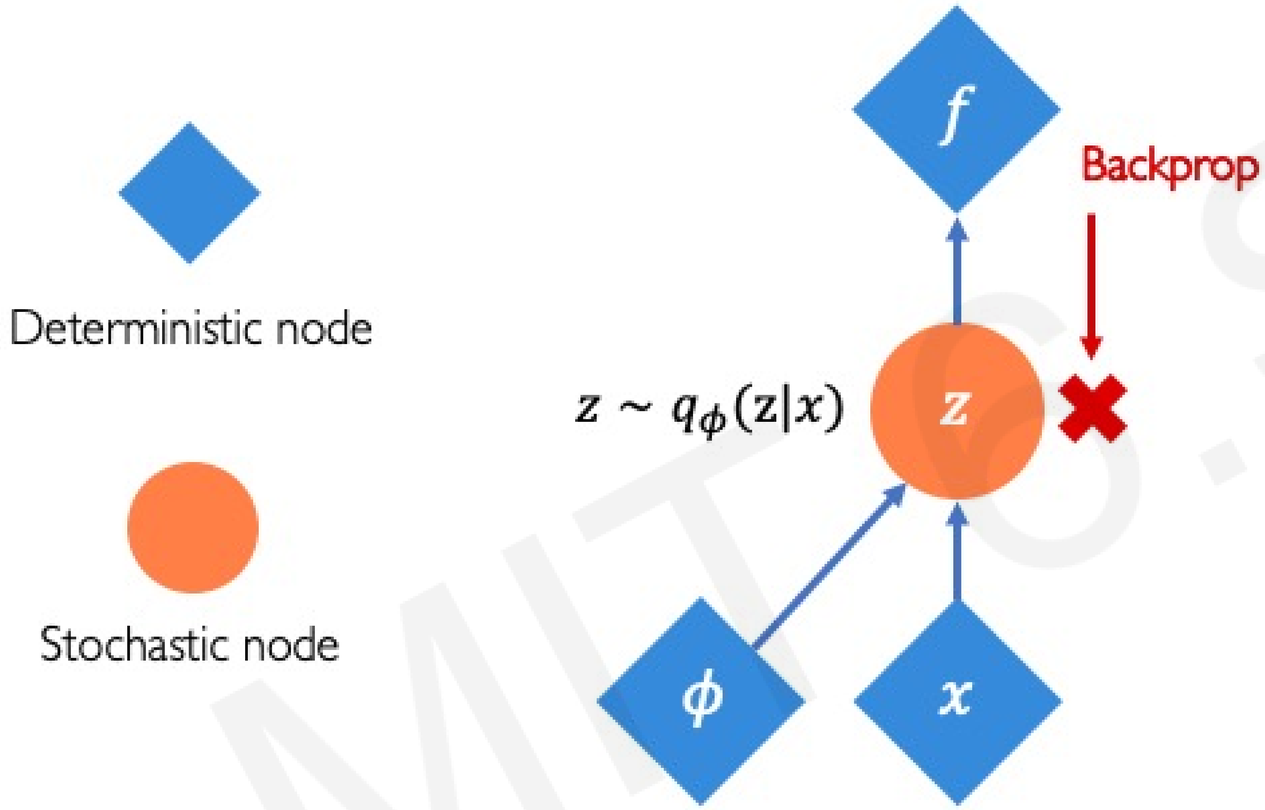
Reparametrizing the sampling layer



Original form

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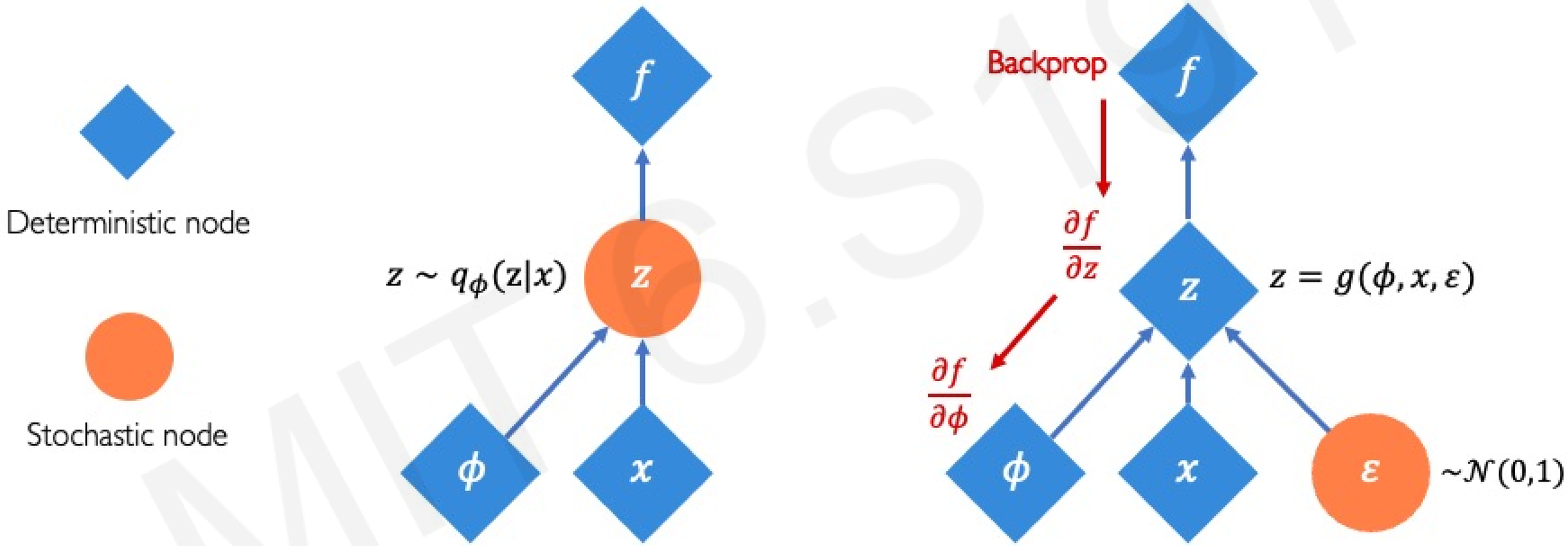
Reparametrizing the sampling layer



Original form

Reparametrized form

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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

Smile

Head pose

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

Enforce diagonal prior on the latent variables to encourage independence

Disentanglement

Latent space disentanglement with β-VAEs

β-VAE loss:

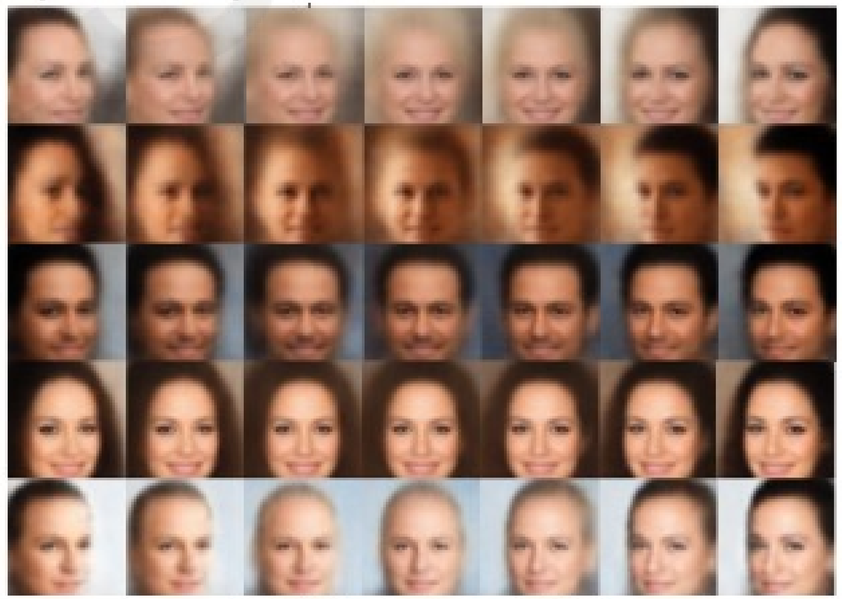
$$\mathcal{L}(\theta, \phi; \mathbf{x}, \mathbf{z}, \beta) = \underbrace{\mathbb{E}_{q_\phi(\mathbf{z}|\mathbf{x})}[\log p_\theta(\mathbf{x}|\mathbf{z})]}_{\textbf{Reconstruction term}} - \boxed{}\, \underbrace{D_{KL}\big(q_\phi(\mathbf{z}|\mathbf{x}) \parallel p(\mathbf{z})\big)}_{\textbf{Regularization term}}$$

β > 1: constrain latent bottleneck, encourage efficient latent encoding → disentanglement

Head rotation (azimuth)

Smile also changing!

Standard VAE (β = 1)

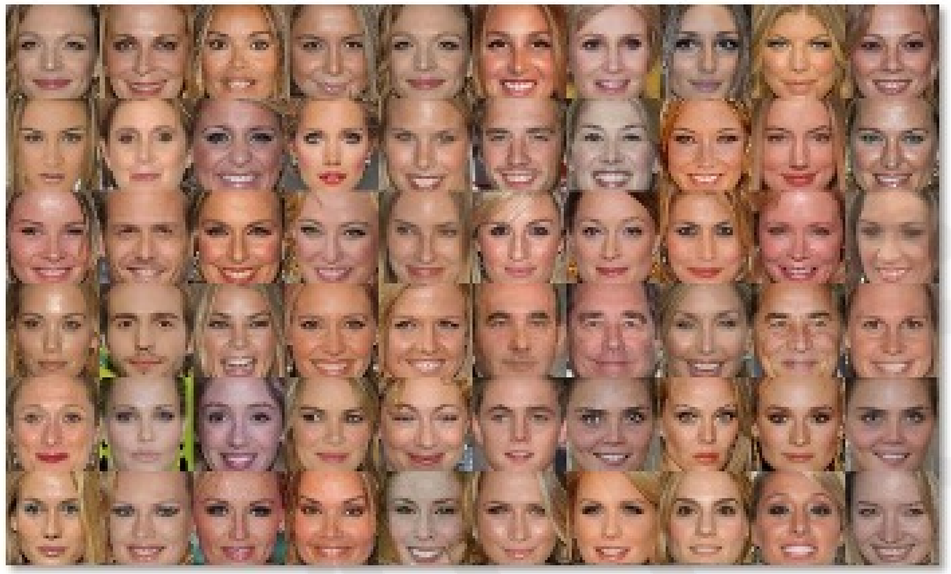


β-VAE (β = 250)

Smile relatively constant!

Why latent variable models? Debiasing

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



Homogeneous skin color, pose

VS

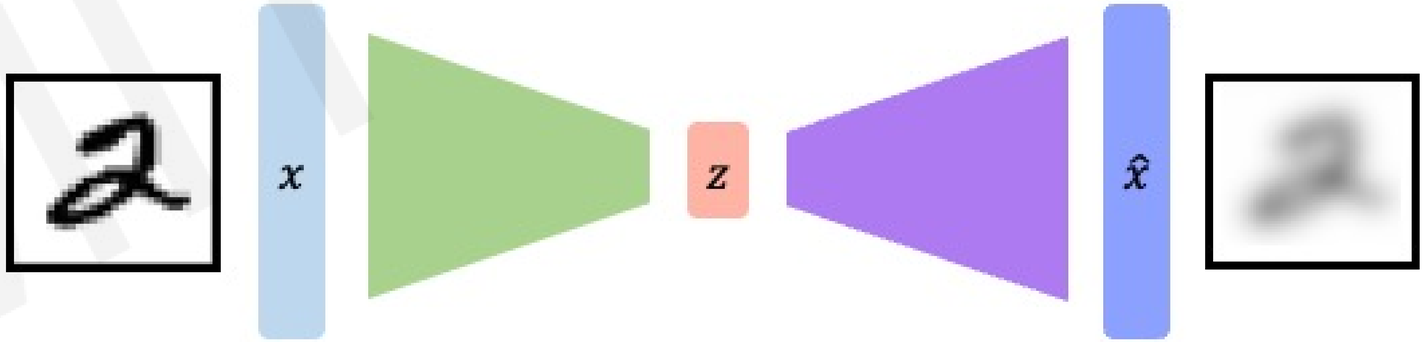
Diverse skin color, pose, illumination

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

Software Lab!

VAE summary

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



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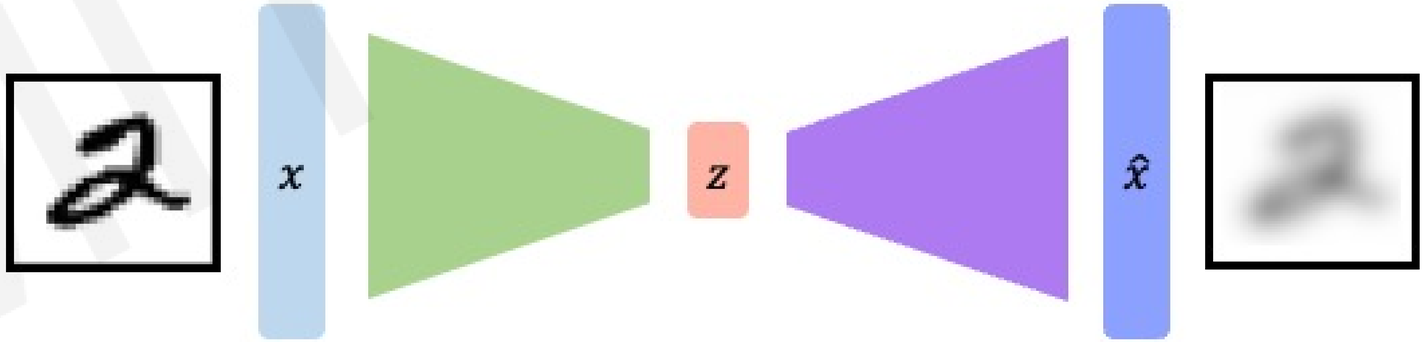

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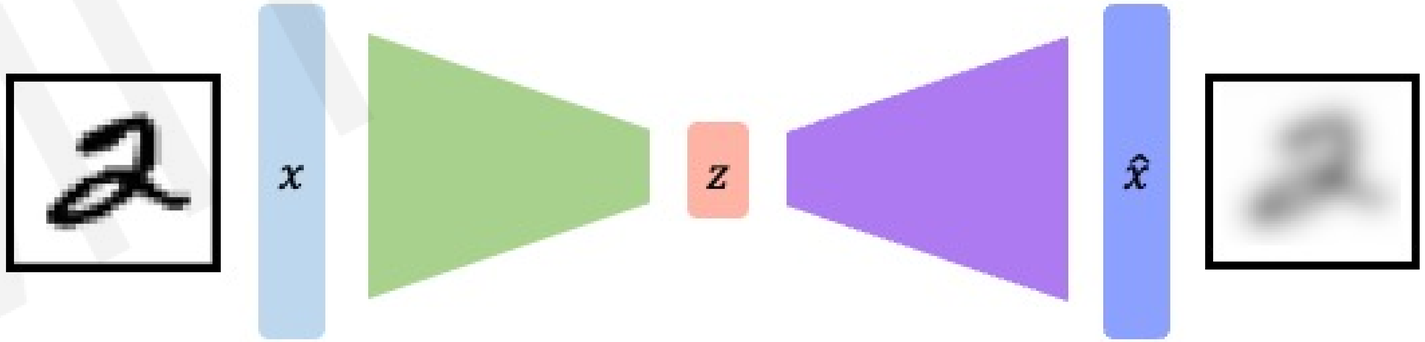

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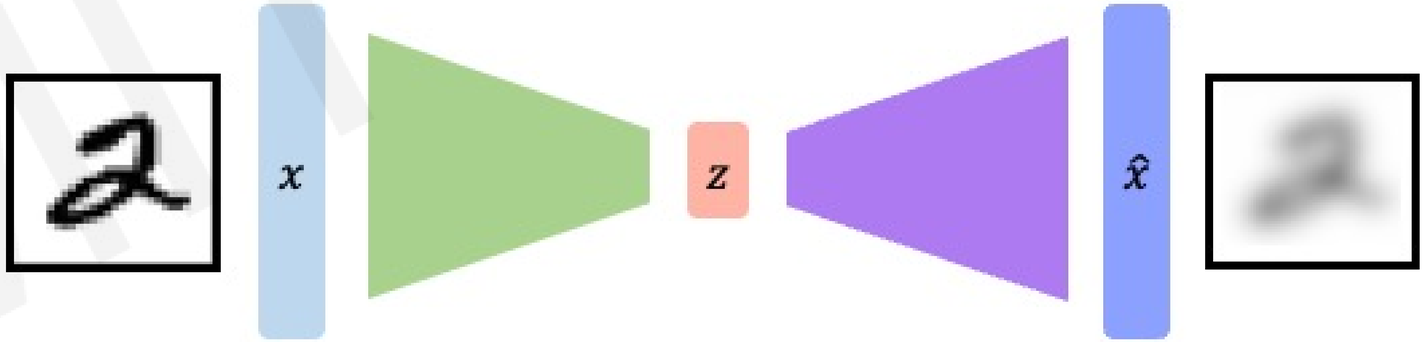

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VAE summary

1. Compress representation of world to something we can use to learn
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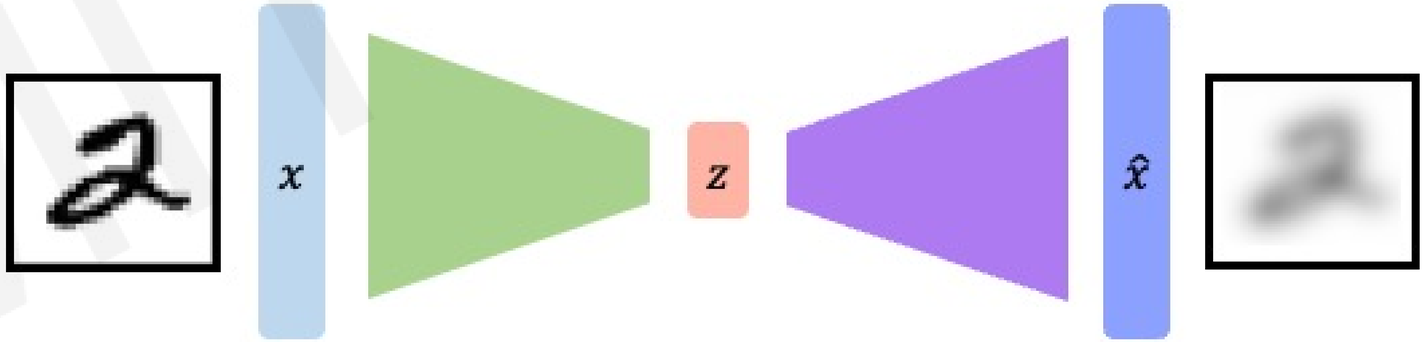
3. Reparameterization trick to train end-to-end
4. Interpret hidden latent variables using perturbation
5. Generating new examples



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Generative Adversarial Networks (GANs)

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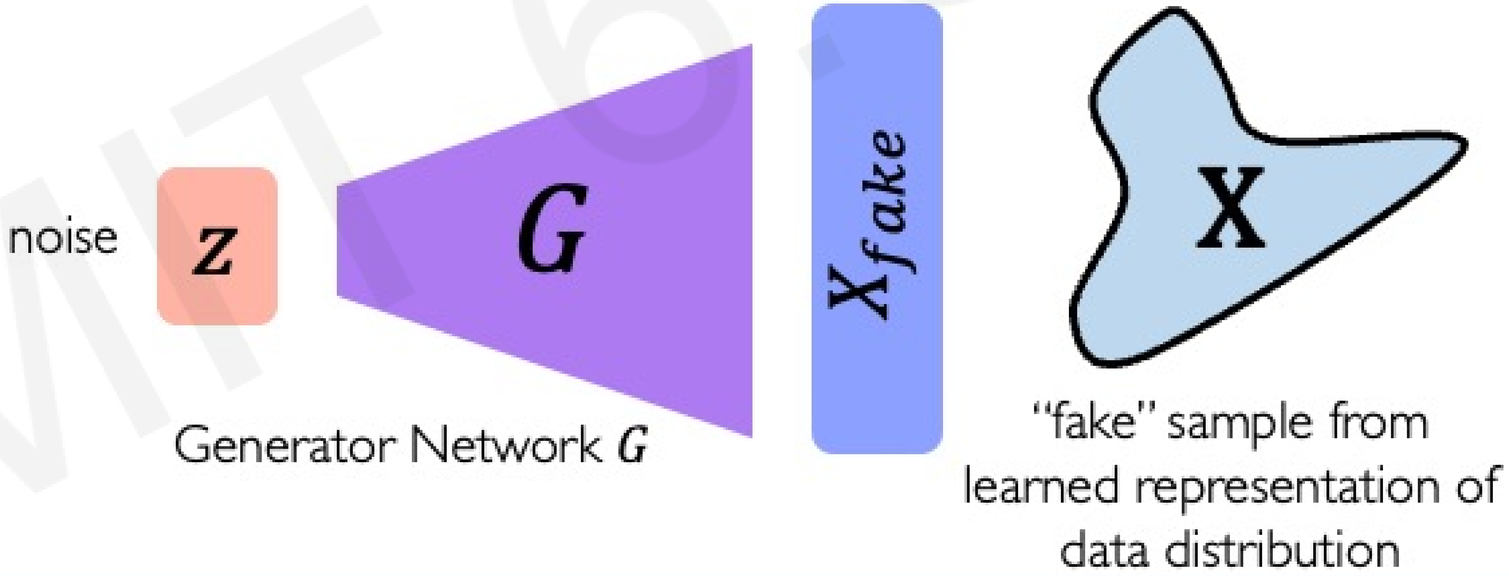
What if we just want to sample?

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 (e.g., noise), learn a transformation to the data distribution.



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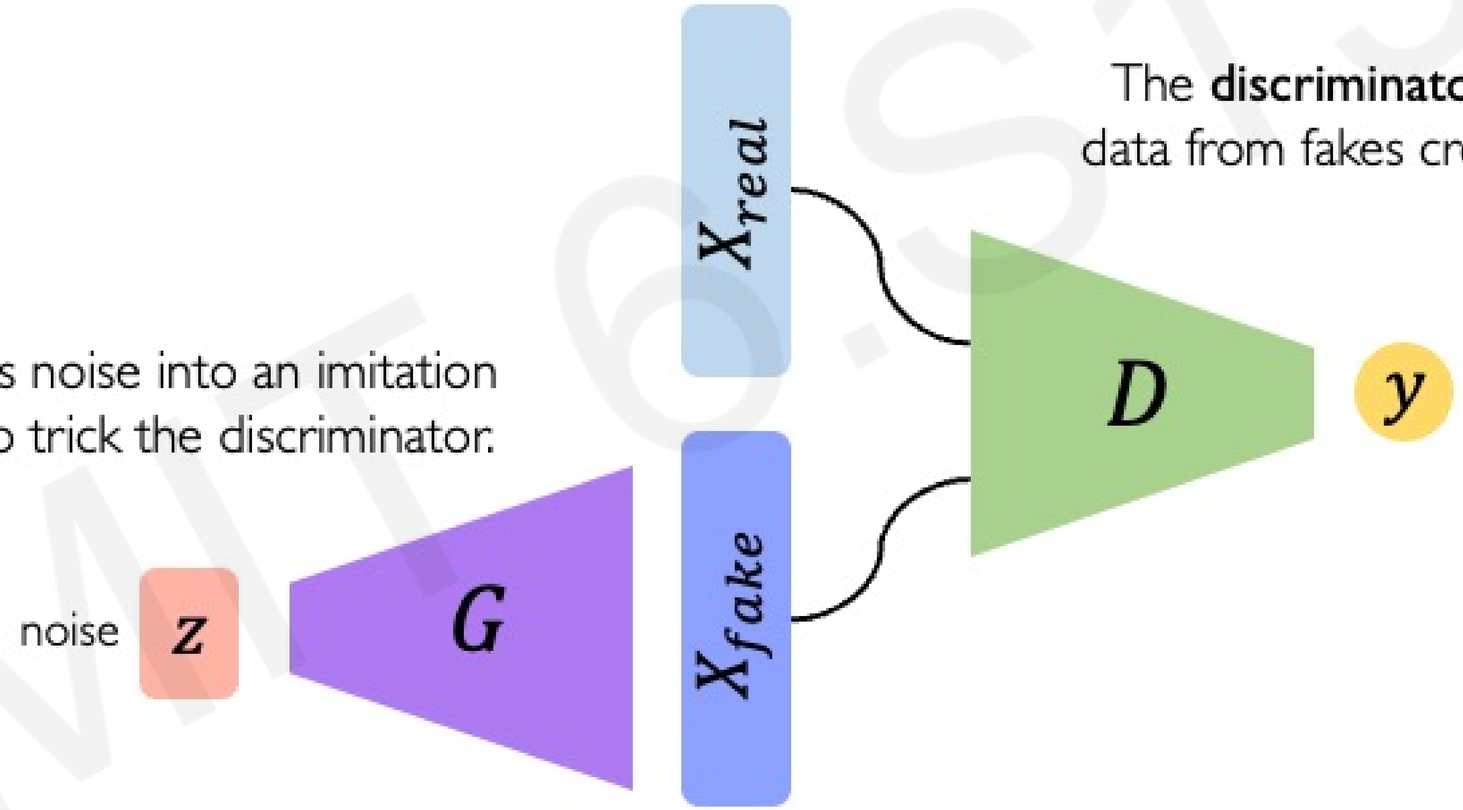
Generative Adversarial Networks (GANs)

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.



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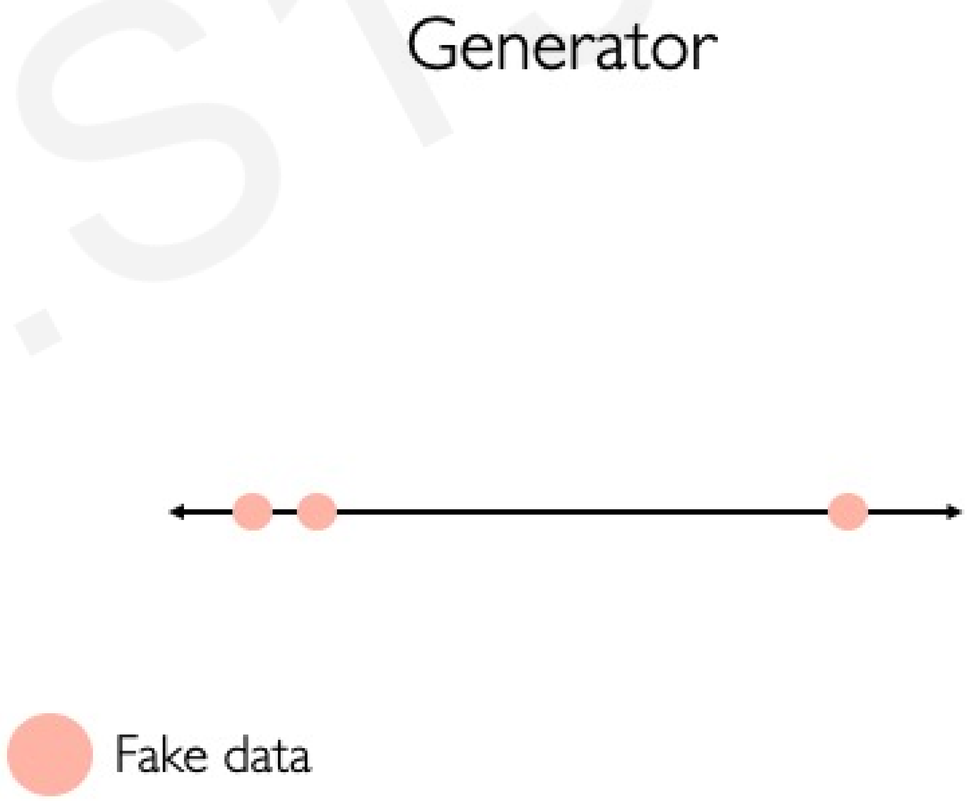
Intuition behind GANs

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



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Intuition behind GANs

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

Discriminator

Generator

Fake data

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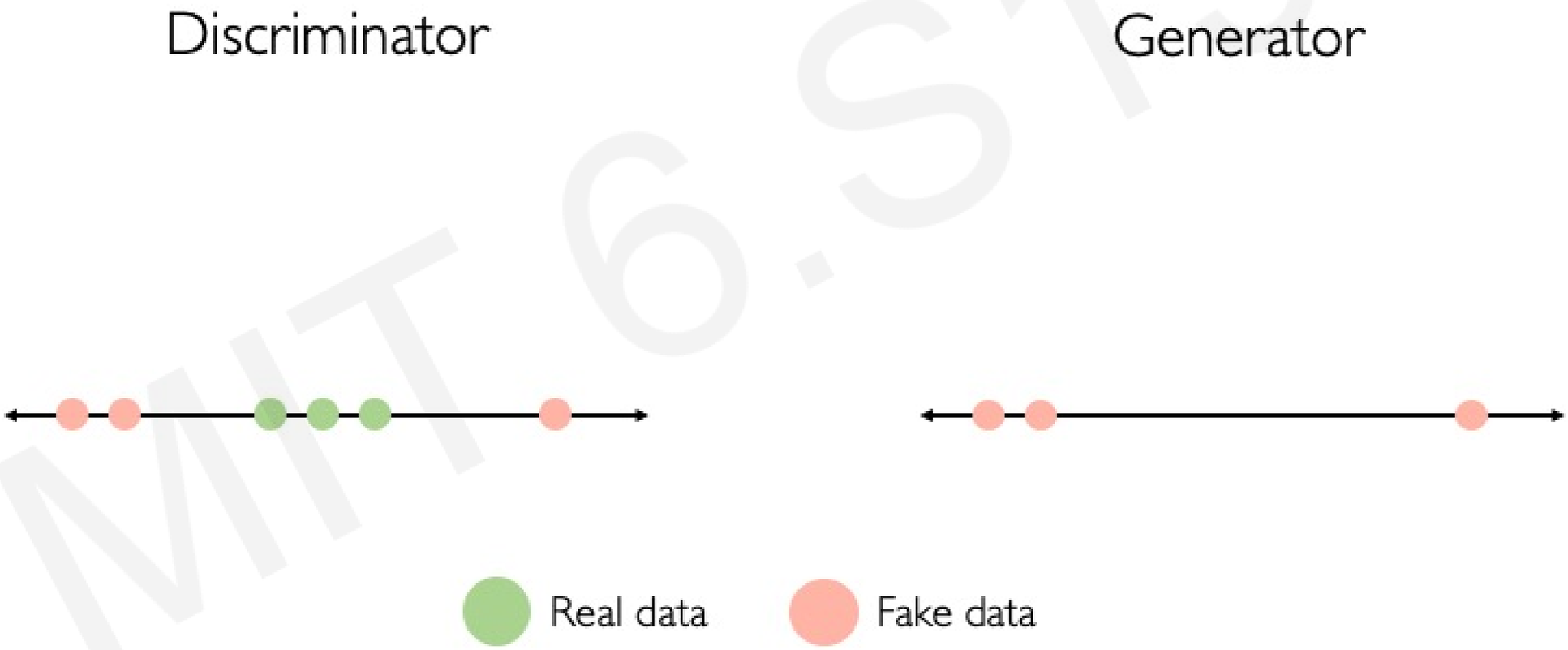
Intuition behind GANs

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



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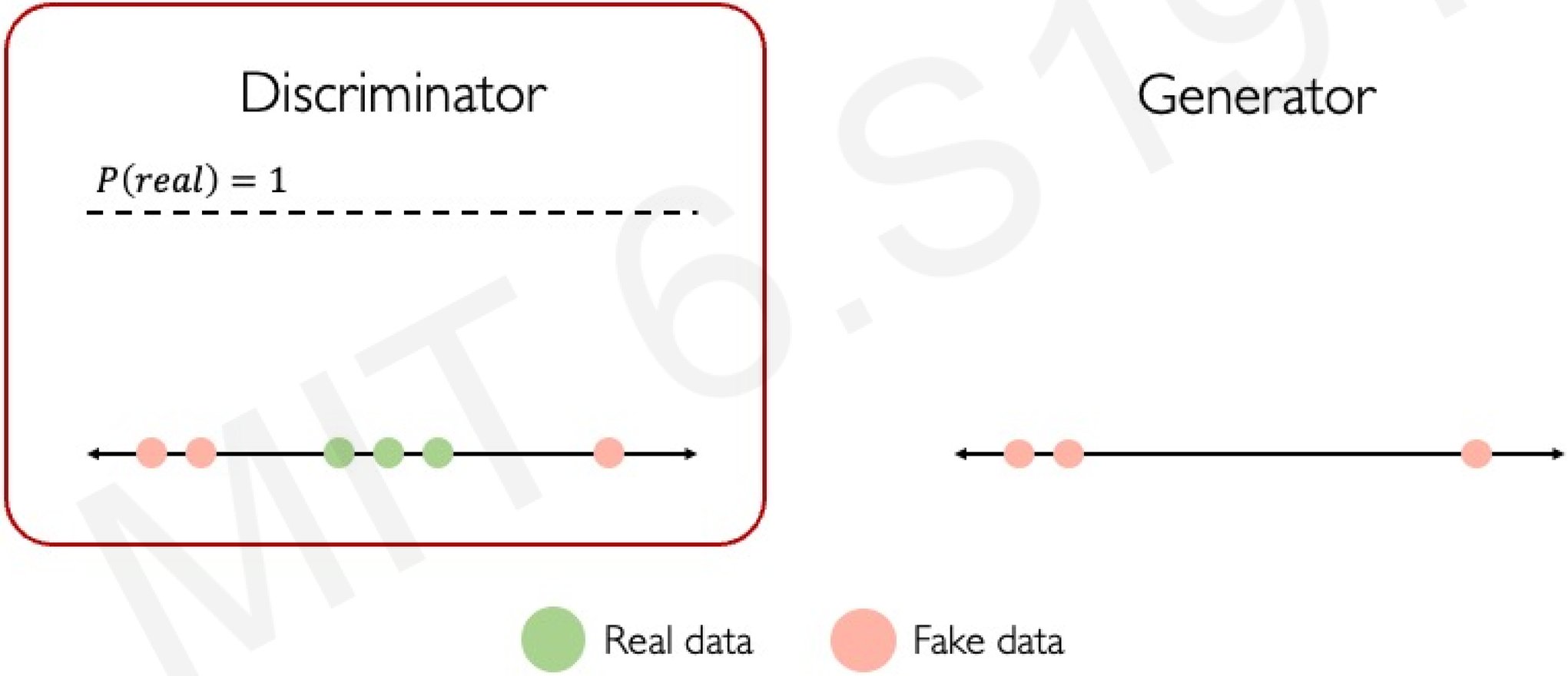
Intuition behind GANs

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



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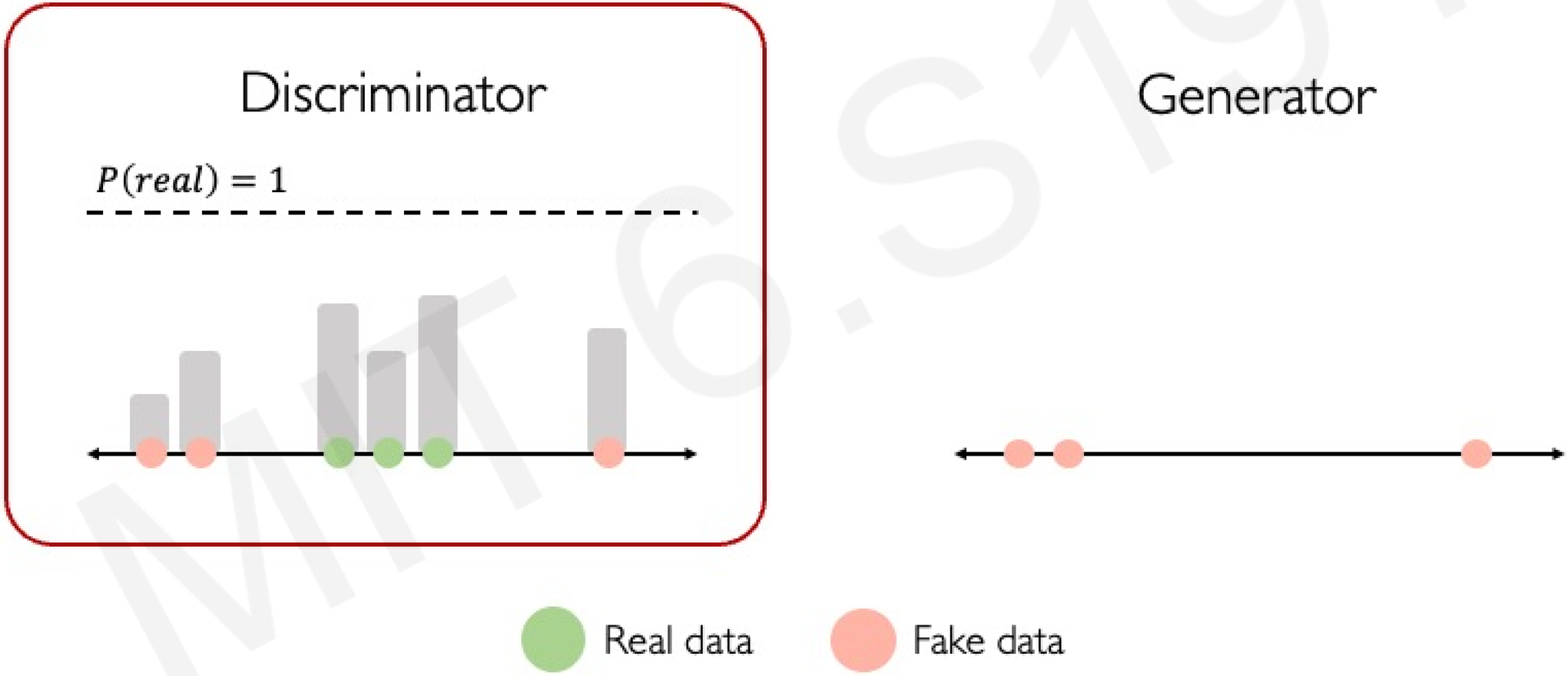

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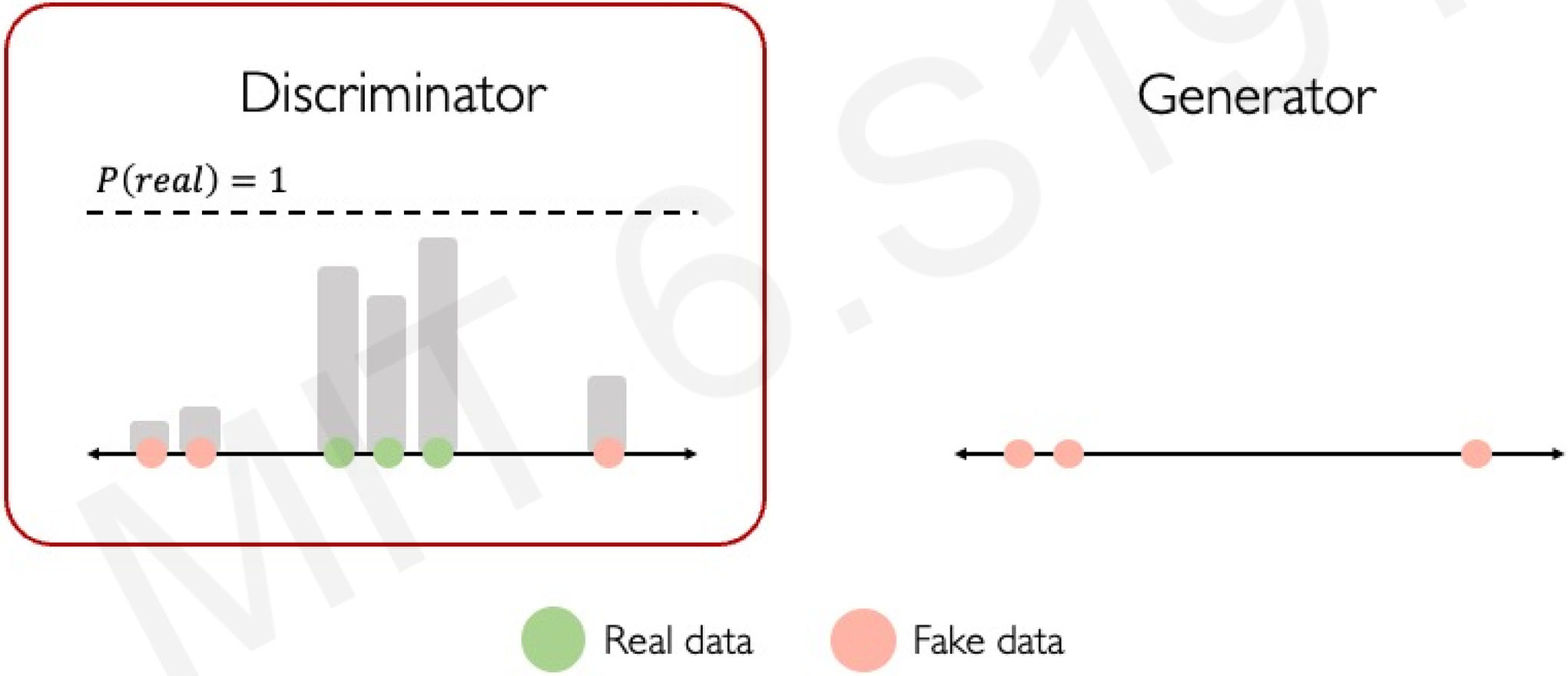

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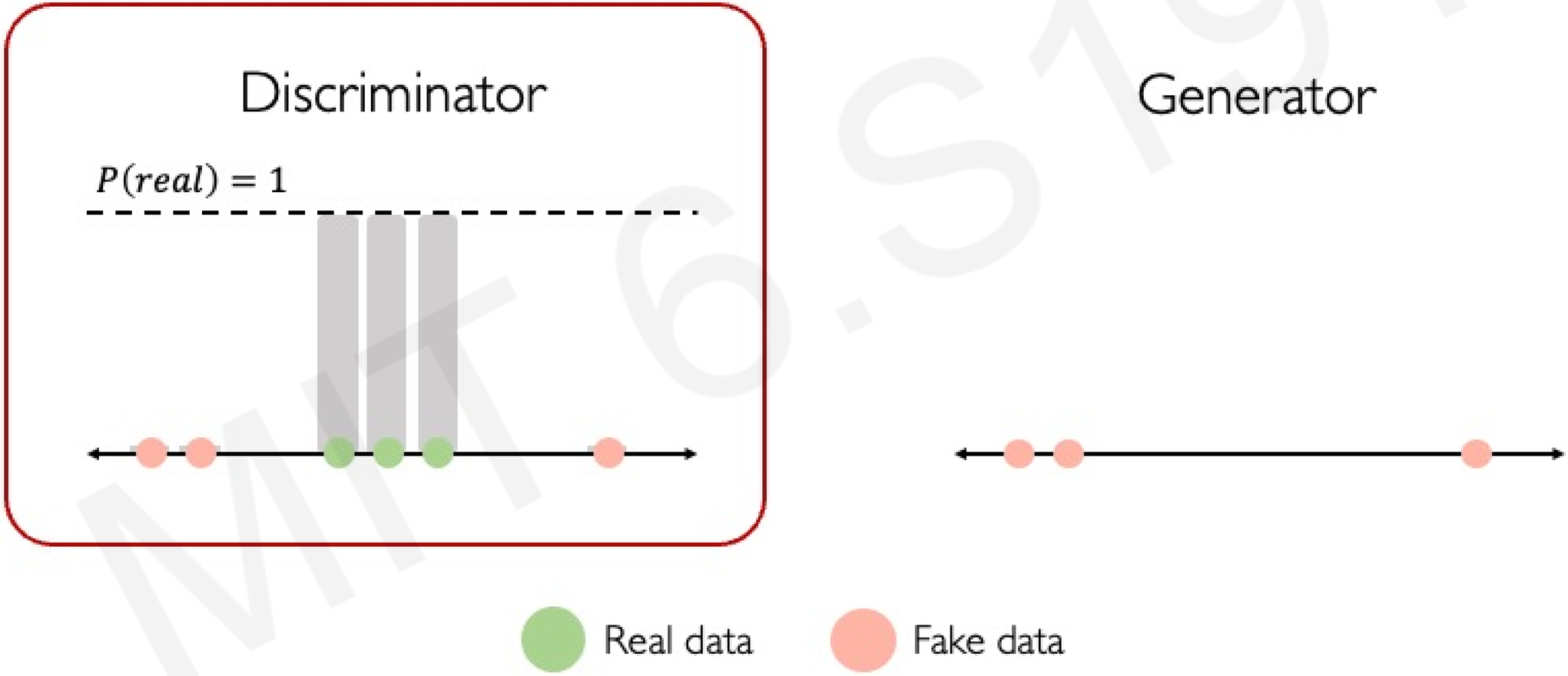

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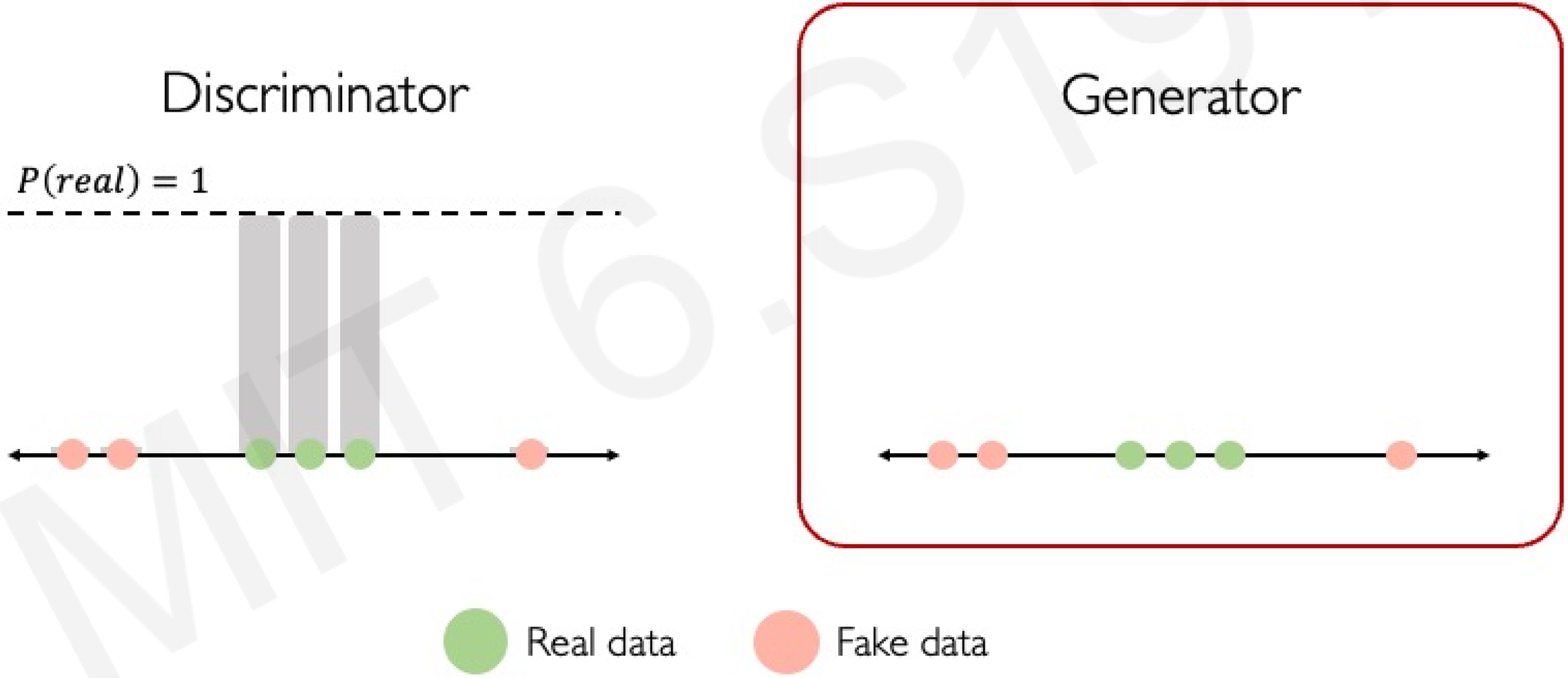
Intuition behind GANs

Generator tries to improve its imitation of the data.



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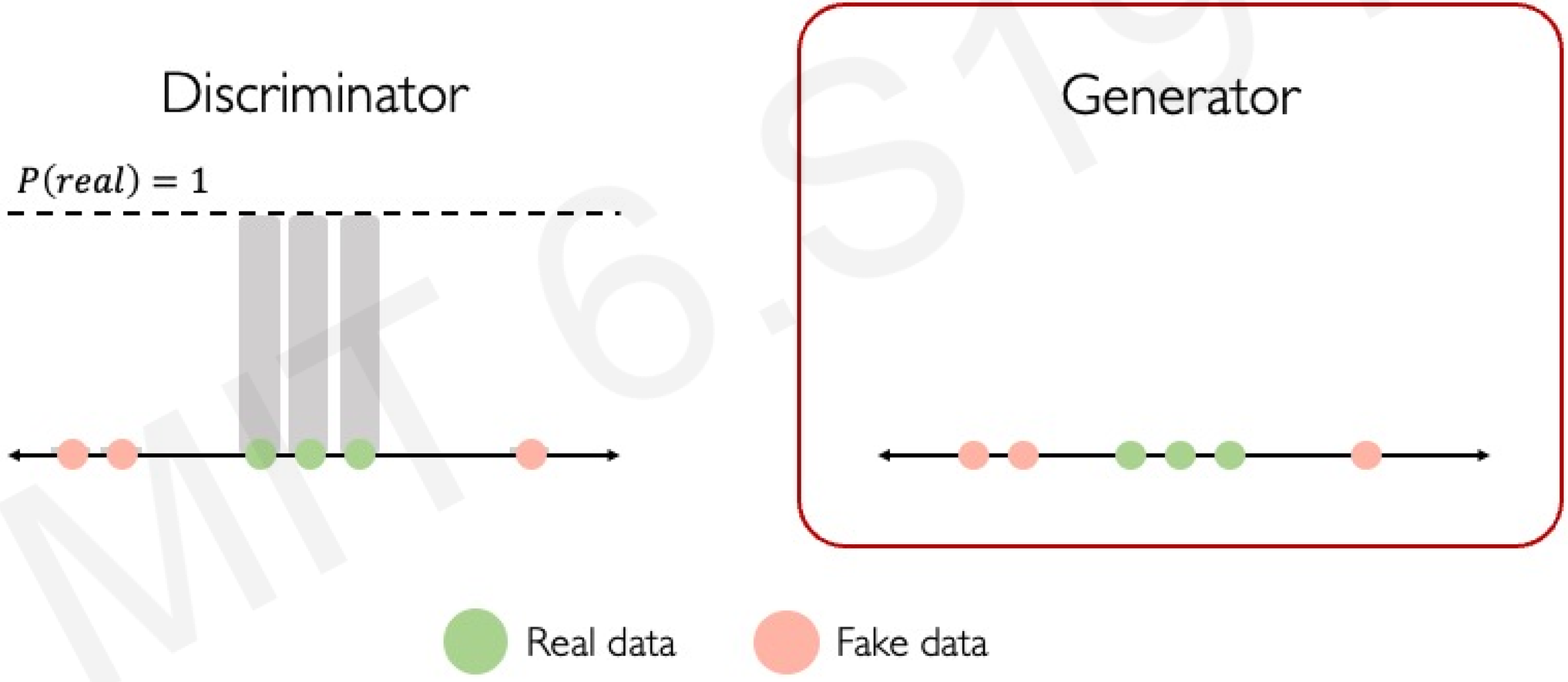

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Intuition behind GANs

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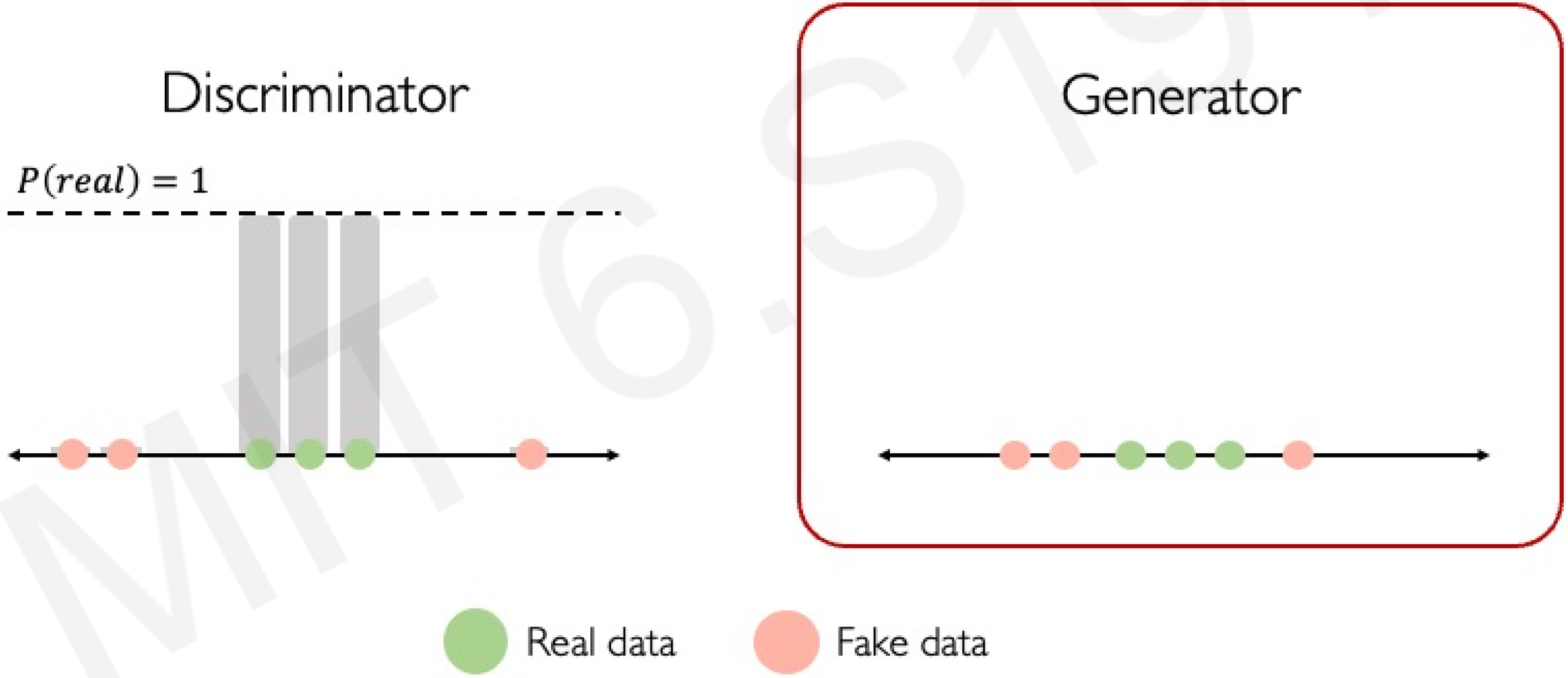

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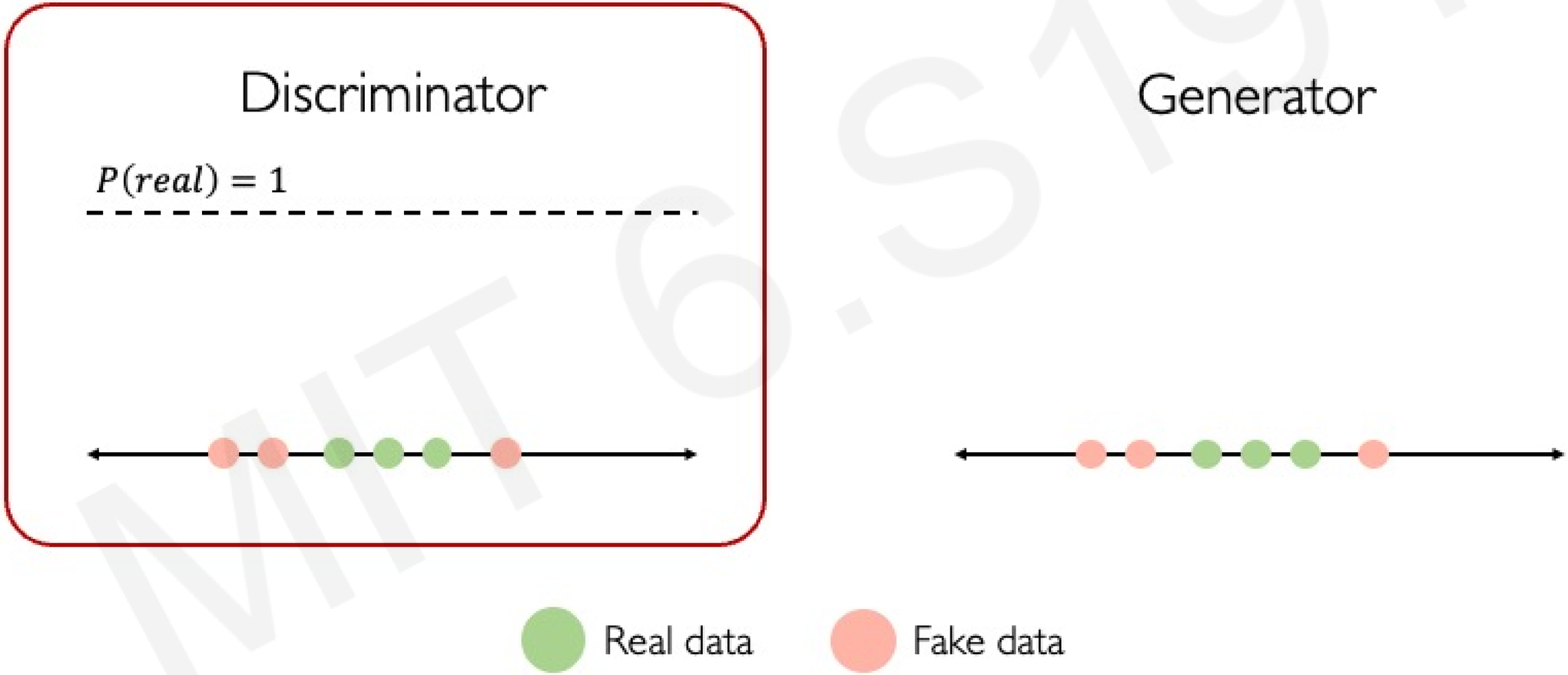
Intuition behind GANs

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



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Intuition behind GANs

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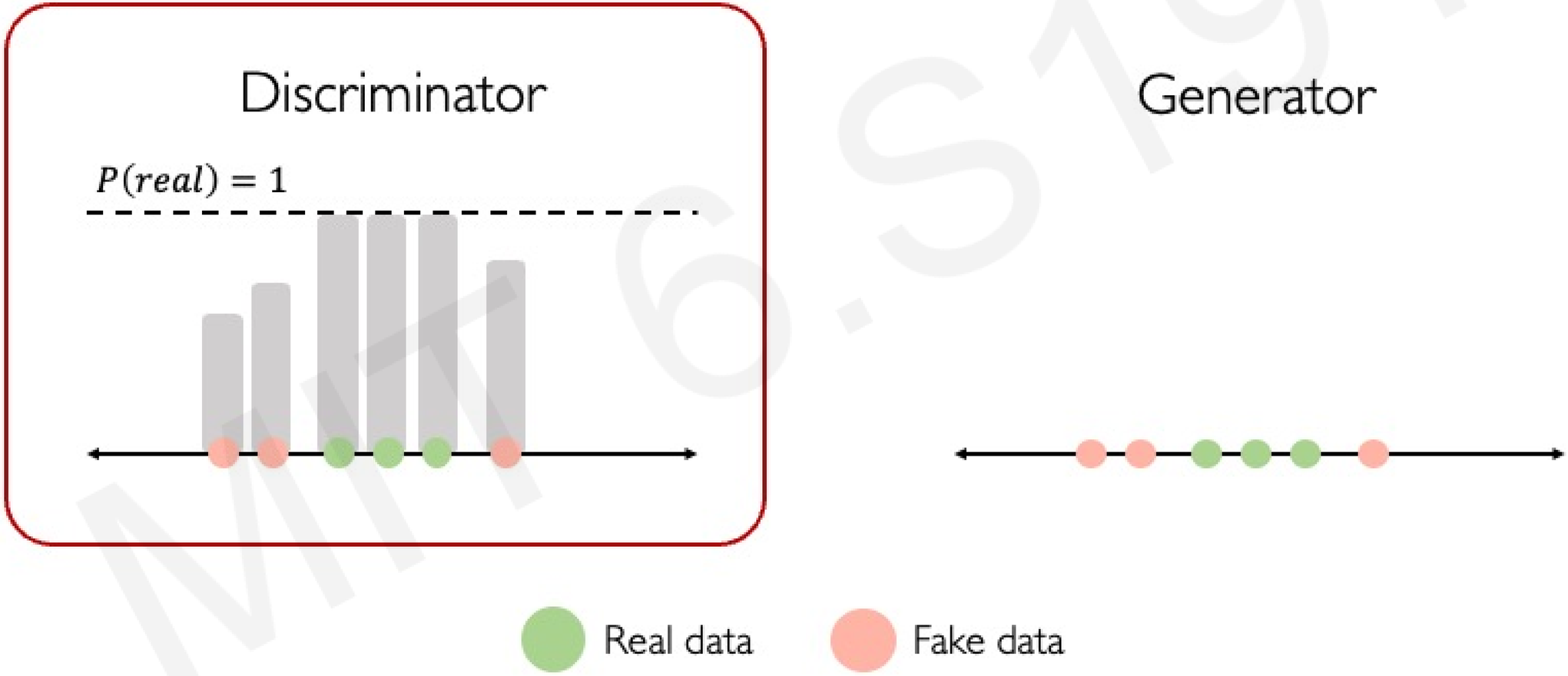

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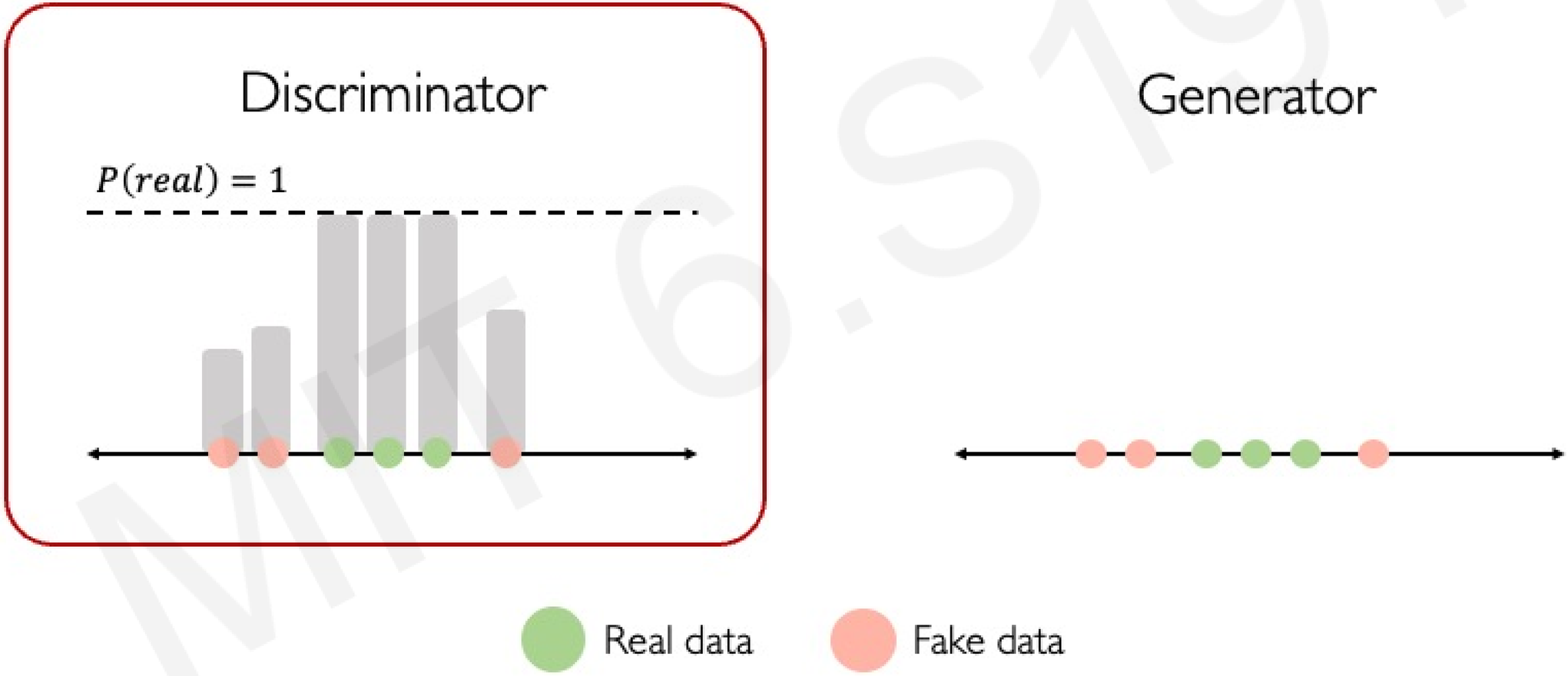

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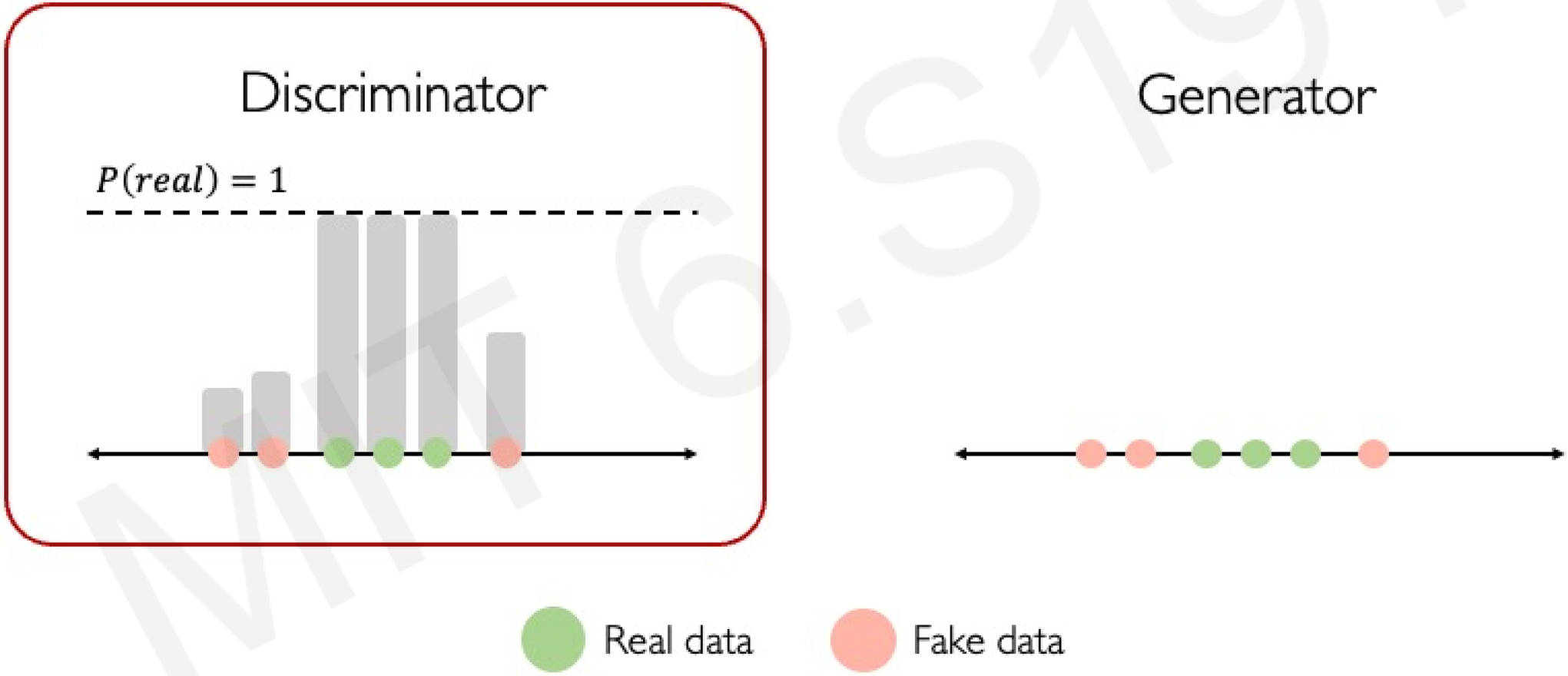

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Intuition behind GANs

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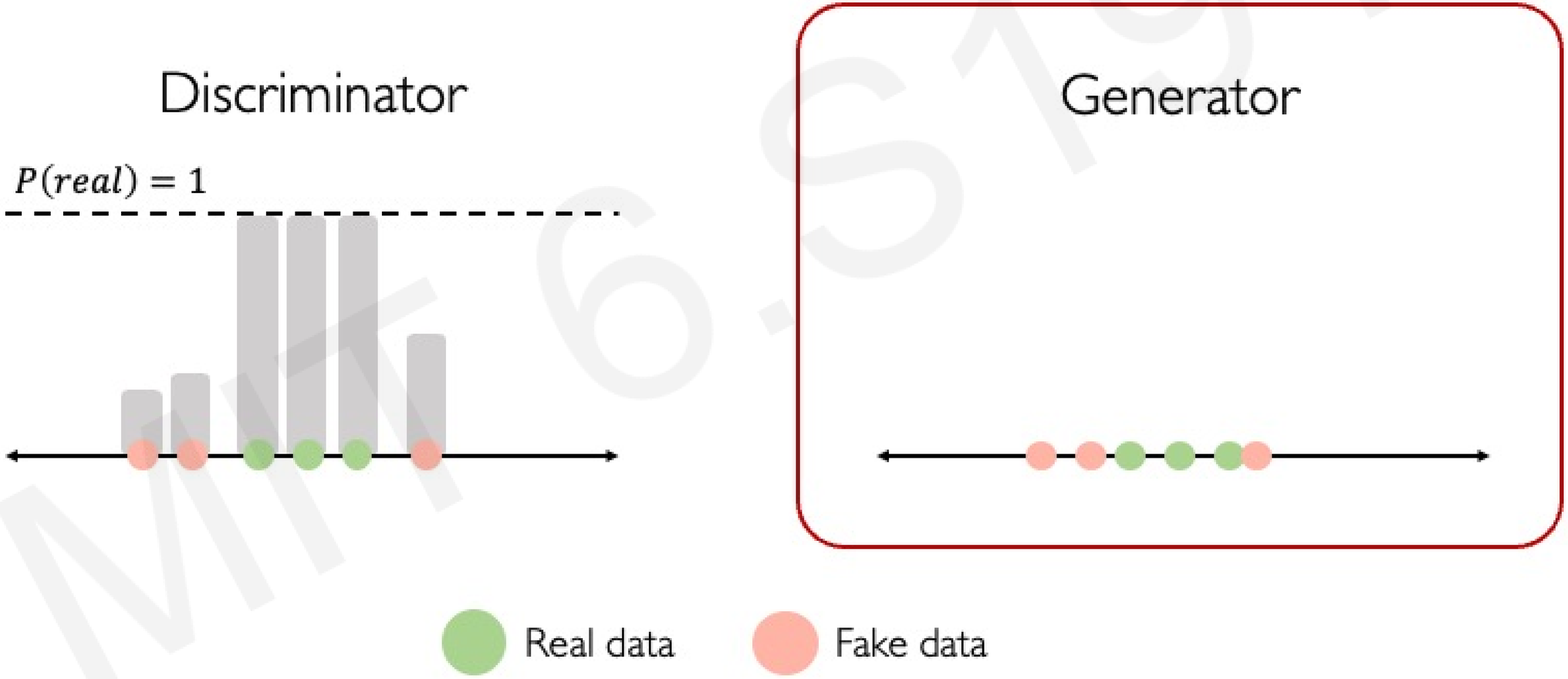

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Intuition behind GANs

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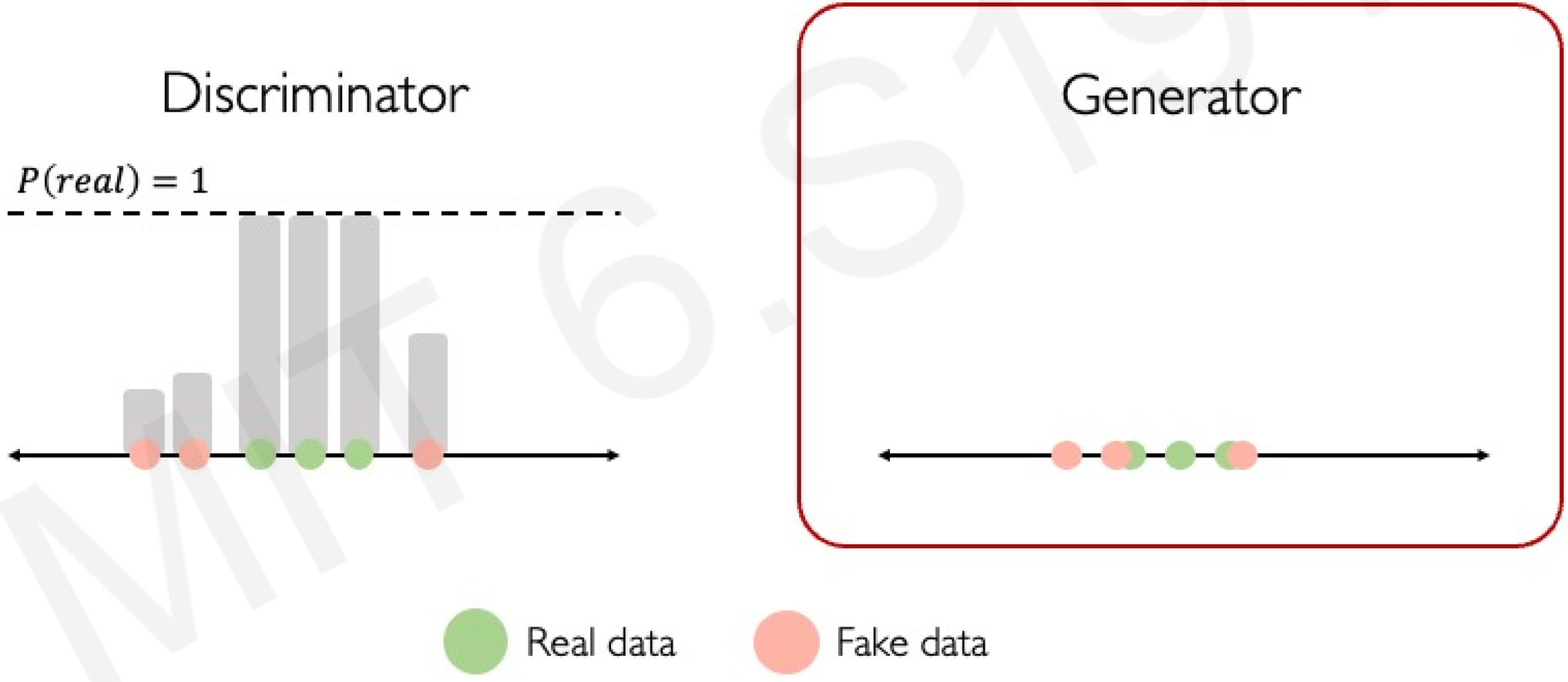

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Intuition behind GANs

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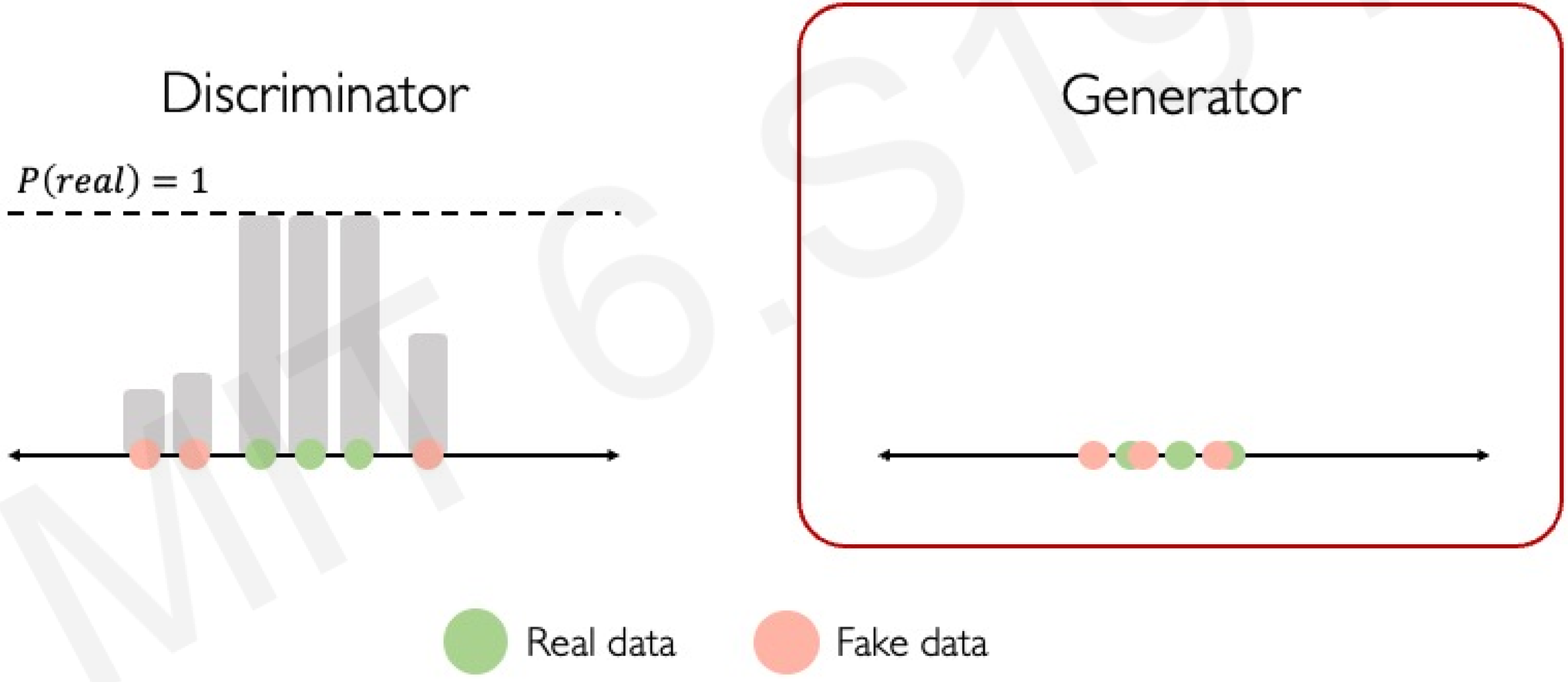

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Intuition behind GANs

Discriminator tries to identify real data from fakes created by the generator.
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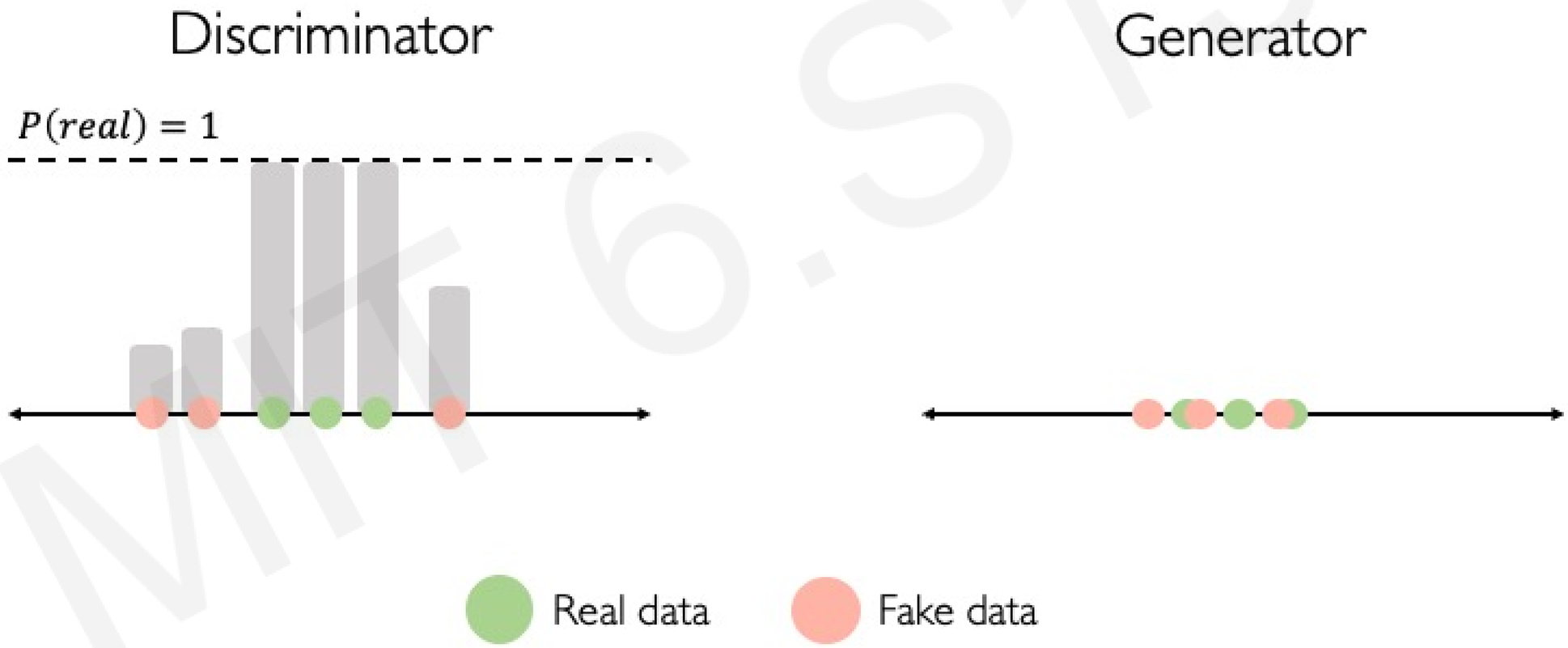

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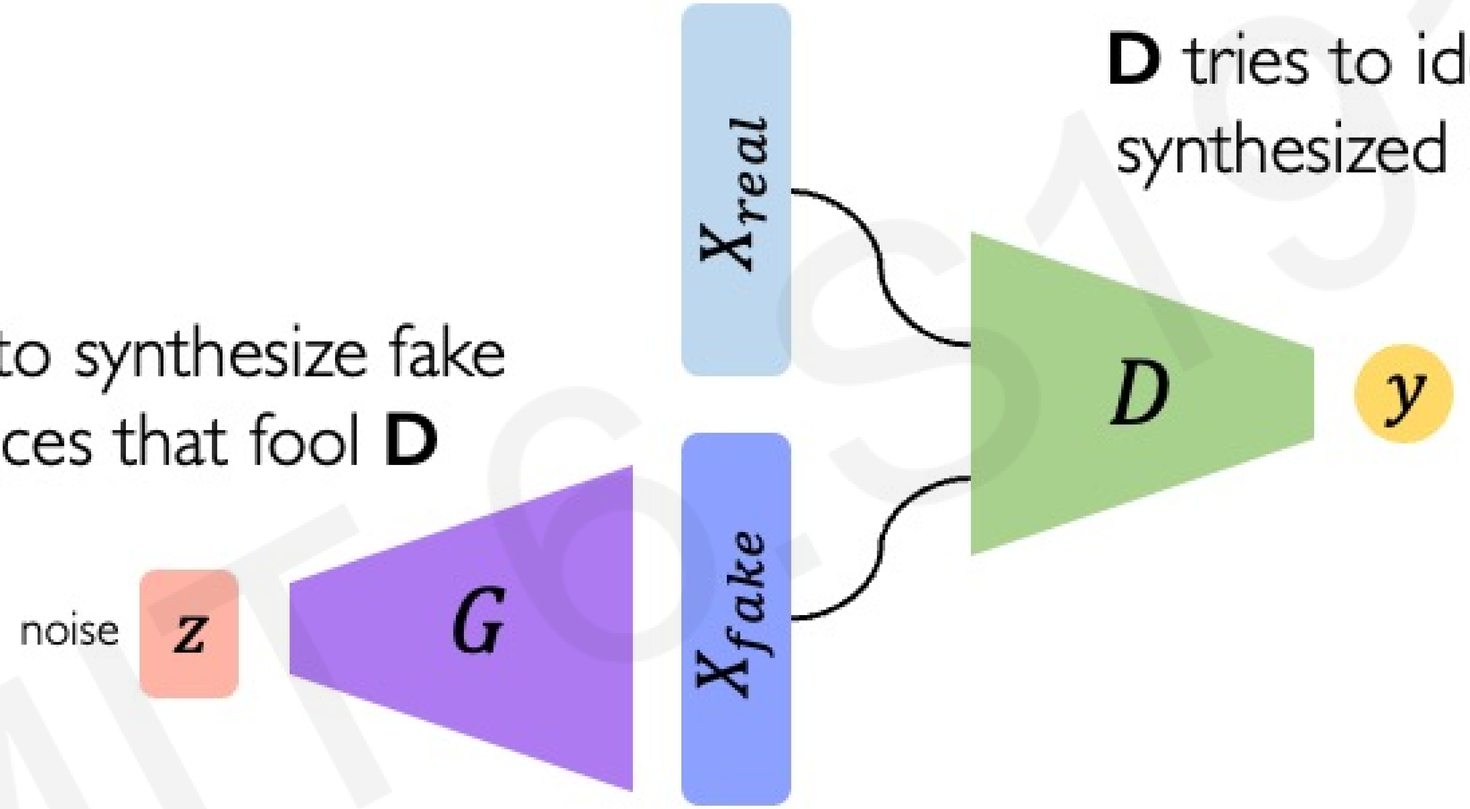
Training GANs

D tries to identify the synthesized instances

G tries to synthesize fake instances that fool **D**



Training: adversarial objectives for **D** and **G**

Global optimum: G reproduces the true data distribution

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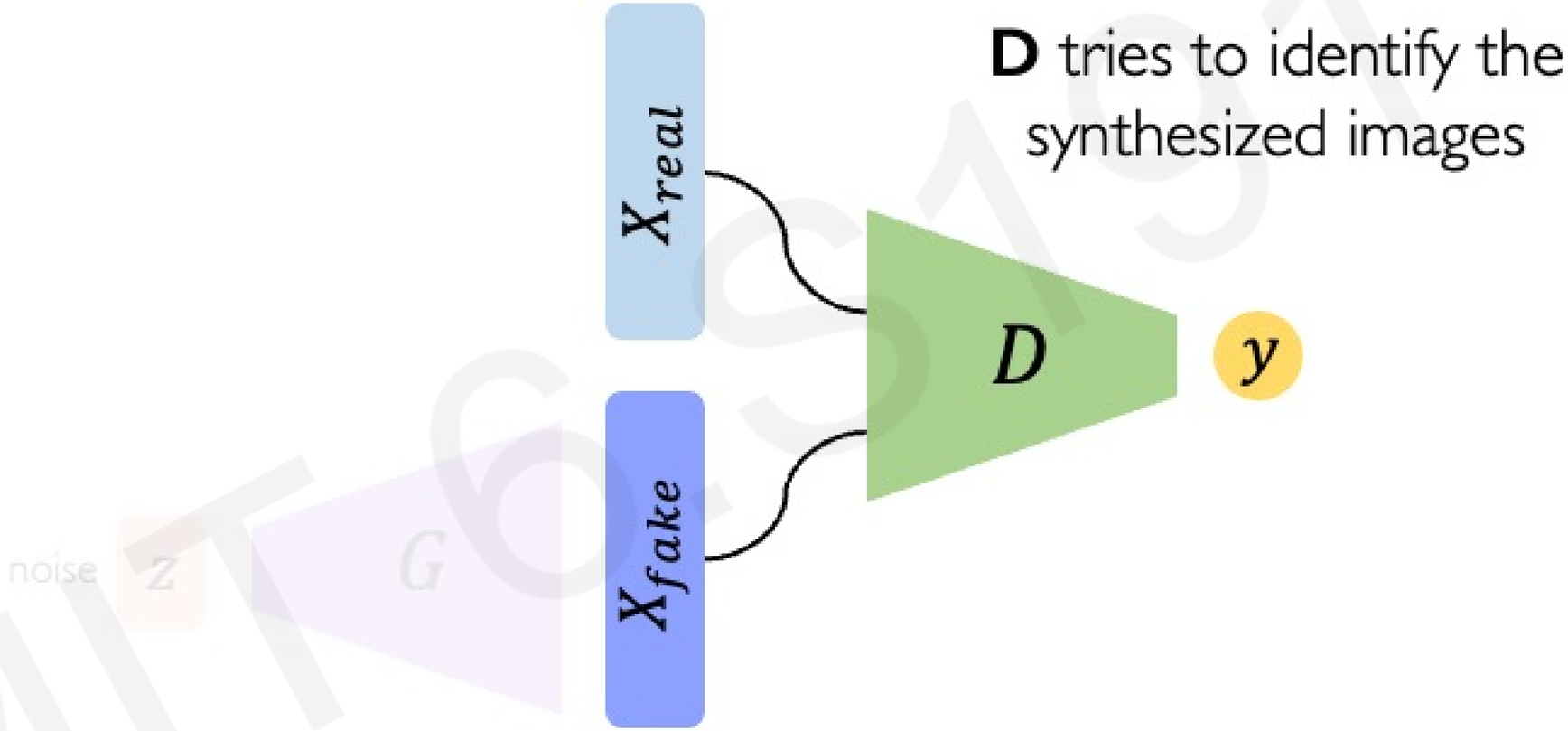
Training GANs: loss function

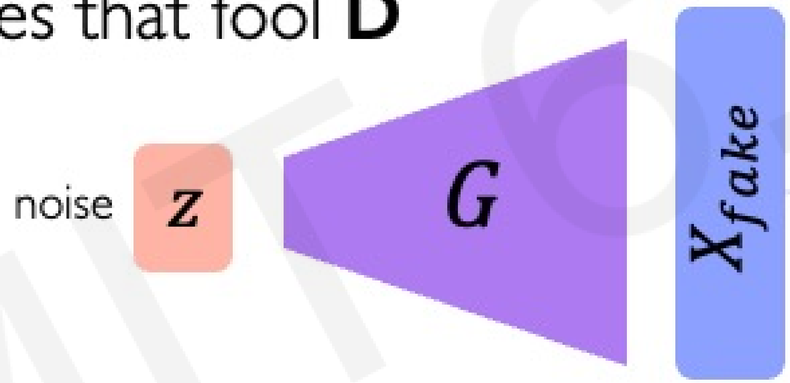


D tries to identify the synthesized images

$$\underbrace{\arg\max_{D}}\ \mathbb{E}_{\mathbf{z},\mathbf{x}}[\ \underbrace{\log D(G(\mathbf{z}))}_{\textbf{Fake}} + \underbrace{\log\left(1 - D(\mathbf{x})\right)}_{\textbf{Real}}\ ]$$

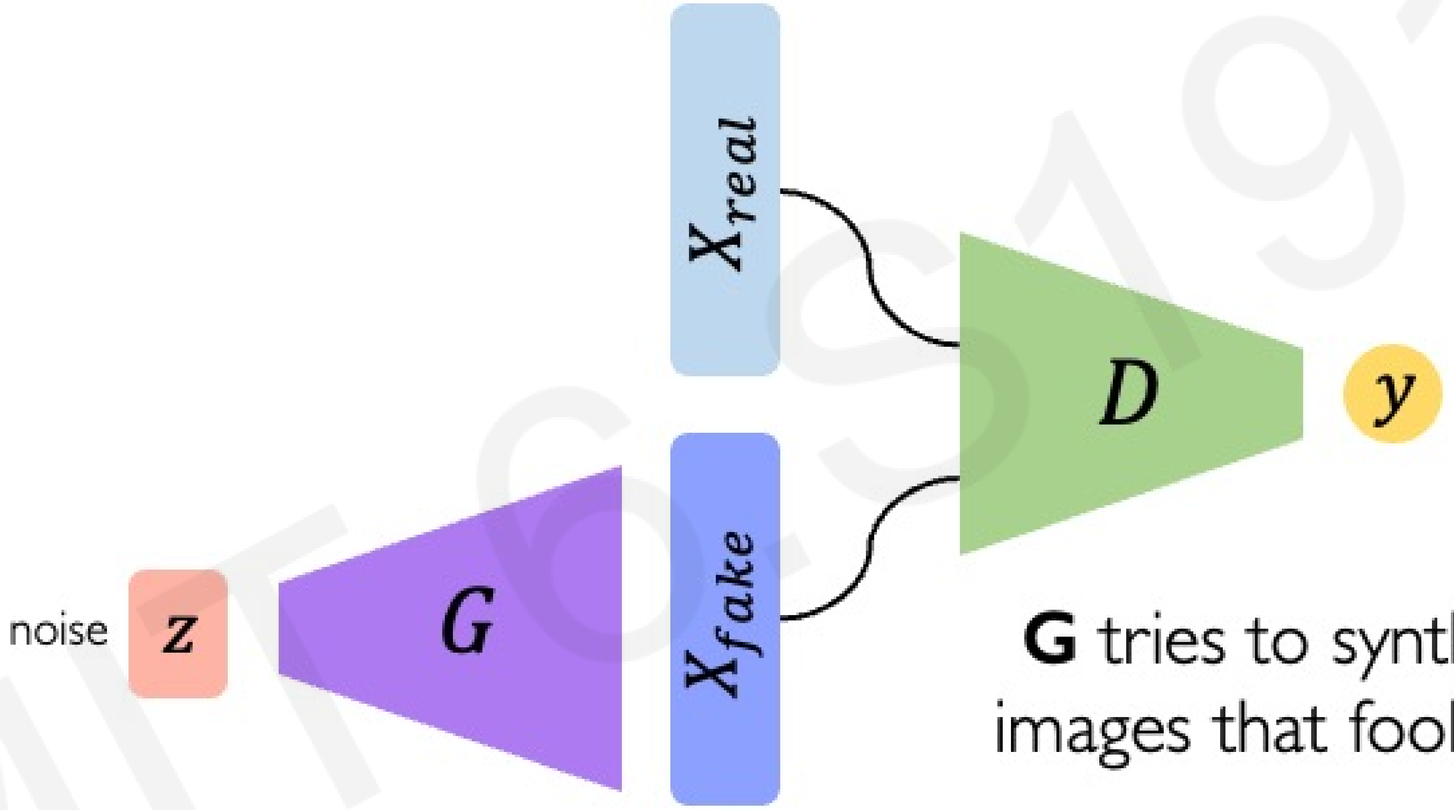
Training GANs: loss function

G tries to synthesize fake images that fool **D**



$$\arg\min_{G} \mathbb{E}_{\mathbf{z},\mathbf{x}}[\, \log D(G(\mathbf{z})) + \log(1 - D(\mathbf{x}))\,]$$

Training GANs: loss function



G tries to synthesize fake images that fool the *best* **D**

$$\arg\min_{G}\max_{D}\ \mathbb{E}_{\mathbf{z},\mathbf{x}}[\ \log D(G(\mathbf{z})) + \log\left(1 - D(\mathbf{x})\right)\ ]$$

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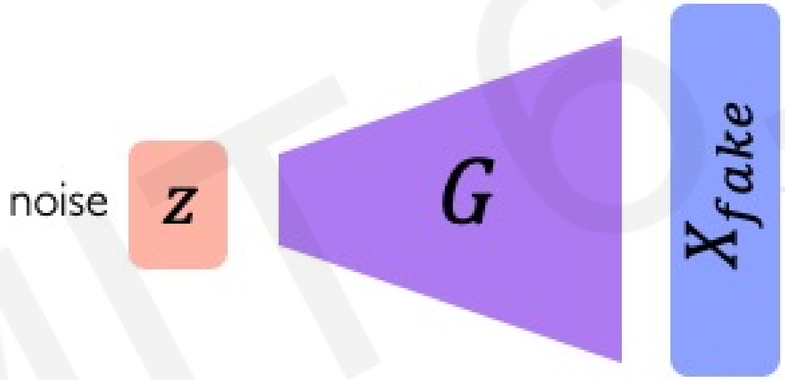
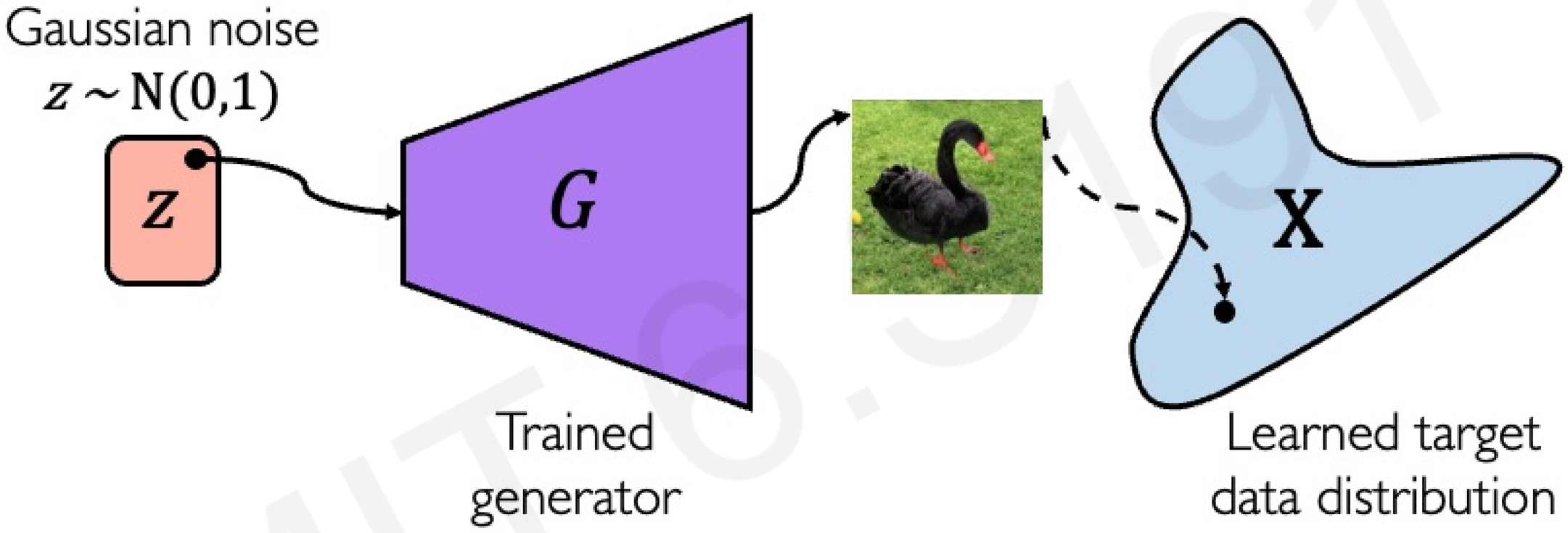
Generating new data with GANs



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

GANs are distribution transformers



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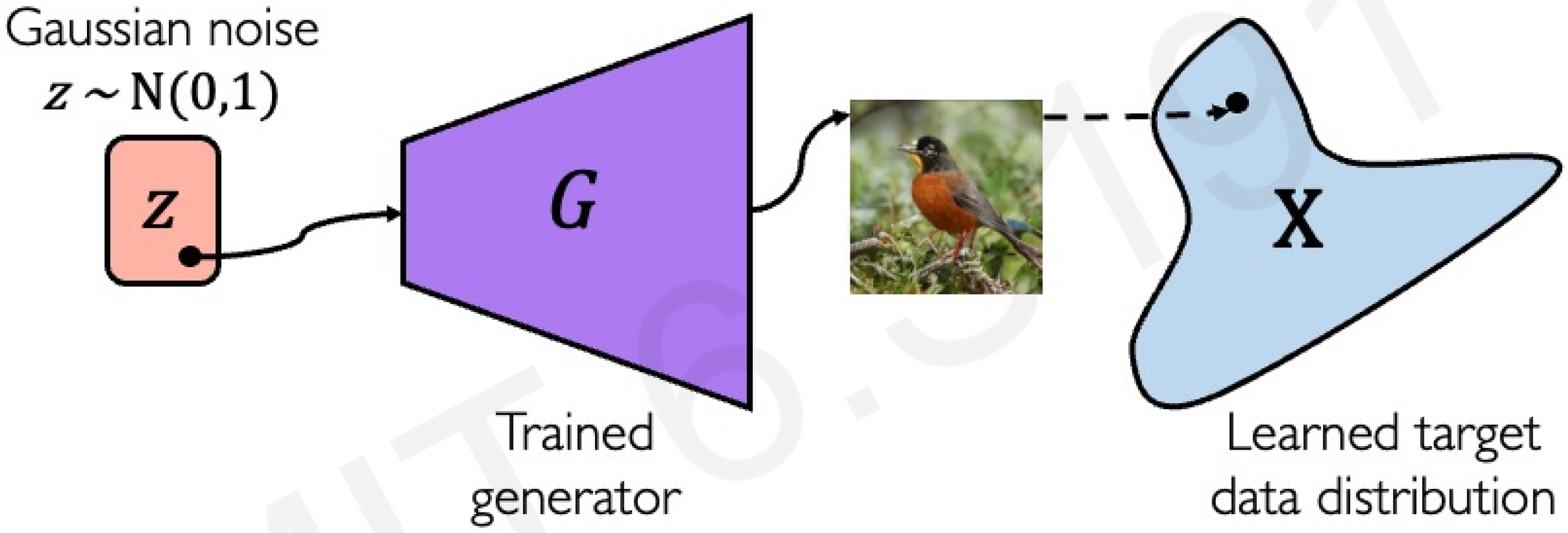
GANs are distribution transformers



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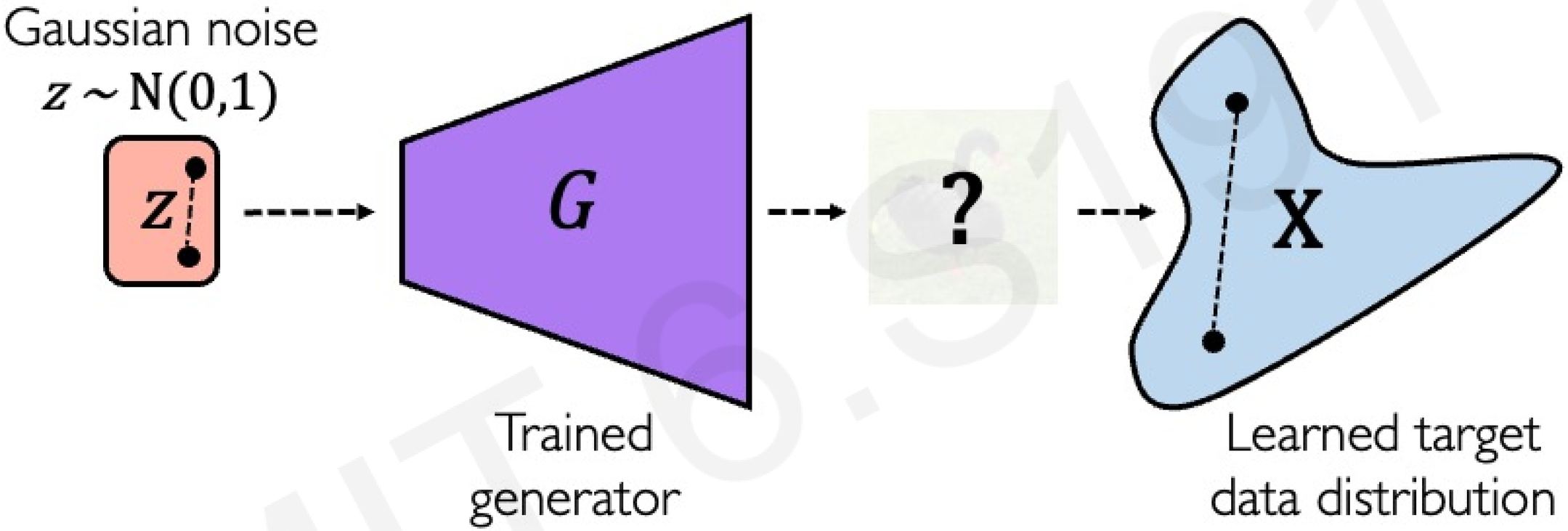
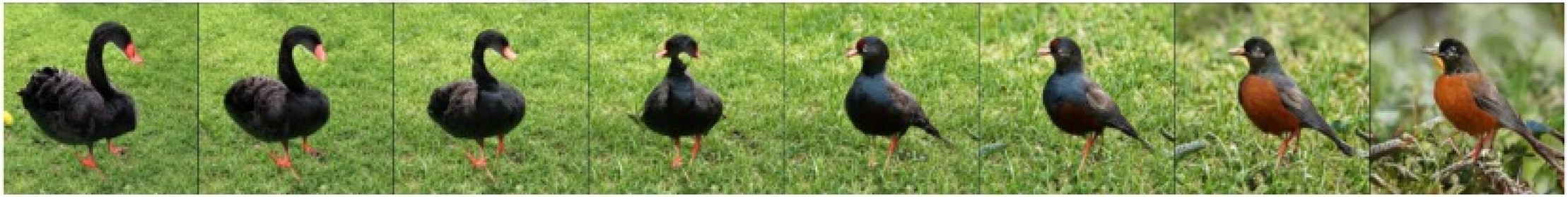
GANs are distribution transformers





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GANs: Advances and Applications

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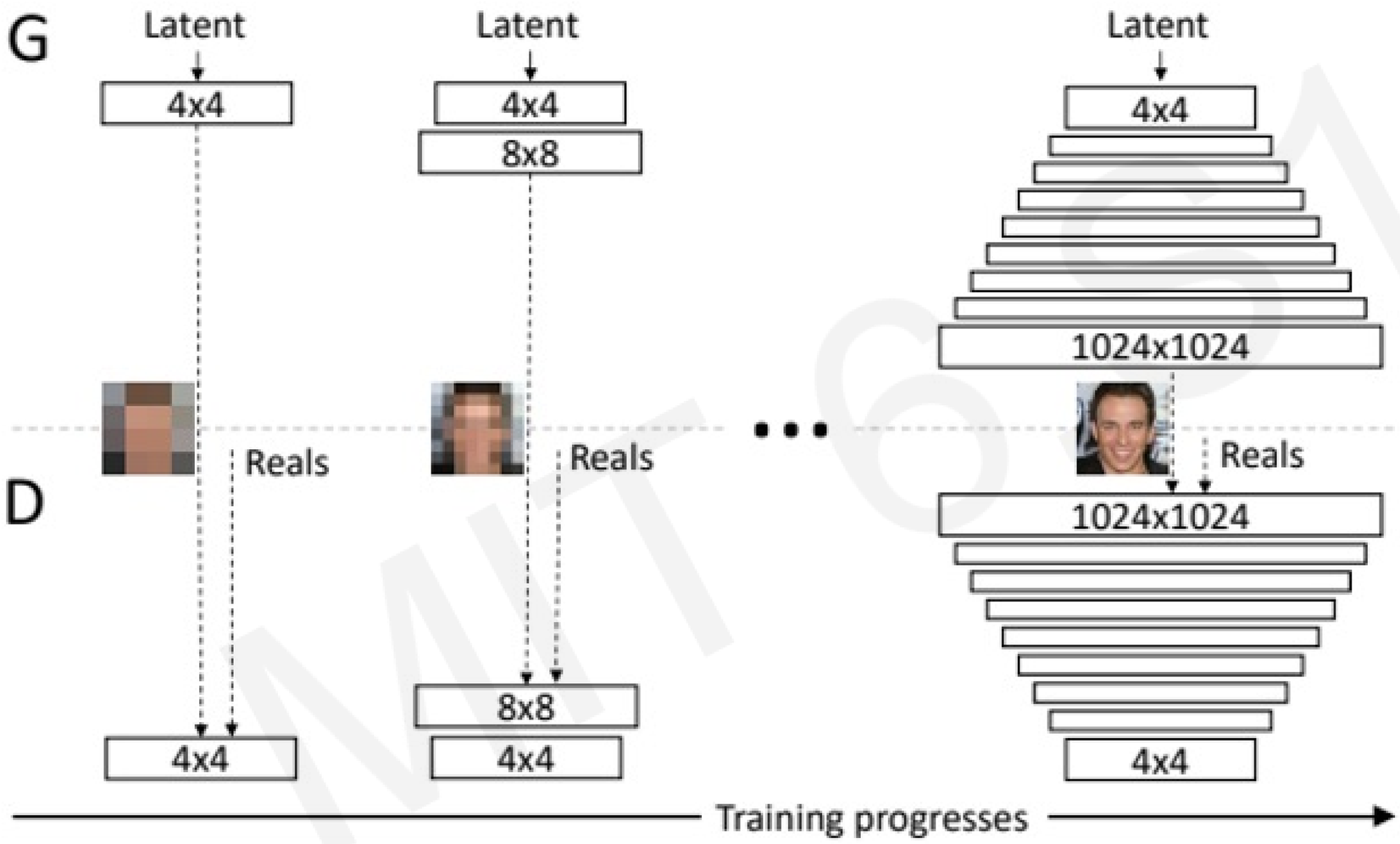
Progressive growing of GANs



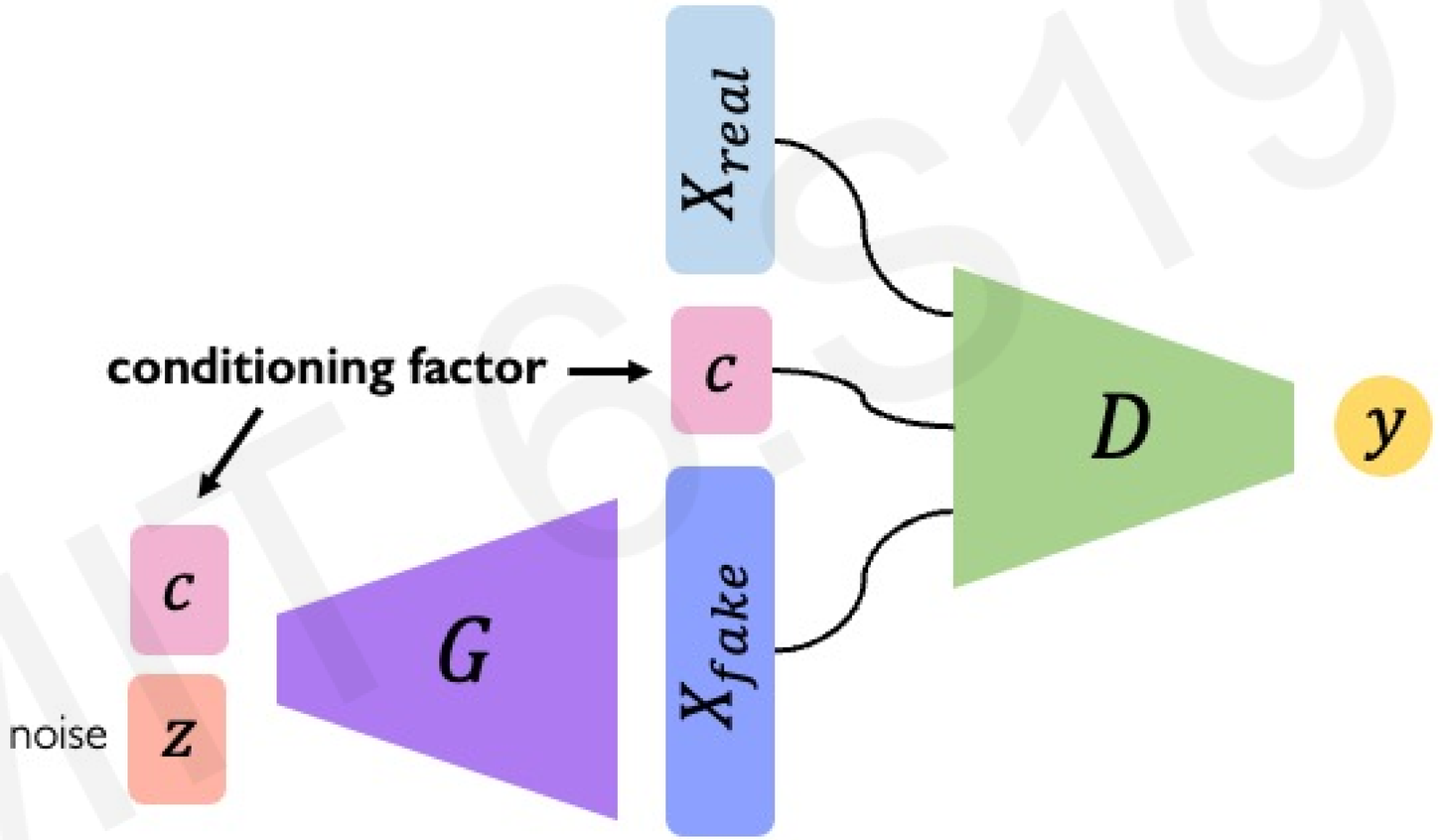
Karras+ *ICLR* 2018; Karras+ *arXiv* 2019. 1/10/23

Progressive growing of GANs: results

Karras+ *ICLR* 2018. 1/10/23

Conditional GANs

What if we want to control the nature of the output, by **conditioning** on a label?



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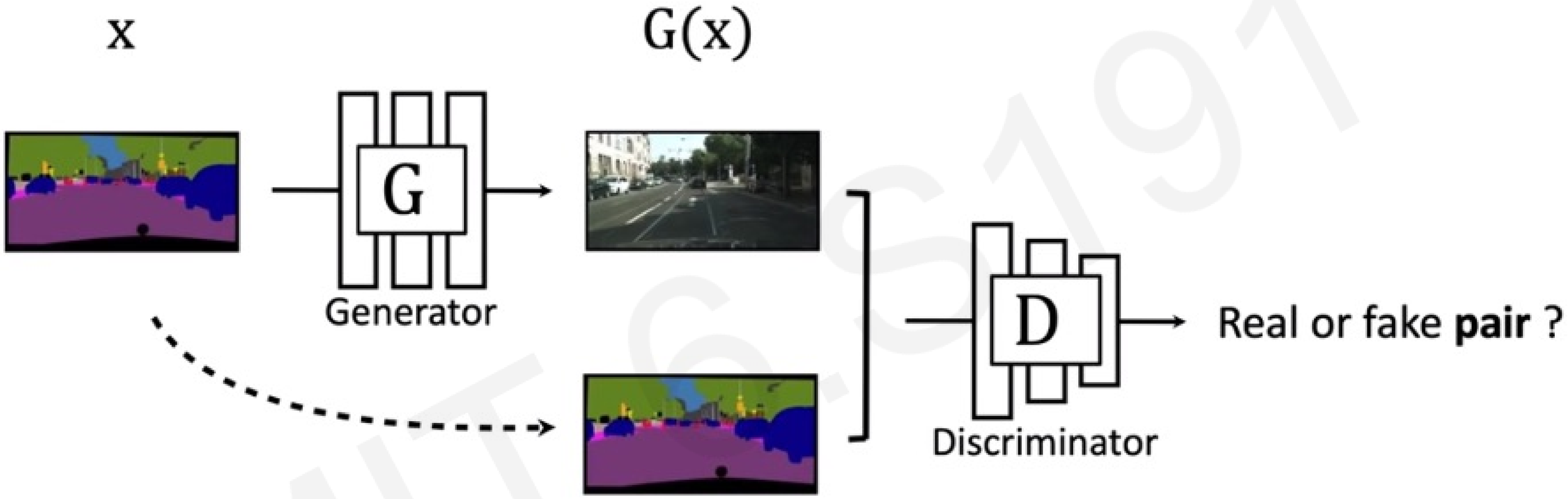
Conditional GANs and pix2pix: paired translation



The discriminator, D, classifies between fake and real **pairs**.
The generator, G, learns to fool the discriminator.

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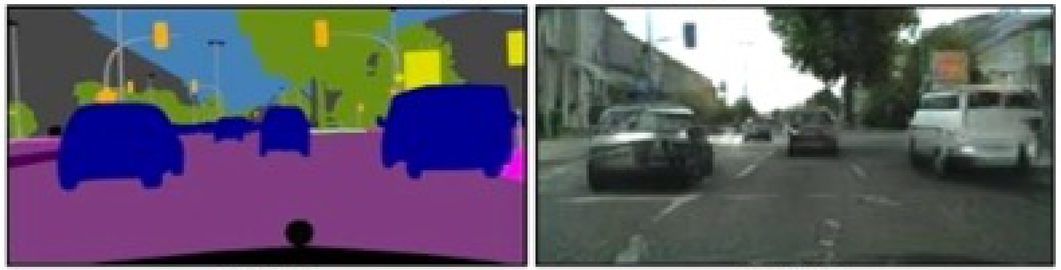
Applications of paired translation

Labels to Street Scene



input output

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Paired translation: results

Map → Aerial View

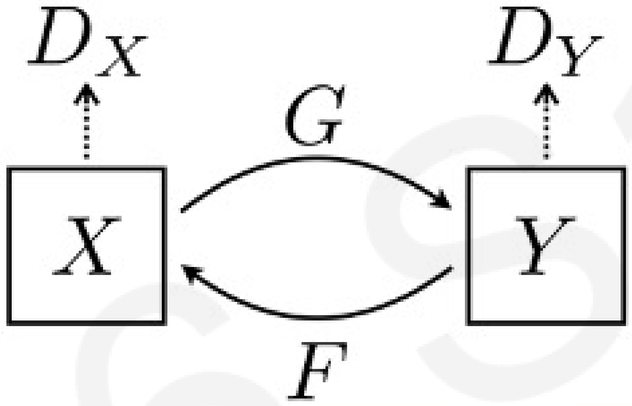
input **output**

Aerial View → Map

input **output**

CycleGAN: domain transformation

CycleGAN learns transformations across domains with unpaired data.



Zhu+ *ICCV* 2017. 1/10/23

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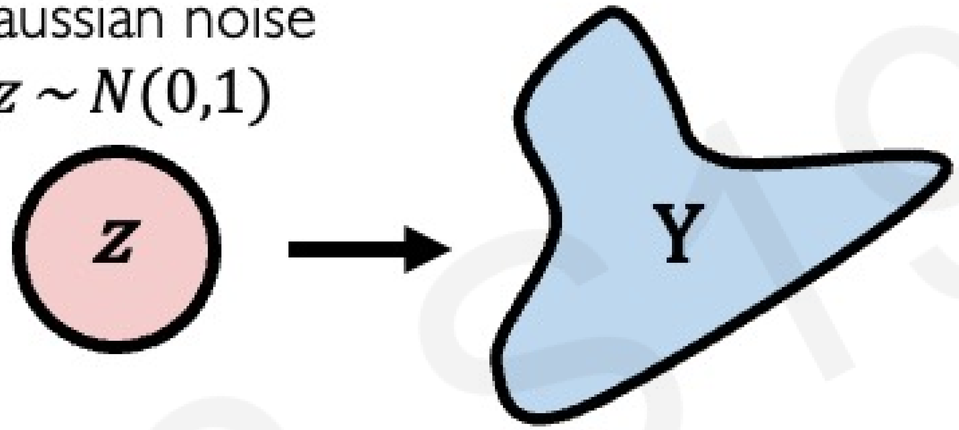
Distribution transformations

GANs:

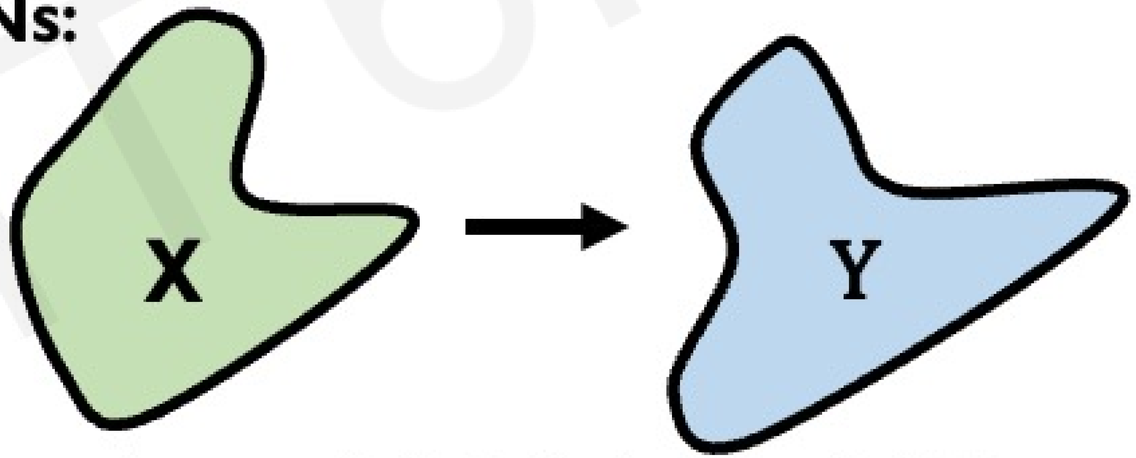
Gaussian noise

$z \sim N(0,1)$



Gaussian noise → target data manifold

CycleGANs:



data manifold X → data manifold Y

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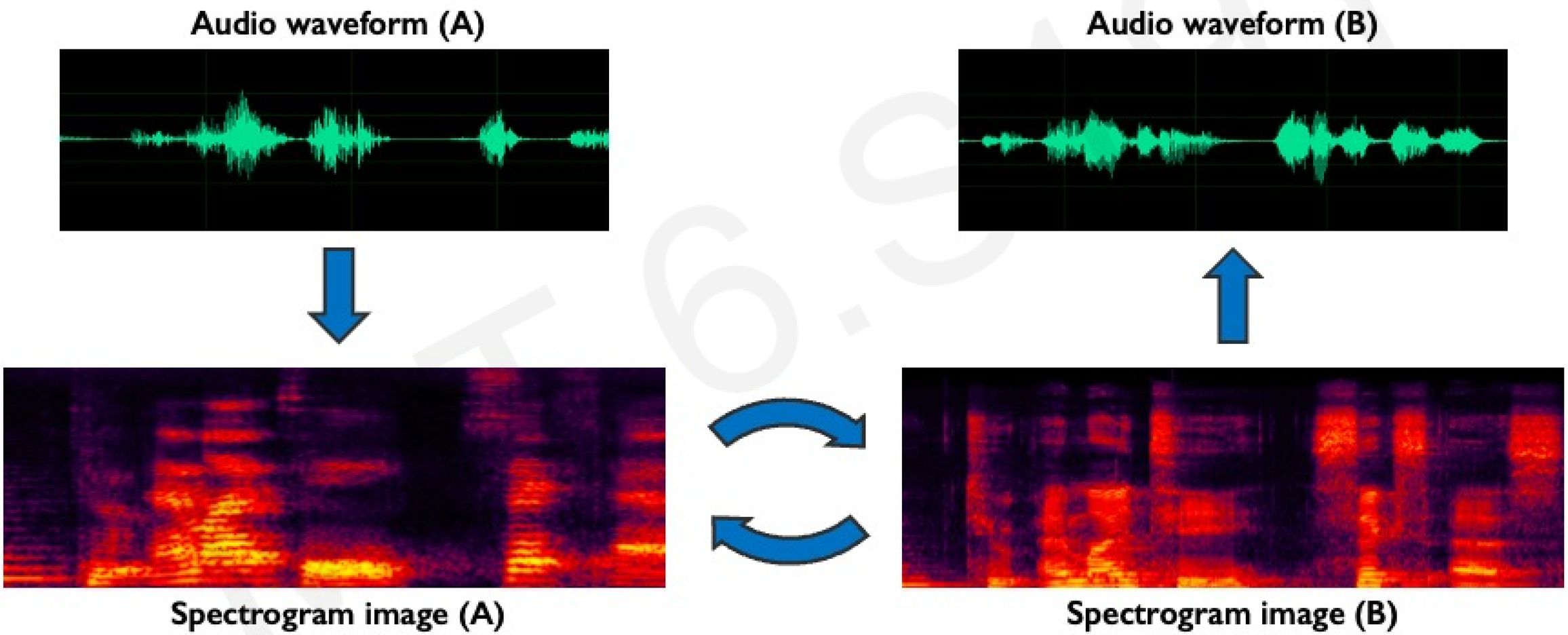
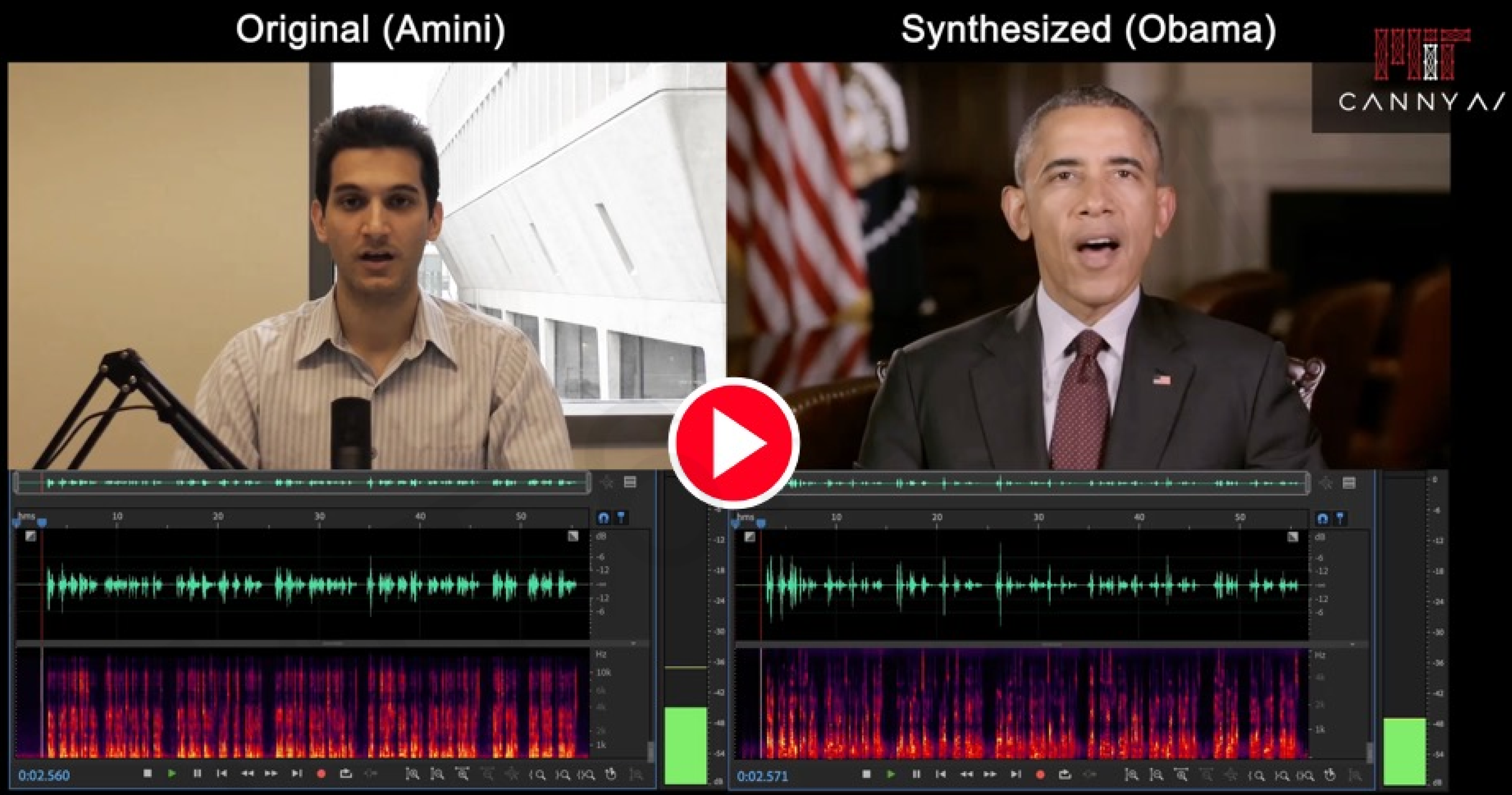
CycleGAN: transforming speech

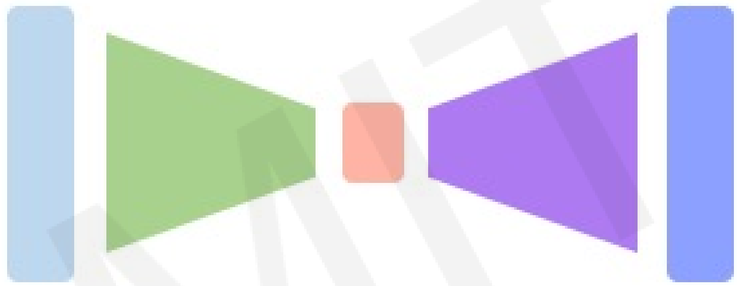



Original (Amini)
Synthesized (Obama)
CANNYAI
0:02.560
0:02.571

Deep Generative Modeling: Summary

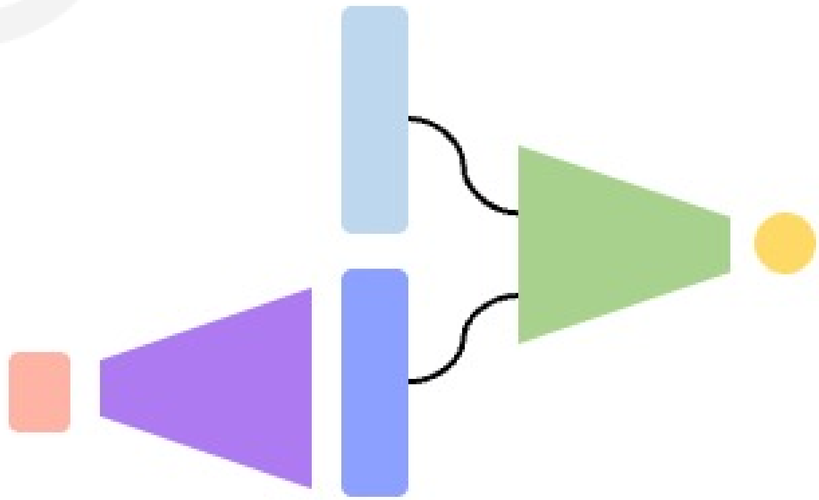
Autoencoders and Variational Autoencoders (VAEs)

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



Generative Adversarial Networks (GANs)

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



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Diffusion Models

...more to come in Lecture 7!

MIT
Introduction to Deep Learning

Lab 2: Facial Detection Systems

Link to download labs:
http://introtodeeplearning.com#schedule

1. Open the lab in Google Colab
2. Start executing code blocks and filling in the #TODOs
3. Need help? Come to 32-123!