Generative adversarial networks

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MILA

"What I cannot create, I do not understand"

- Richard Feynman

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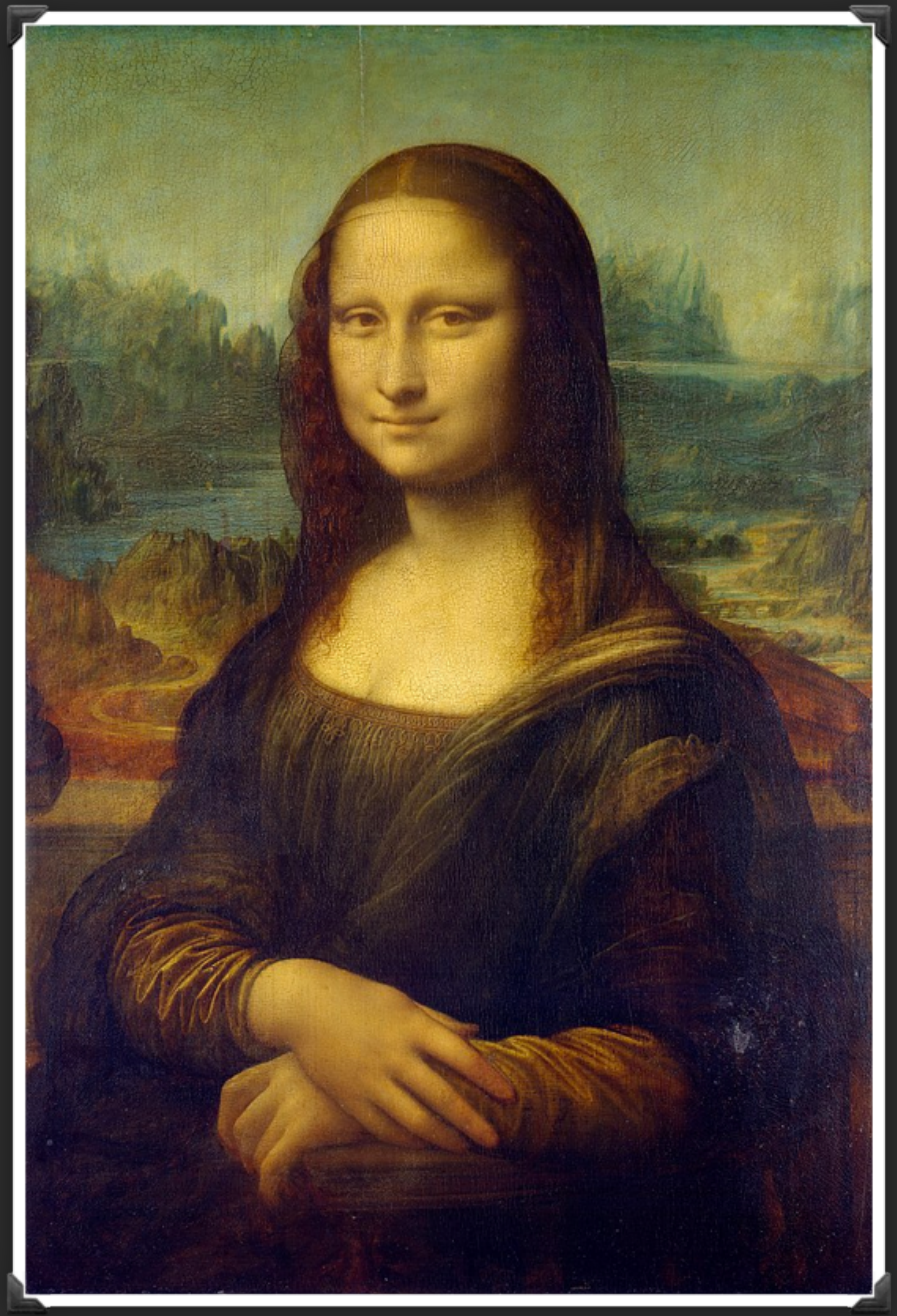
http://poussiecat.eklablog.com/great-mouse-detective-c26082364



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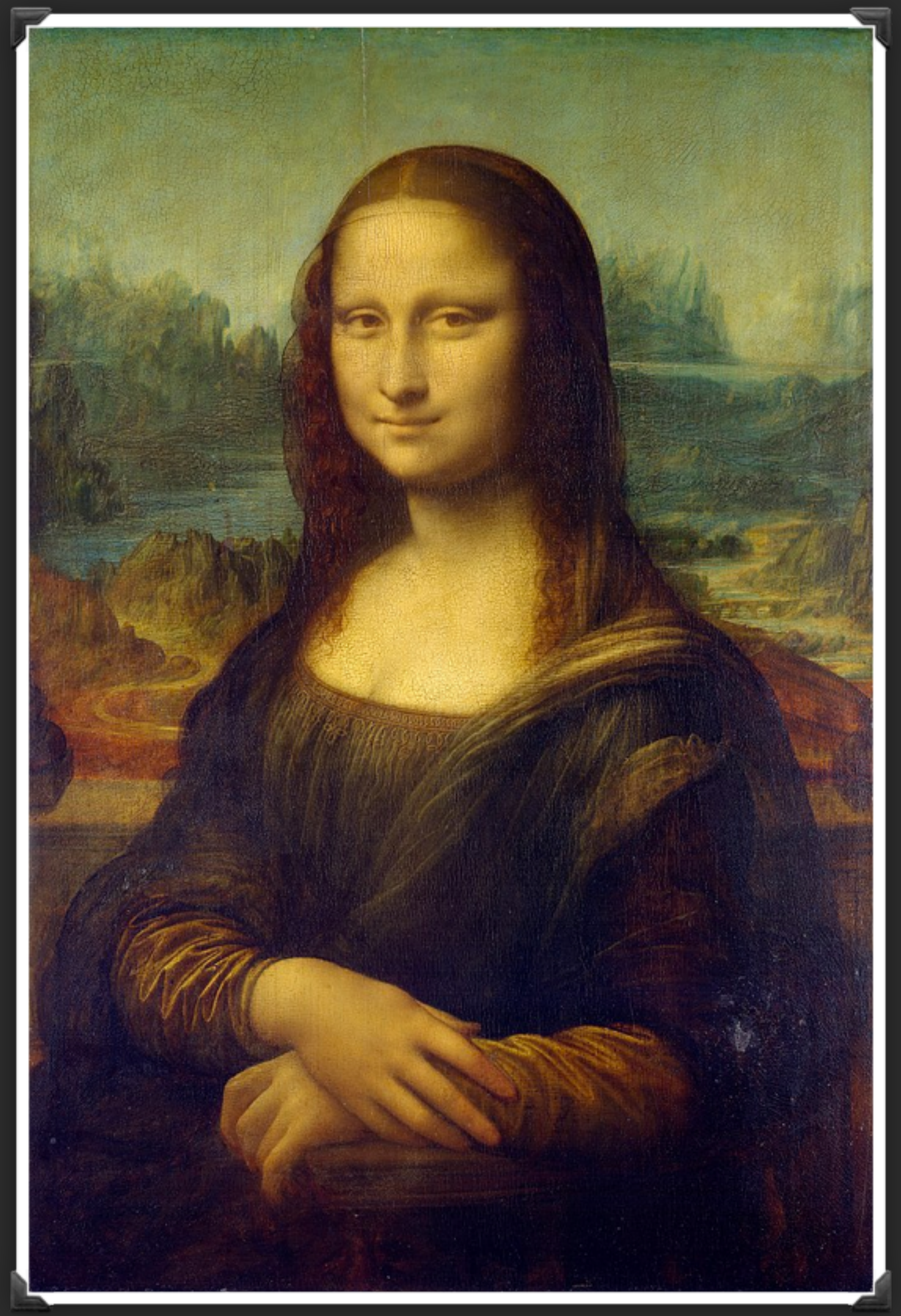
discriminator



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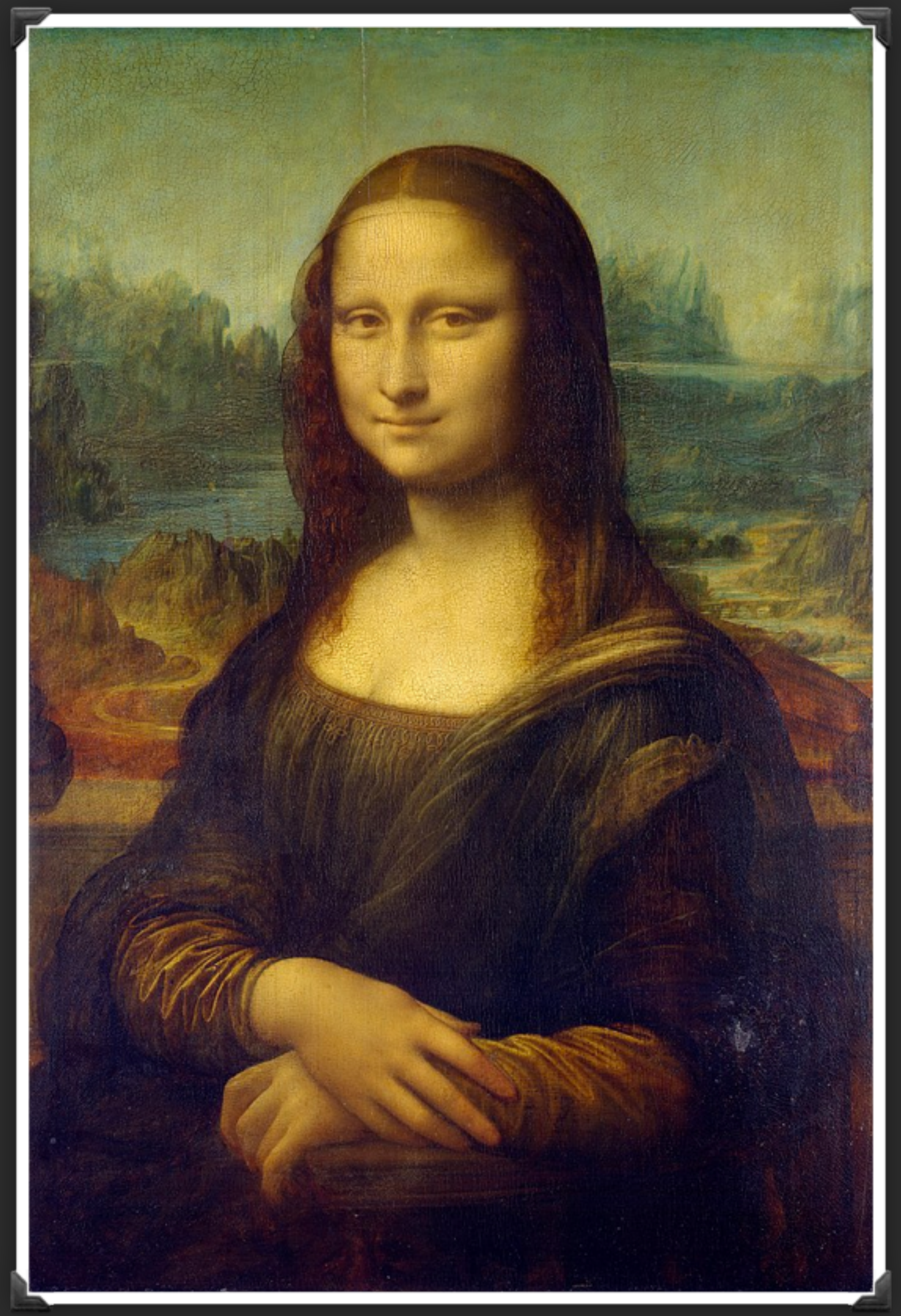

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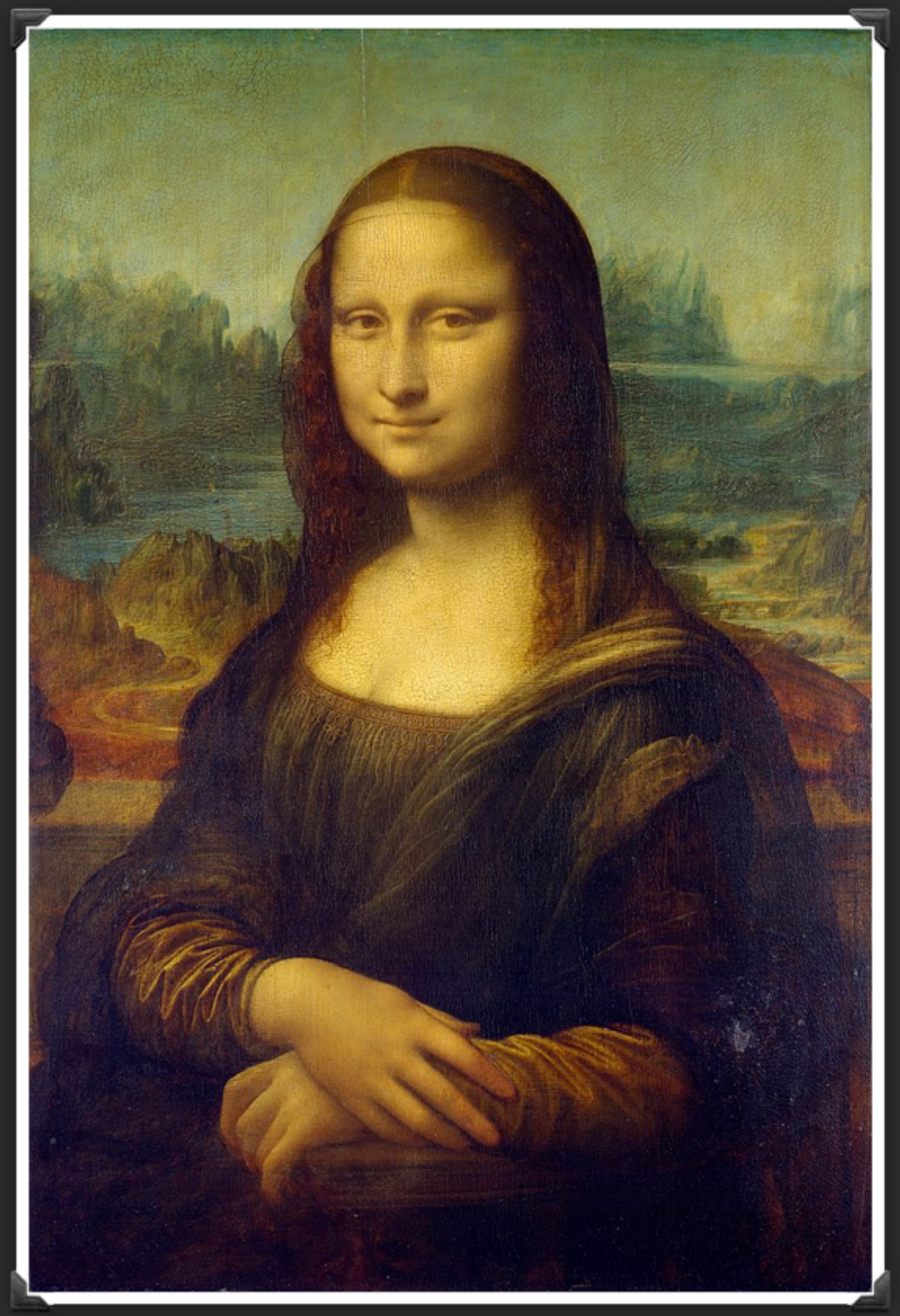

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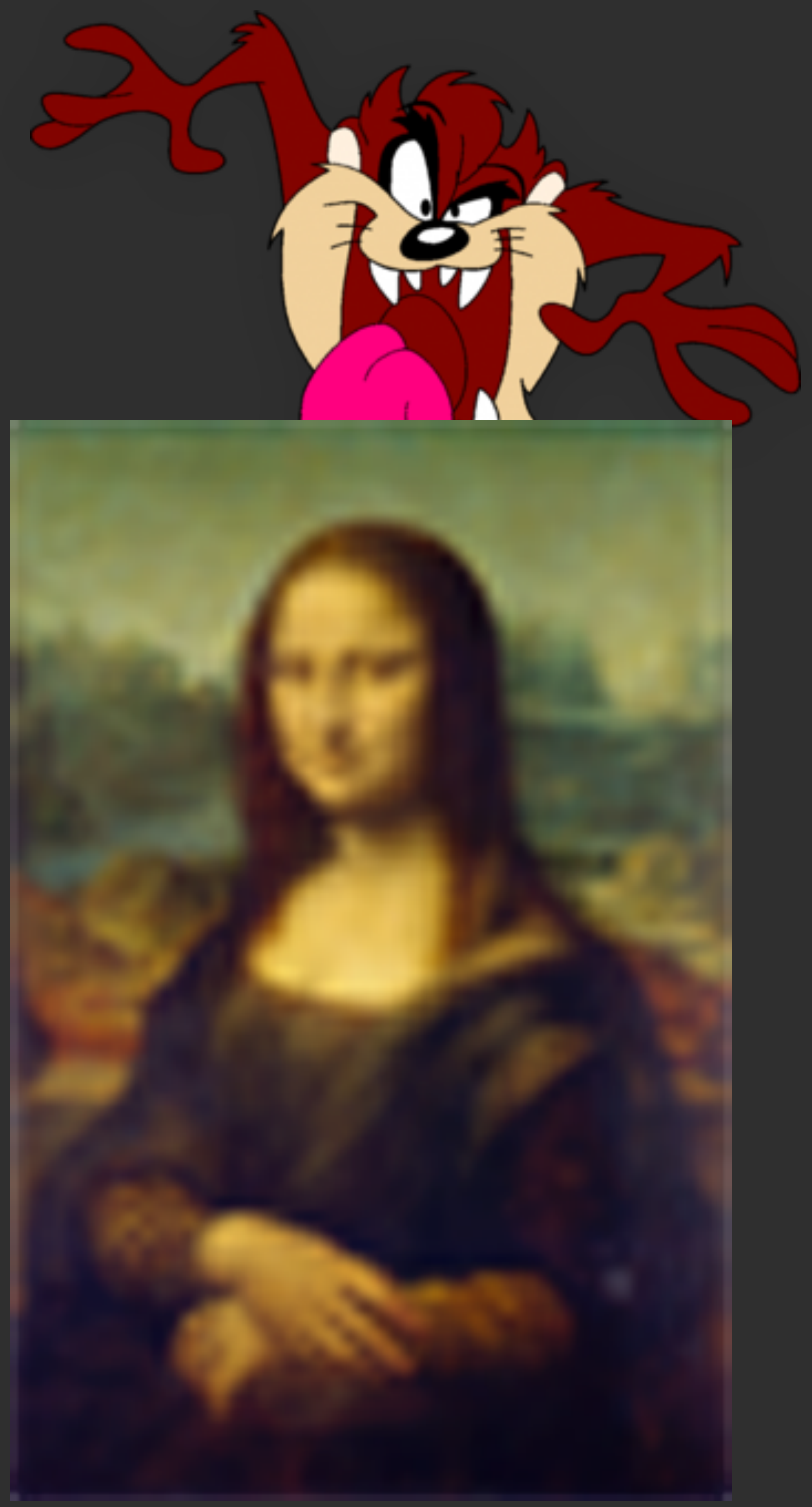

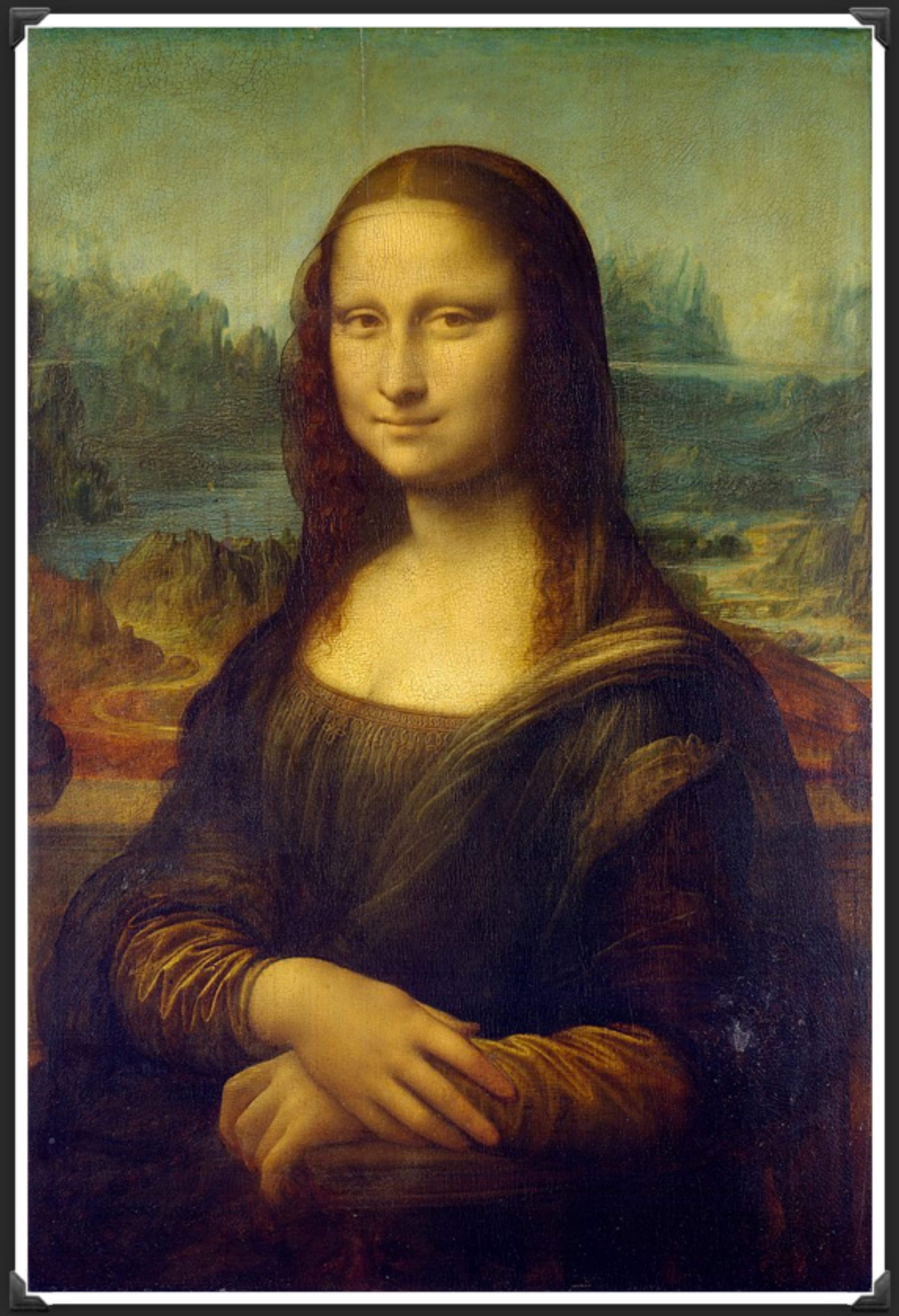

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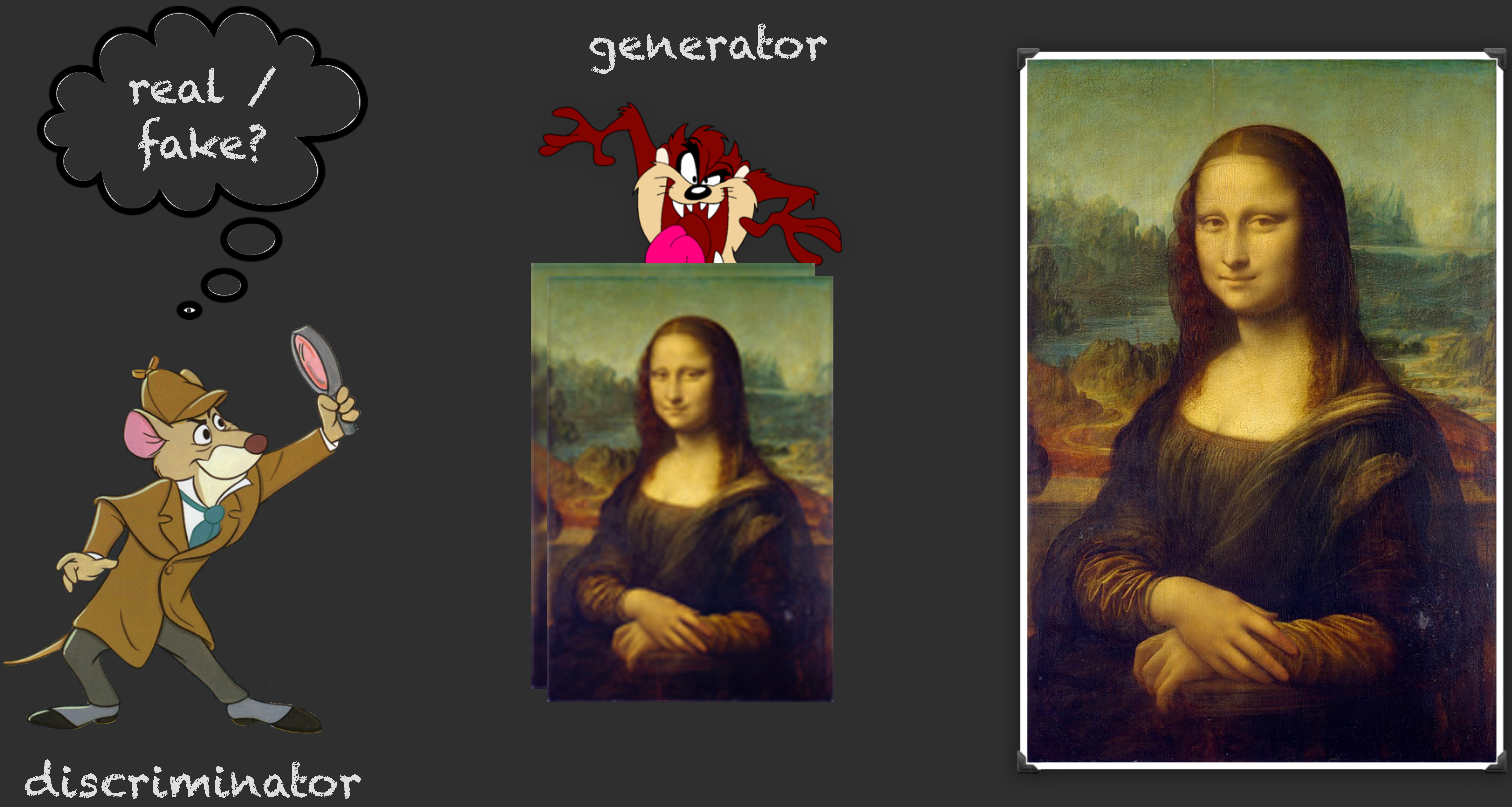

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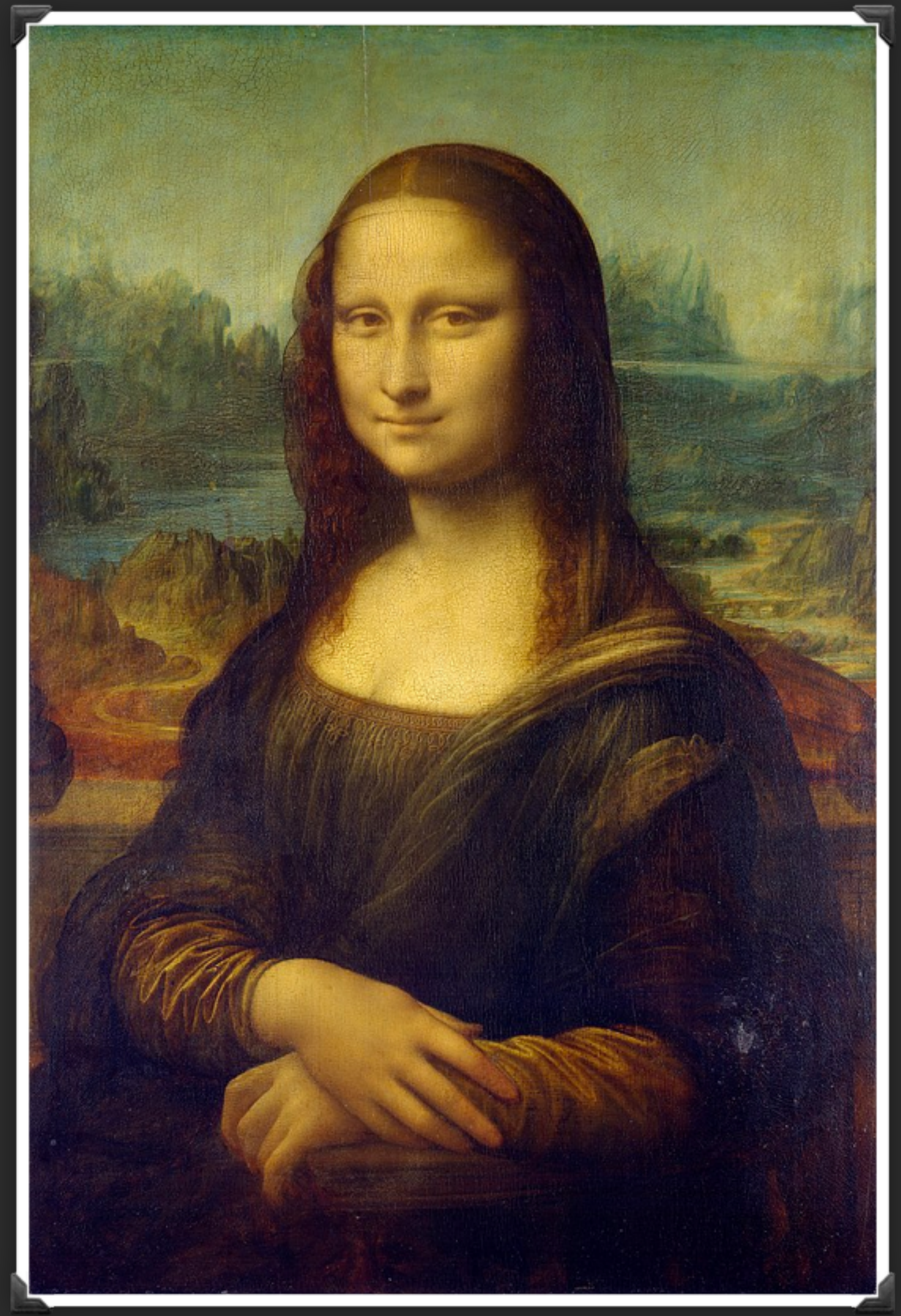

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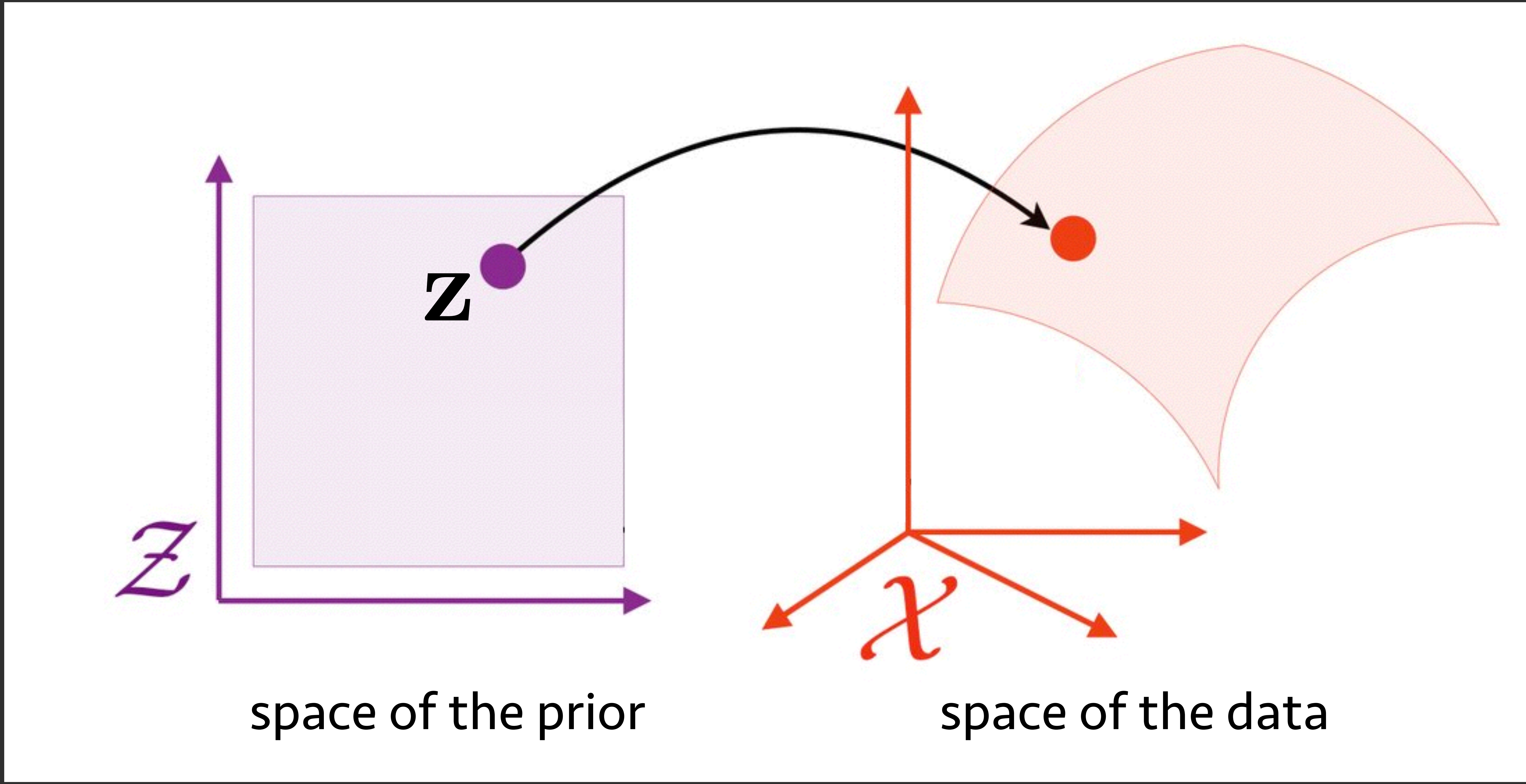
- This is done through two adversaries (generator and discriminator) which compute against each other in a zero-sum game
- Both networks compute against each other until Nash equilibrium
- Theoretically, the game that GANs play is equivalent to minimising some measure of divergence between two distributions (real and fake)



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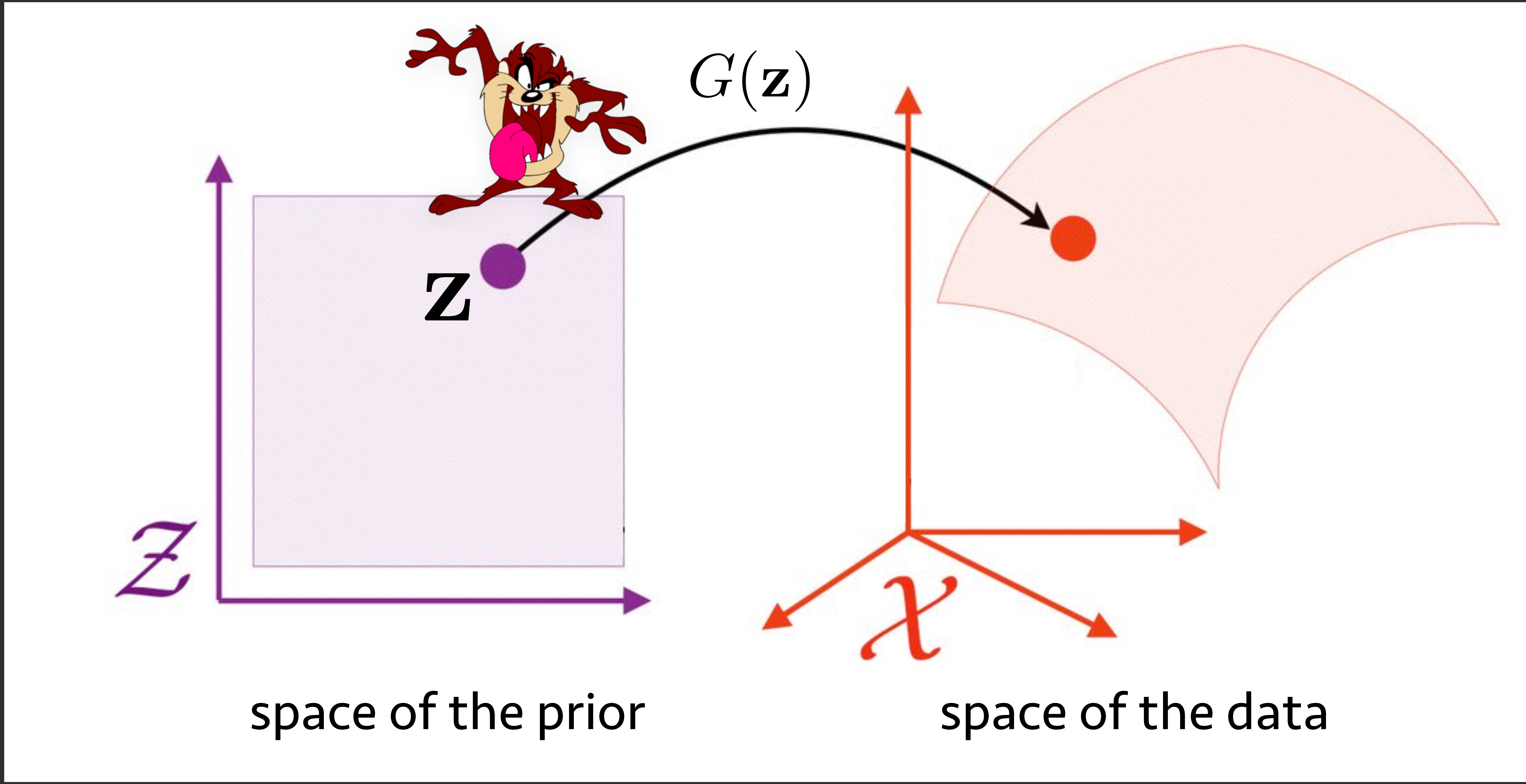

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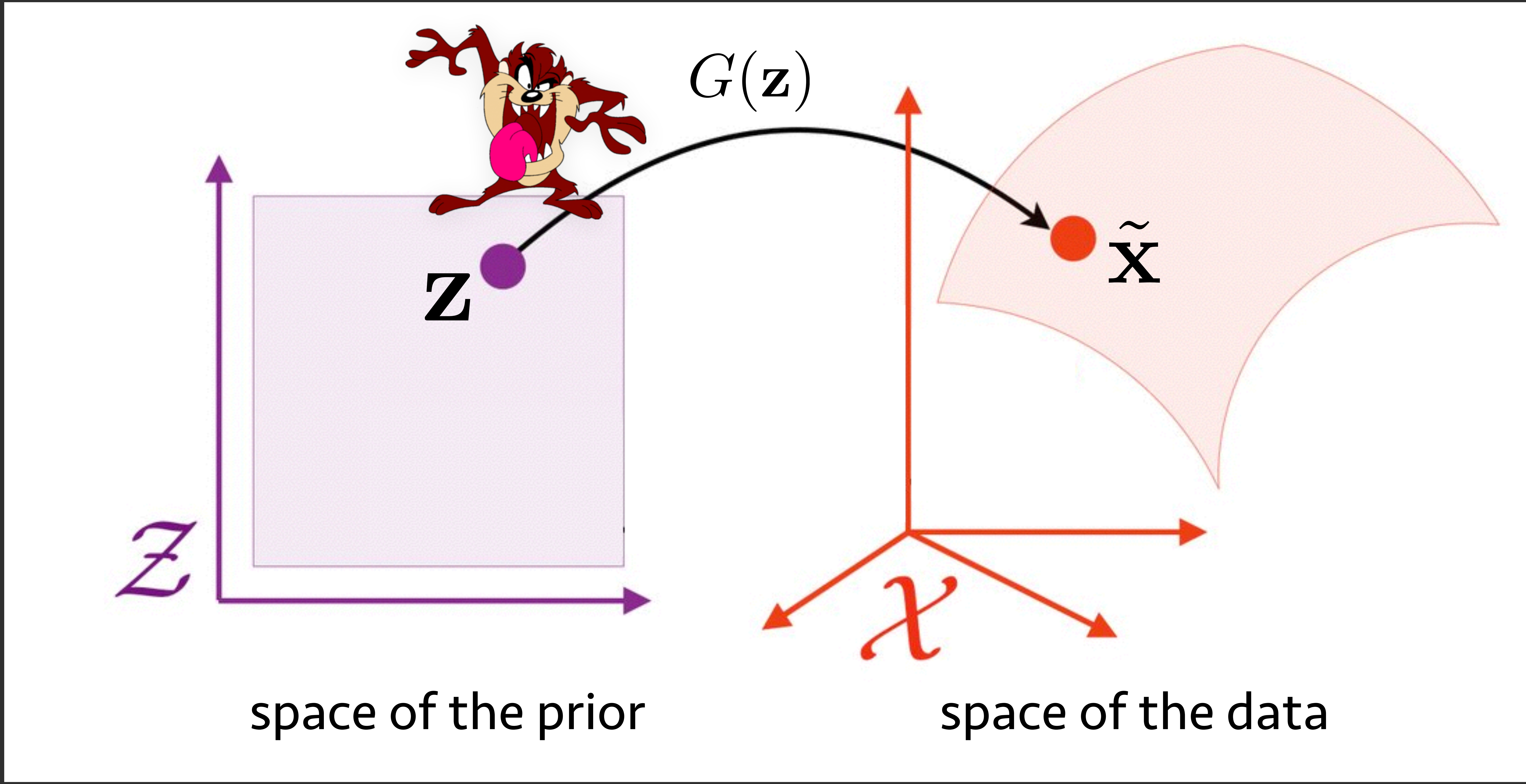

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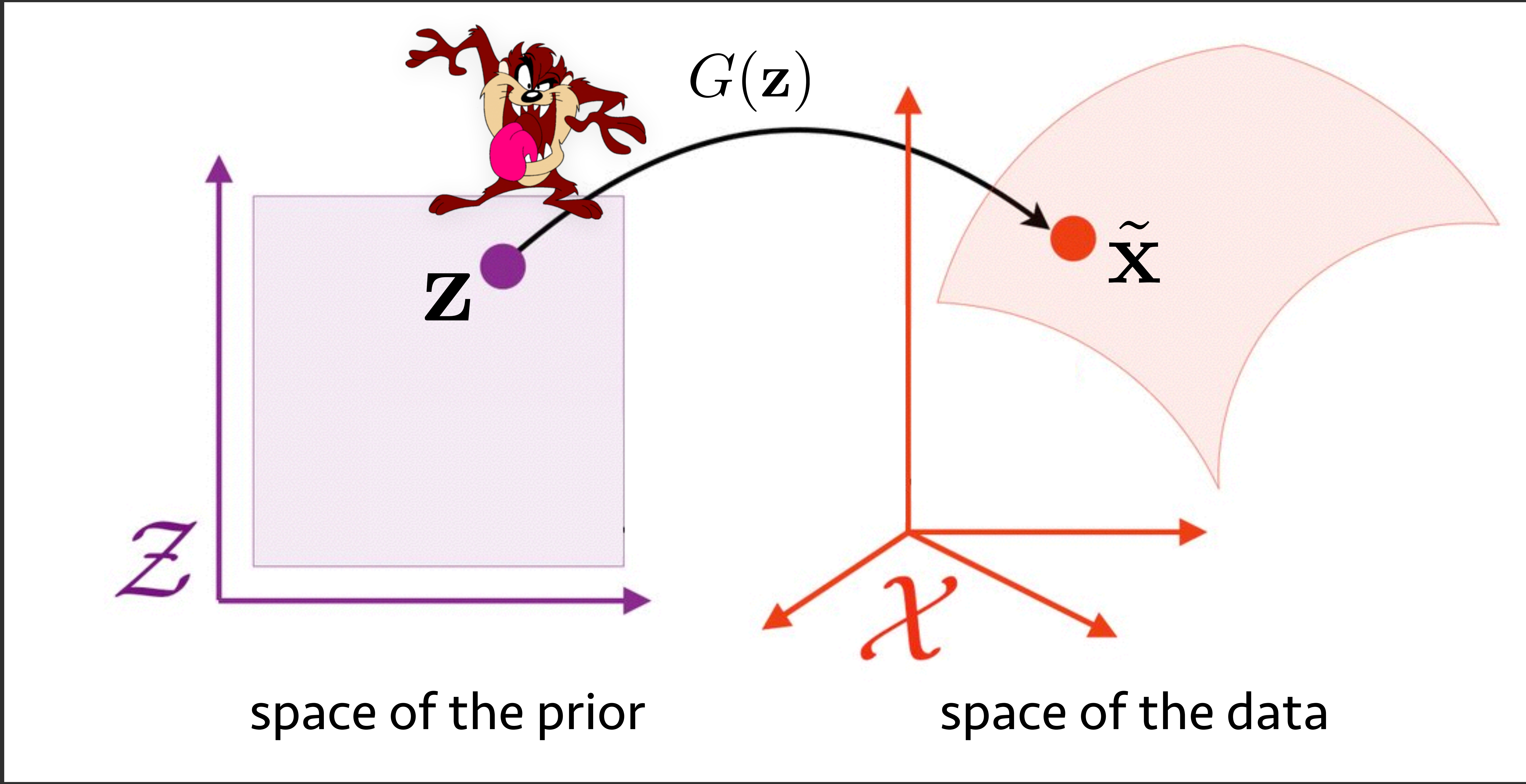

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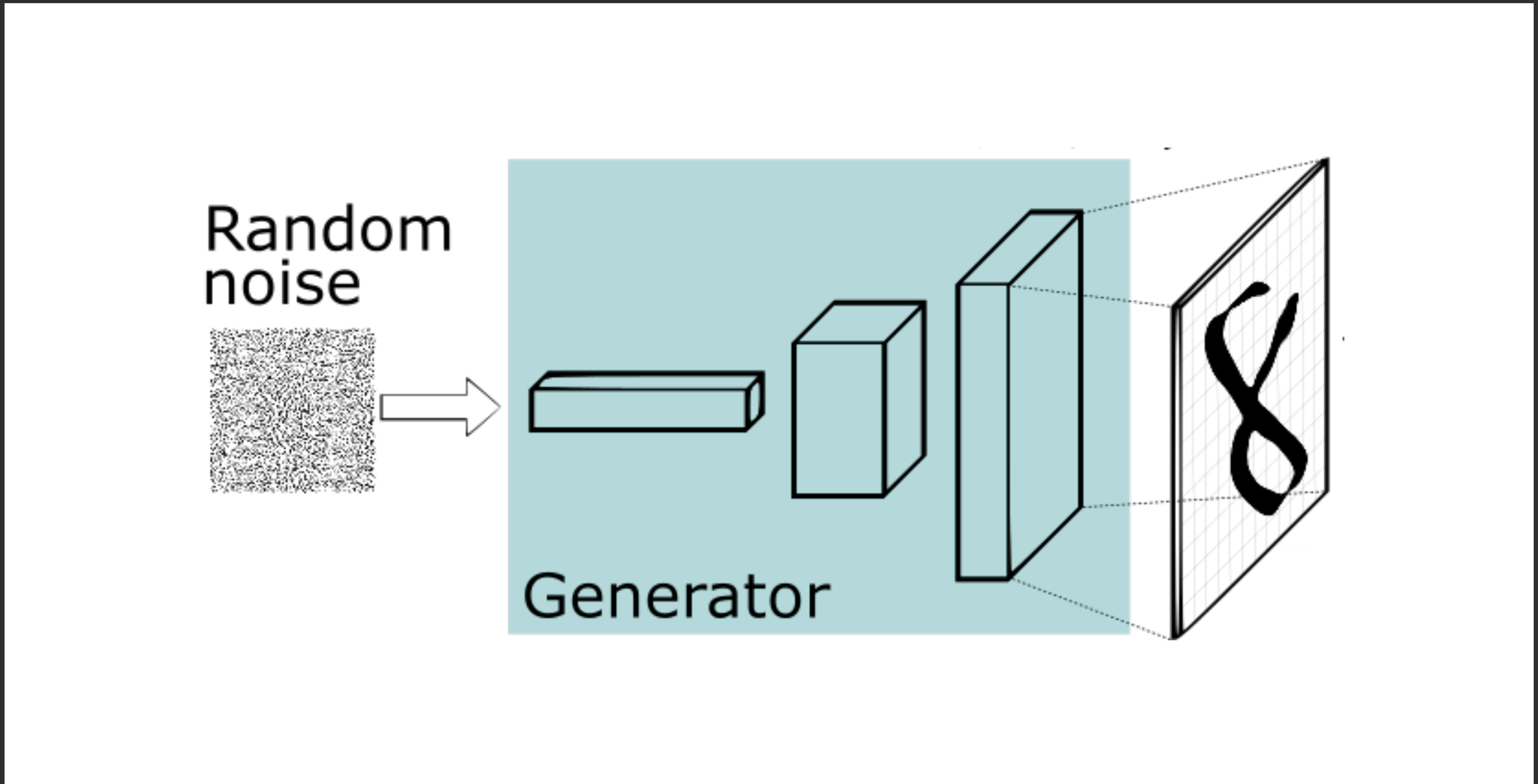
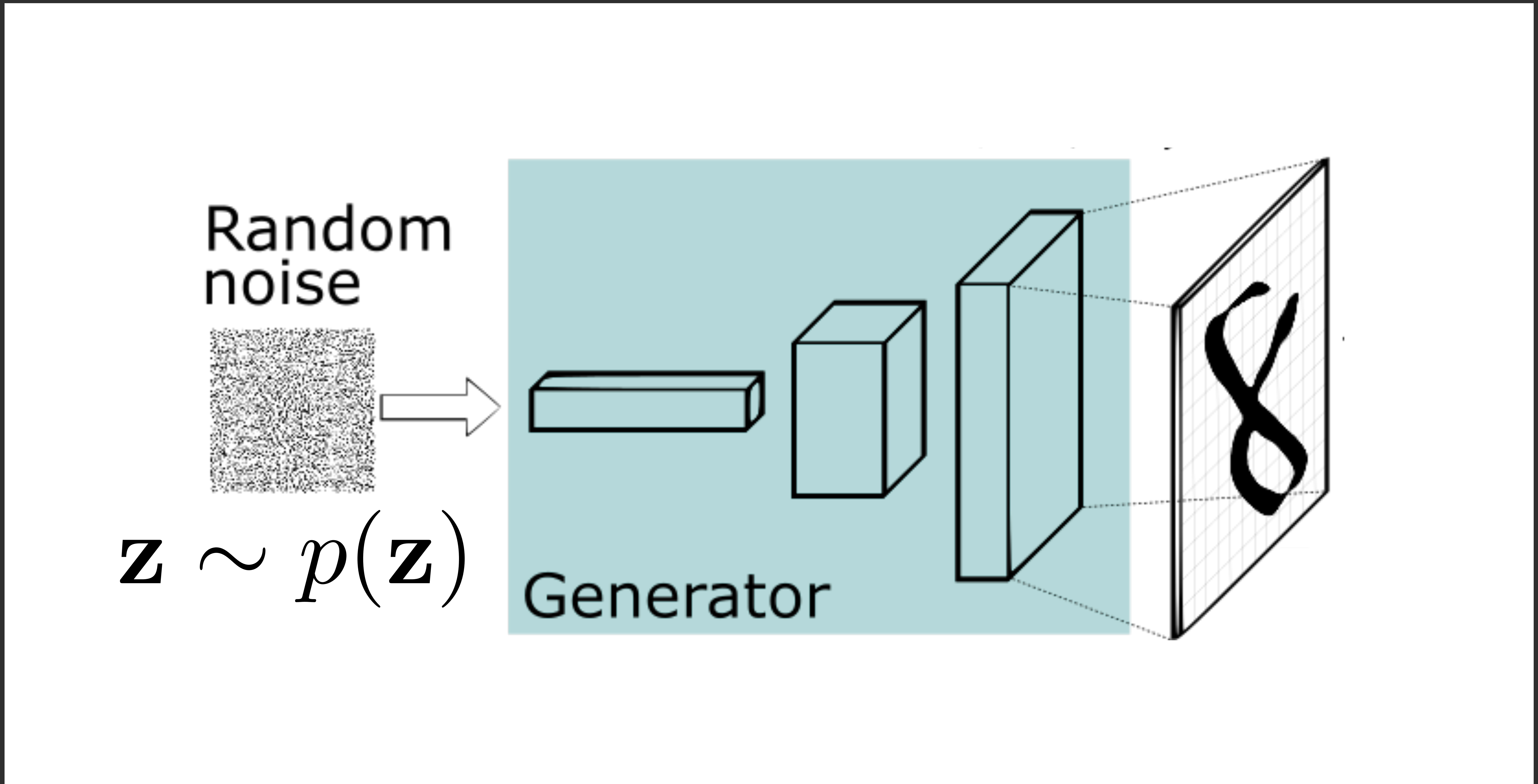
We can model arbitrary distributions by sampling from a simple distribution (prior) and mapping the sample through a sufficiently powerful function (generator)



https://deeplearning4j.org/generative-adversarial-network



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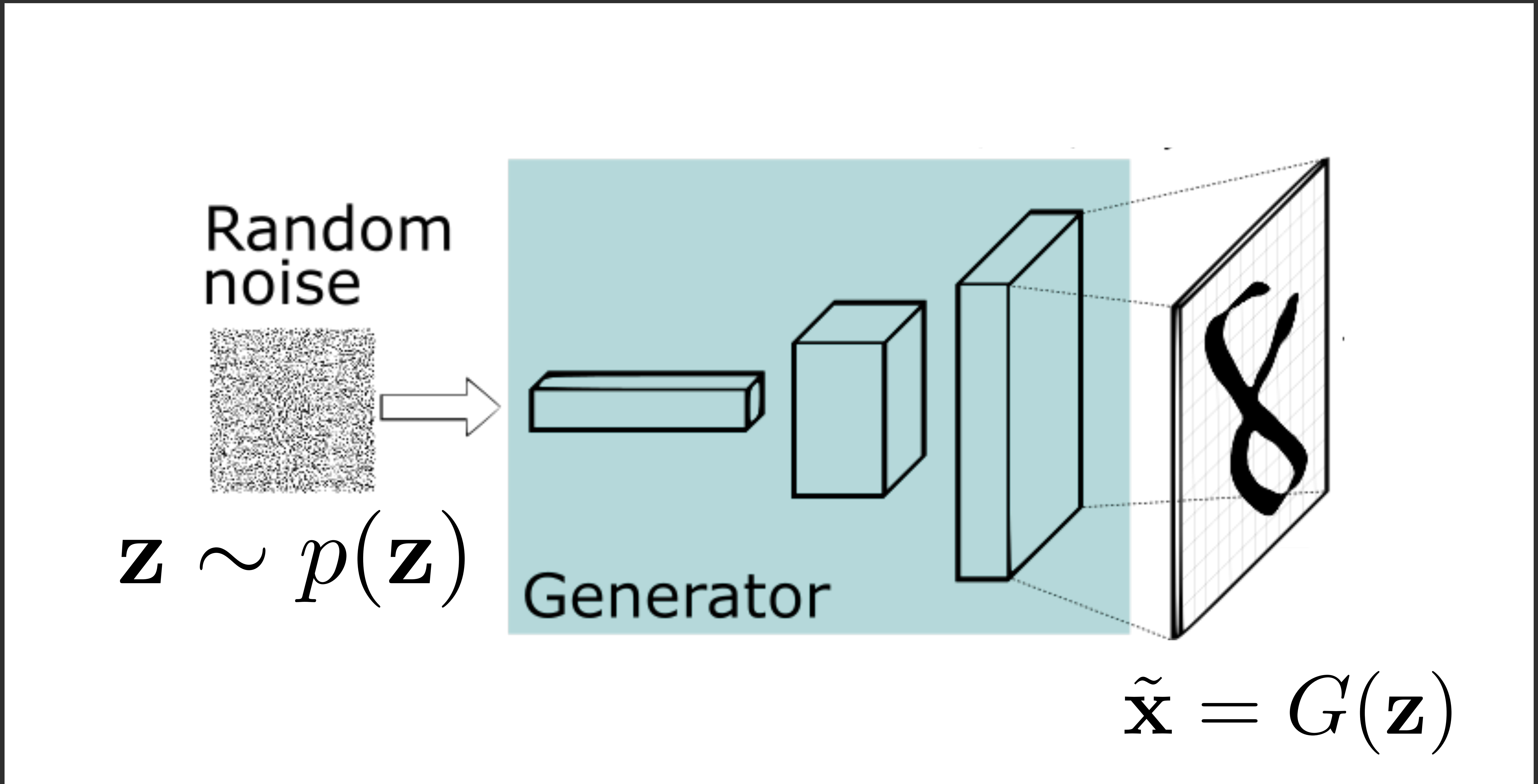

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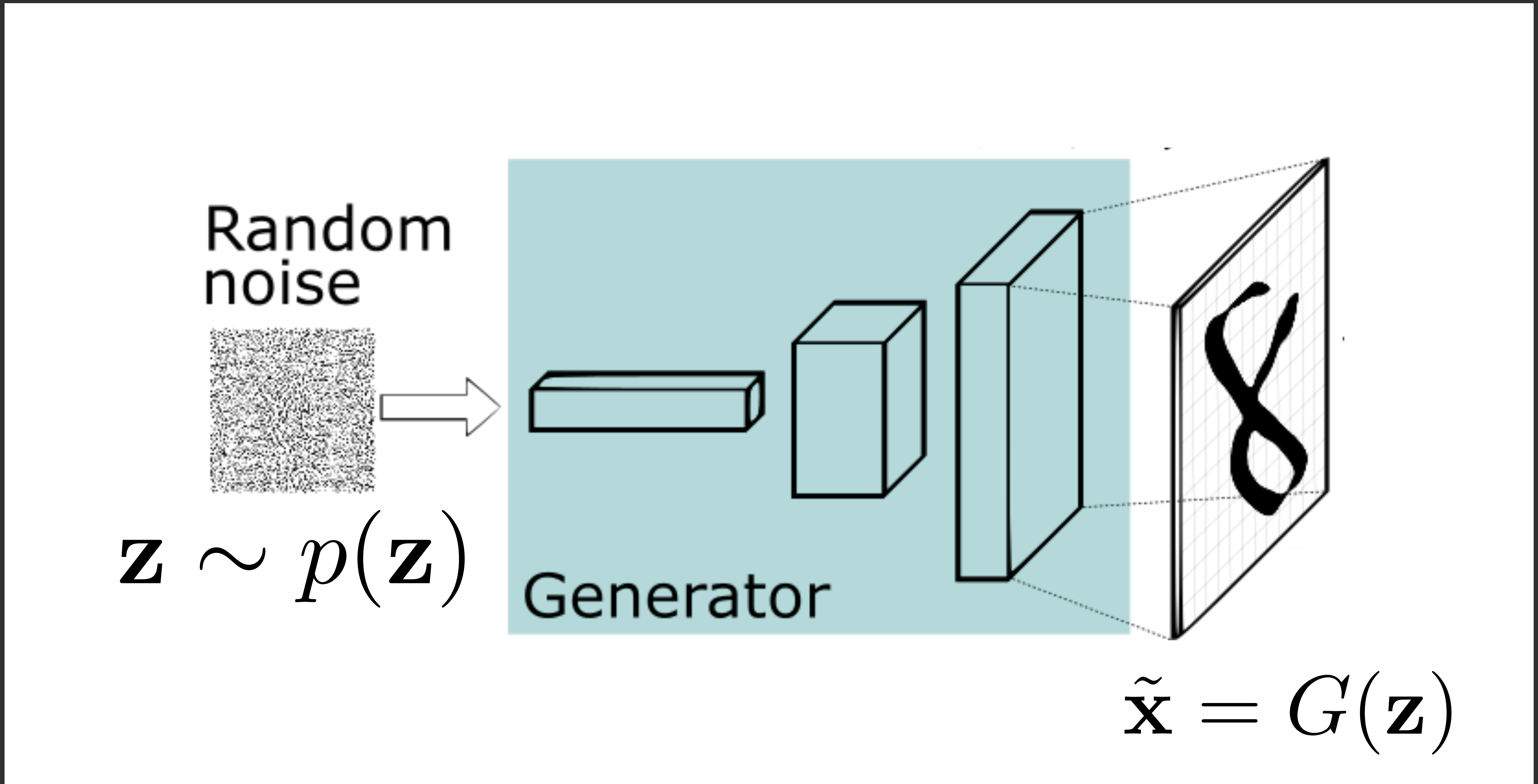

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The generator takes noise (a source of stochasticity) and transforms it into something that could plausibly come from the real data

https://www.etsy.com/listing/216241958/musical-wooden-box-hand-crank-music-box
https://www.mathworks.com/matlabcentral/answers/180778-plotting-a-3d-gaussian-function-using-surf

$$\mathbf{z} \sim p(\mathbf{z})$$

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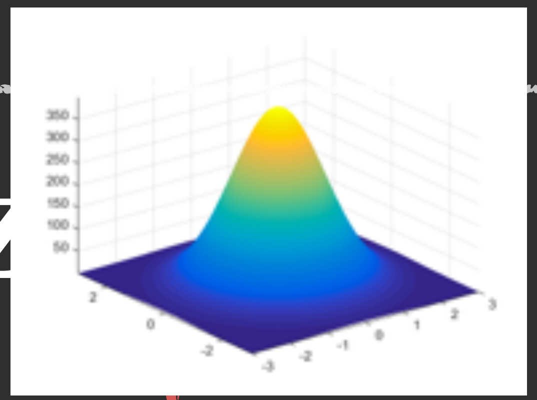

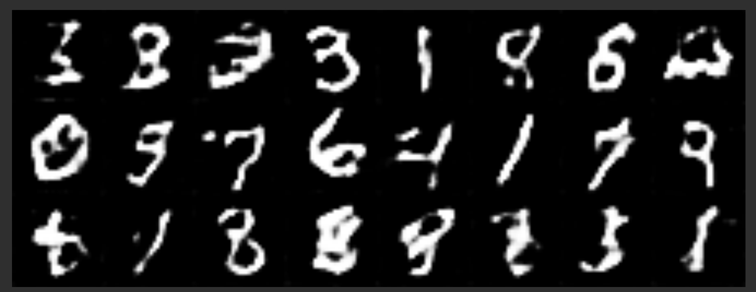

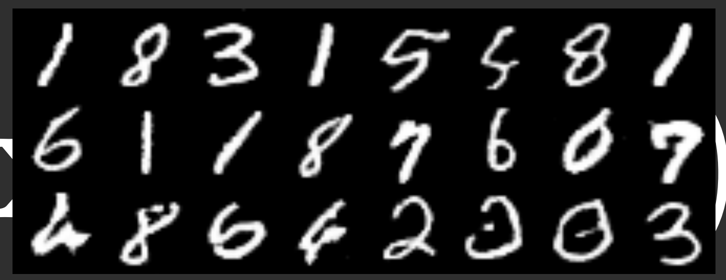

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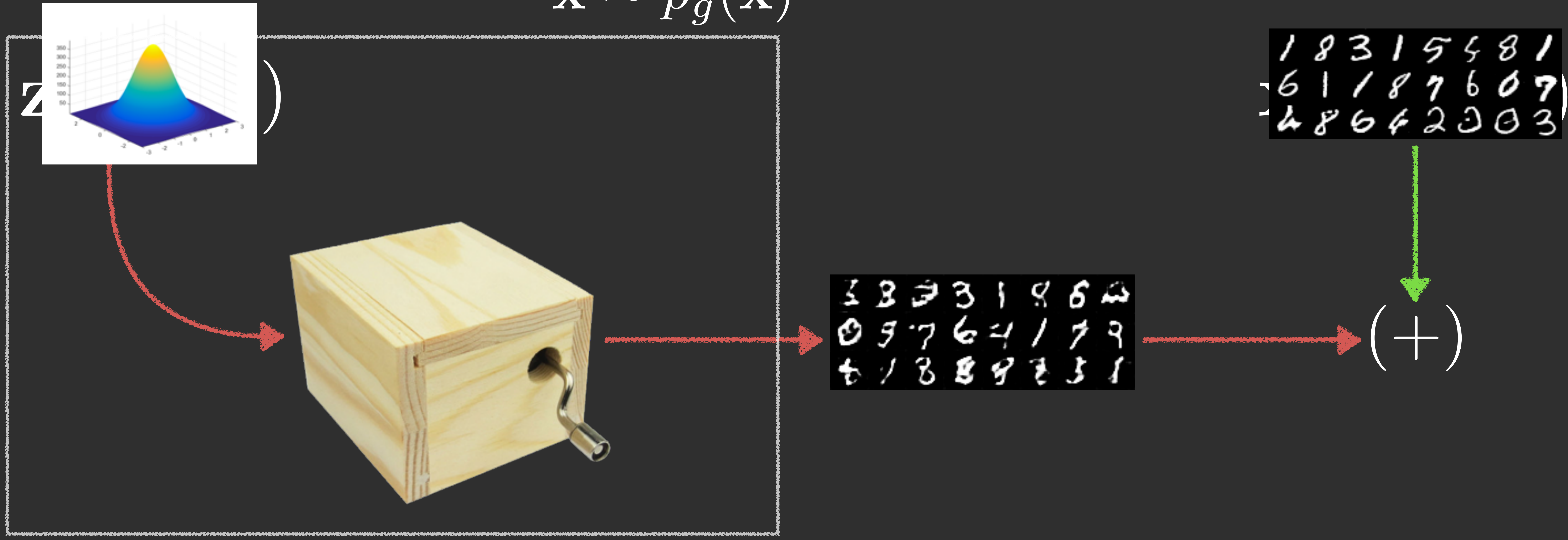

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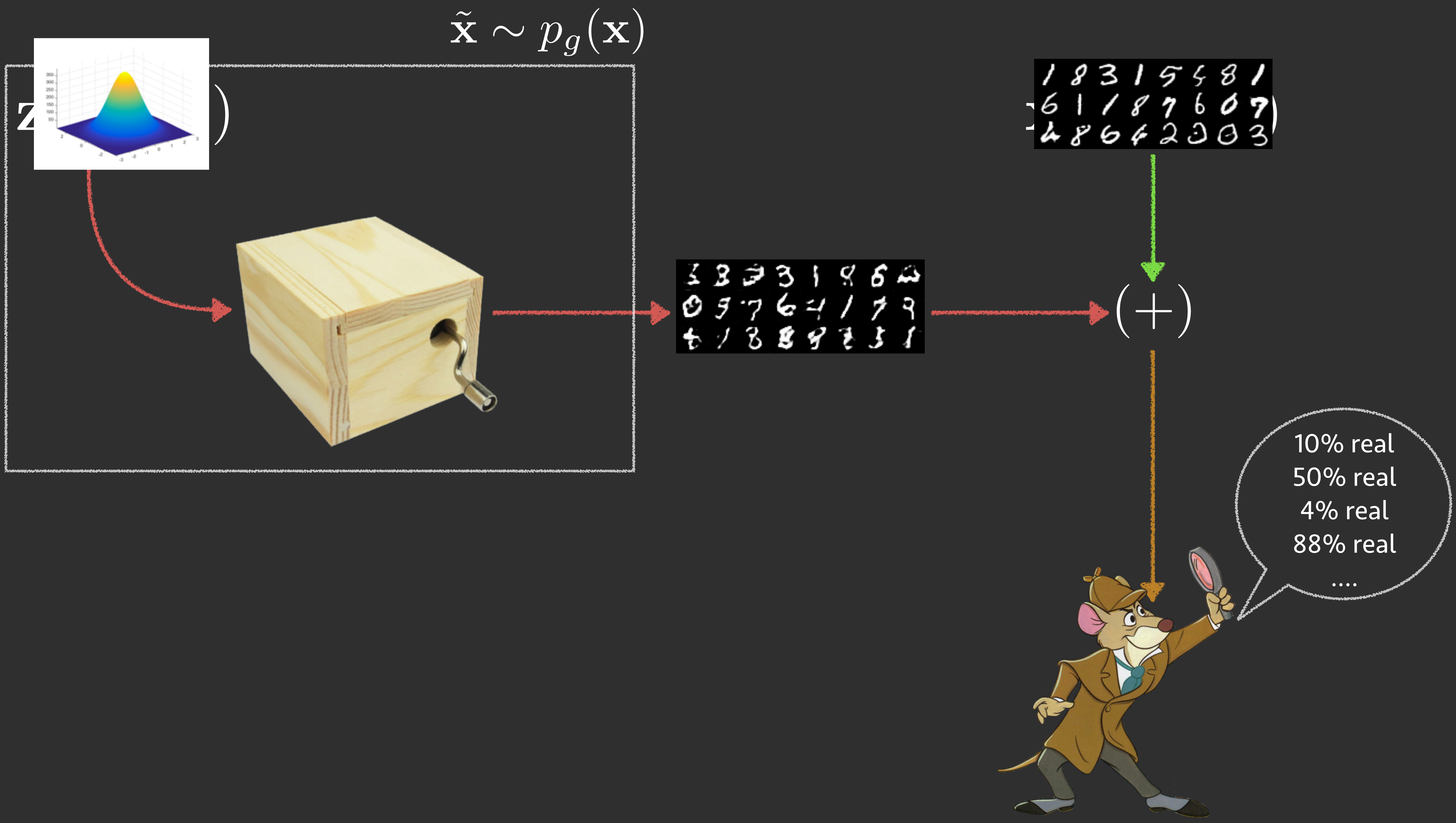

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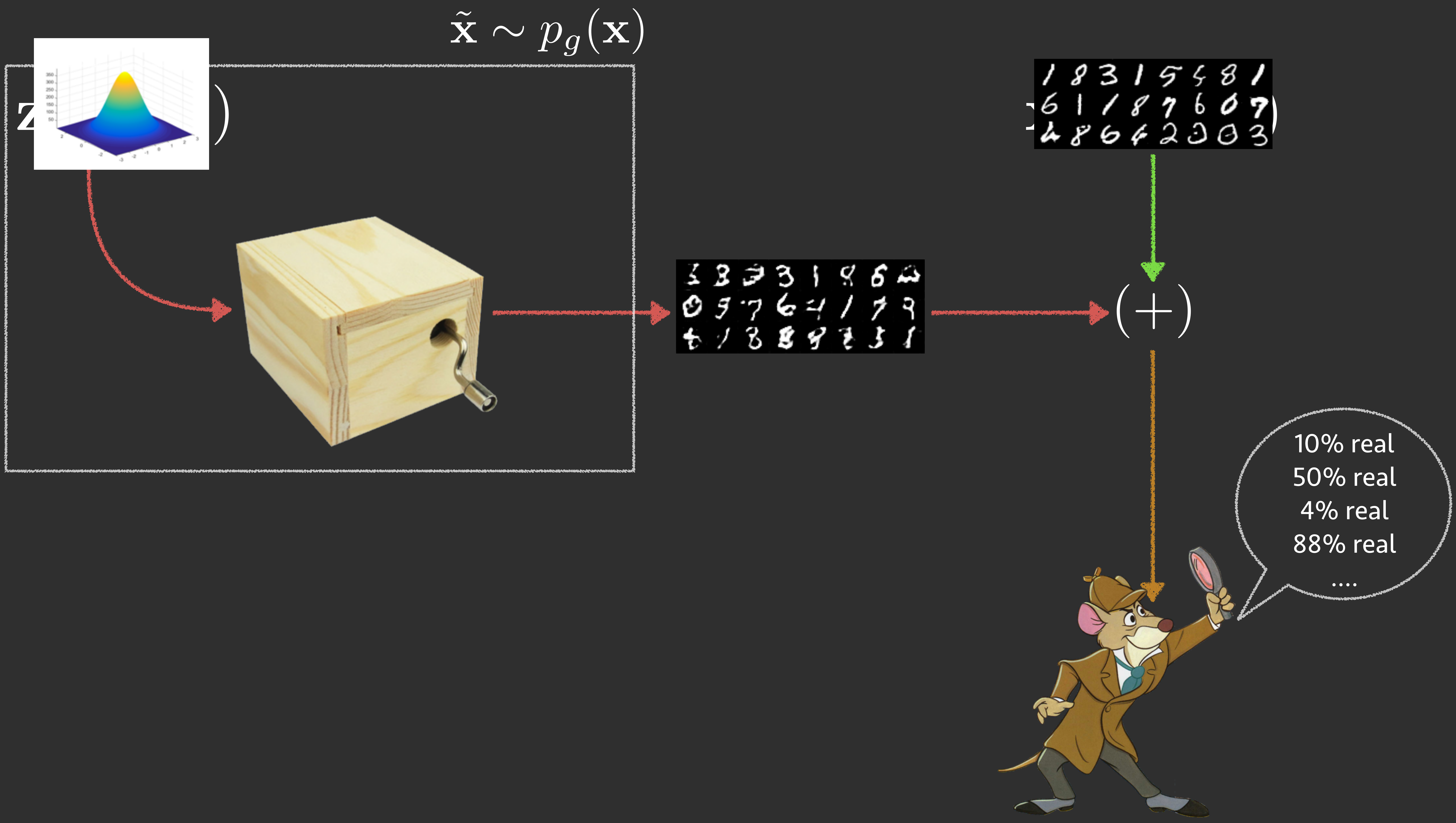

How does the generator try to fool the discriminator?

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- Denote $L(y_1, y_2)$ to be squared error: $(y_1 - y_2)^2$

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  - LSGAN (Mao et al)

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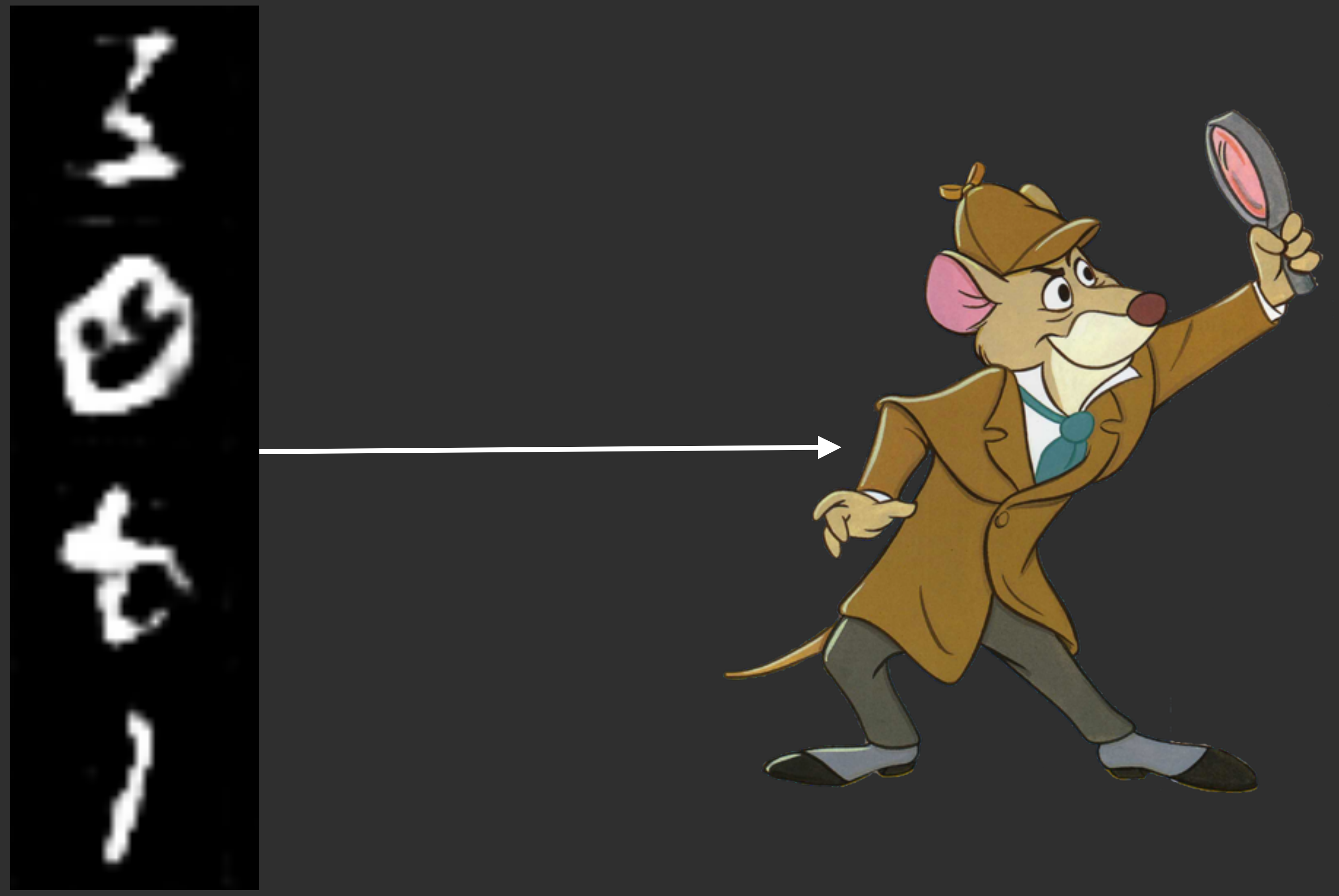
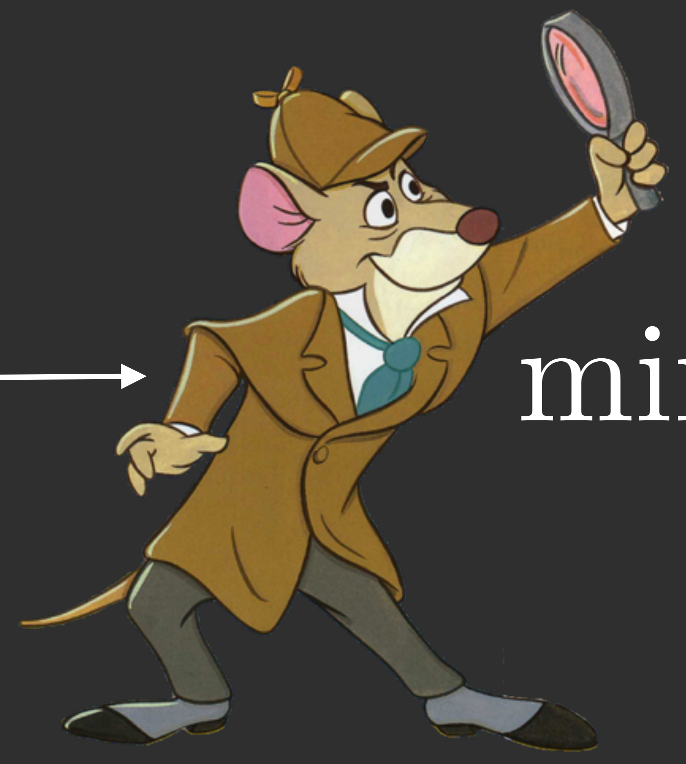


$$\min \ (D(G(\mathbf{z})) - 0)^2$$

. . .

$\nabla_{D(\mathbf{x})} L(D(\mathbf{x}), 0)$



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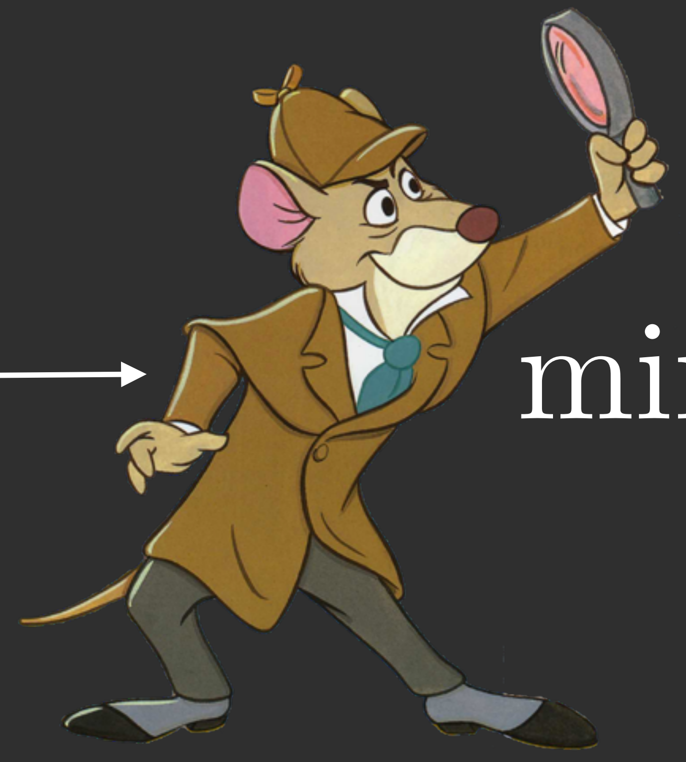

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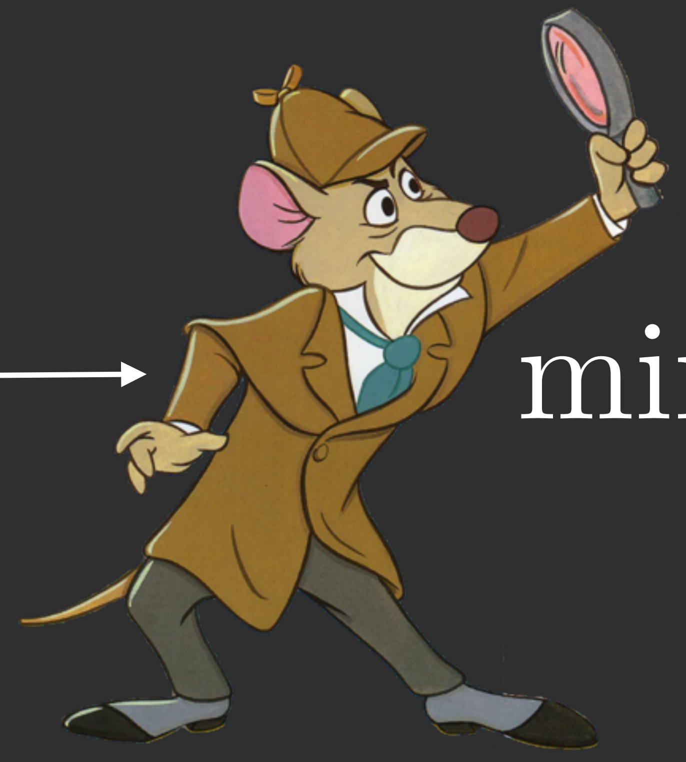

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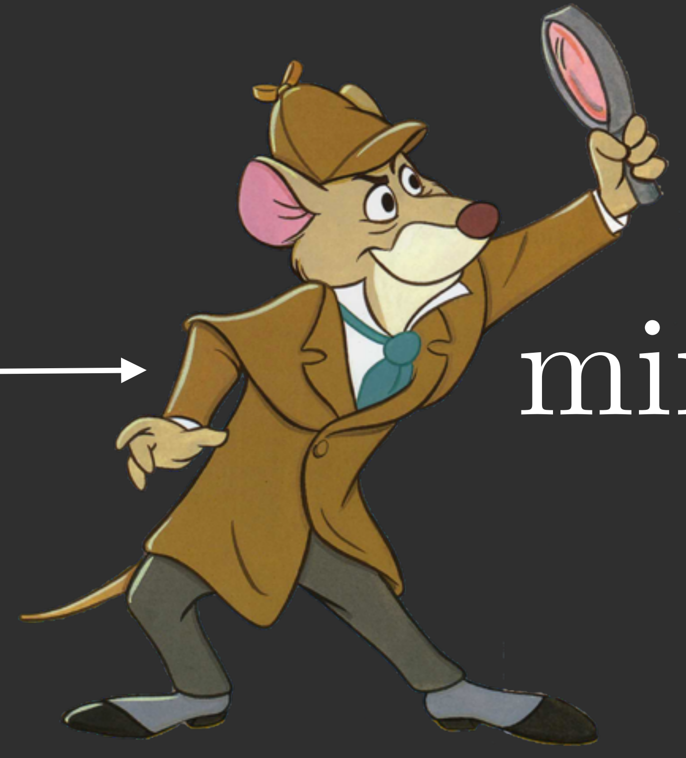

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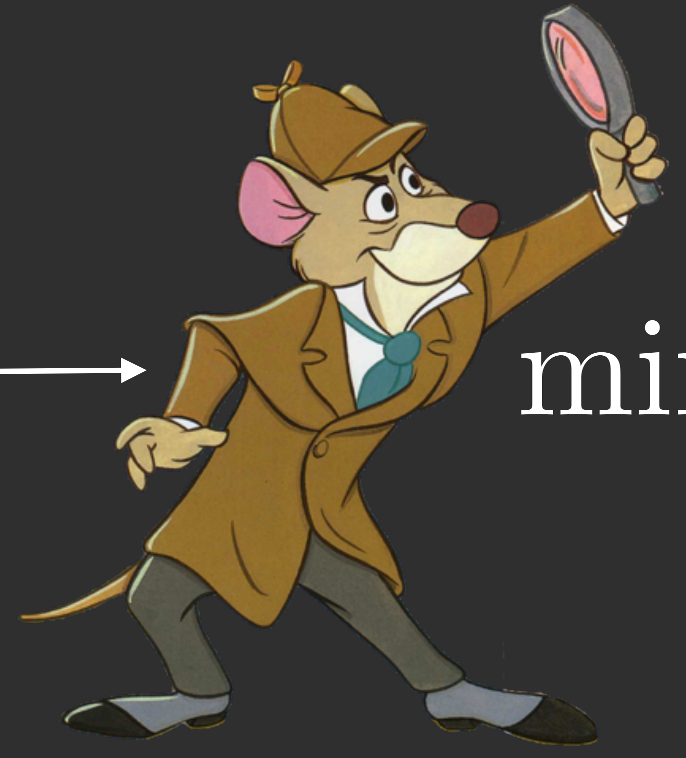

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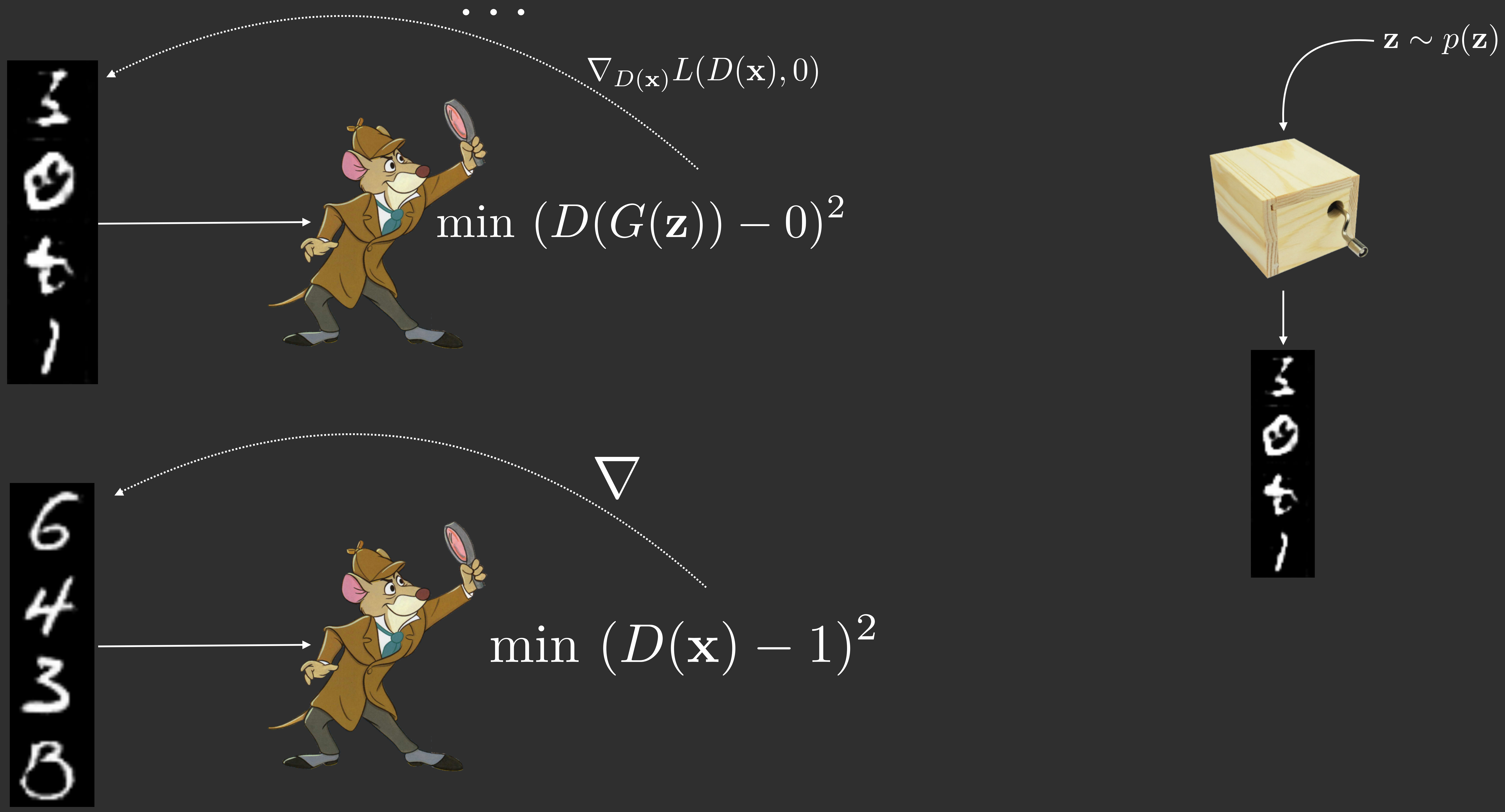

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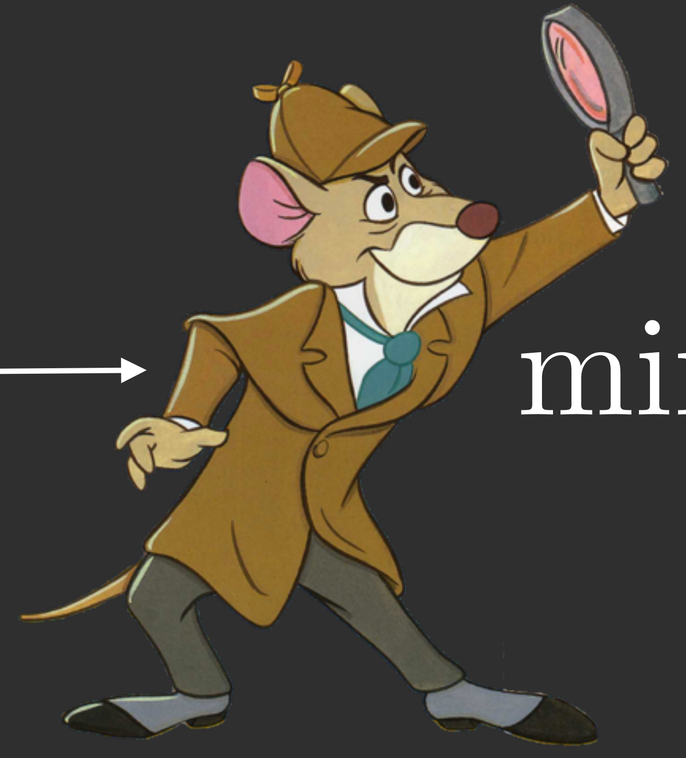

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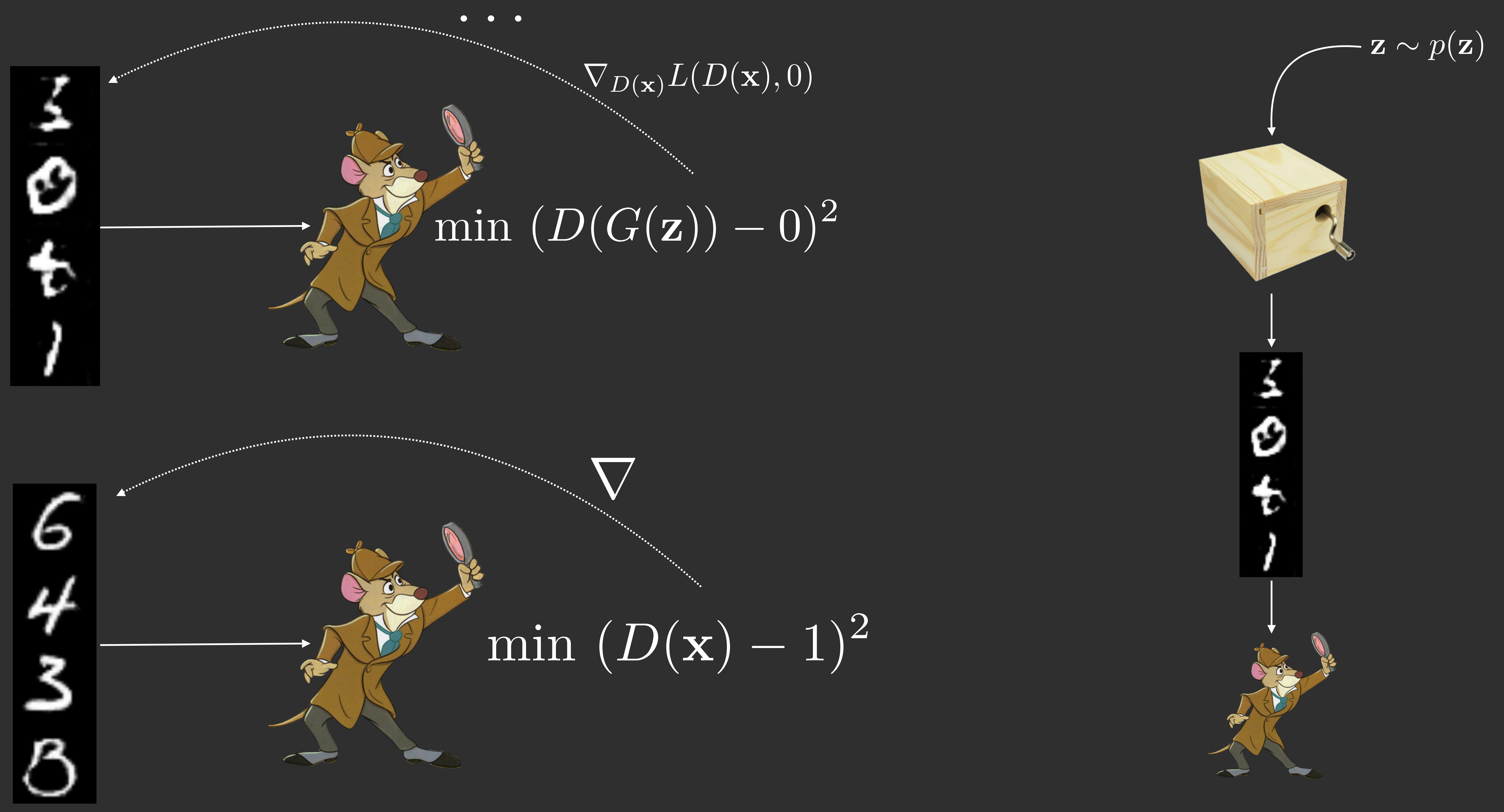
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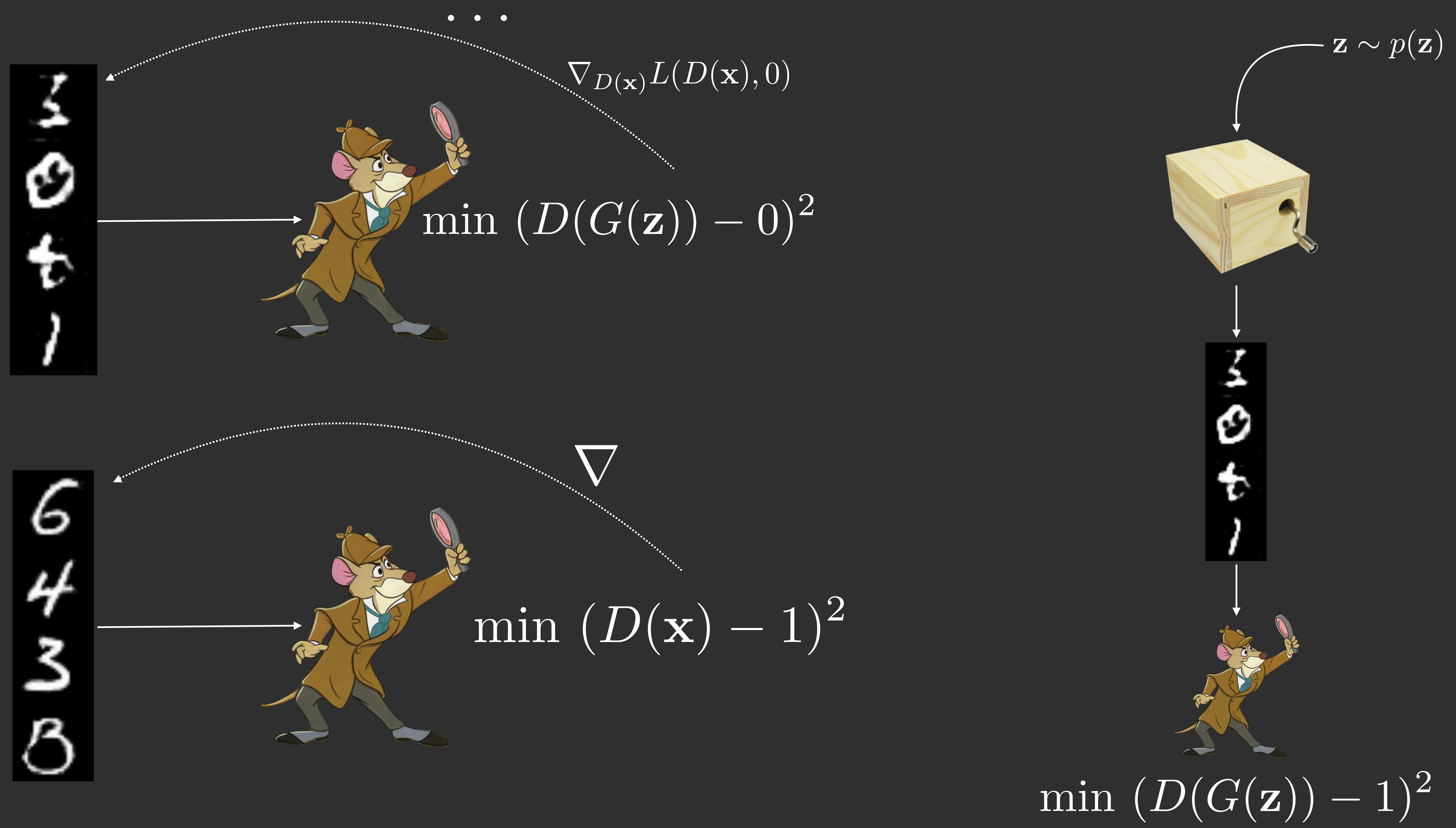

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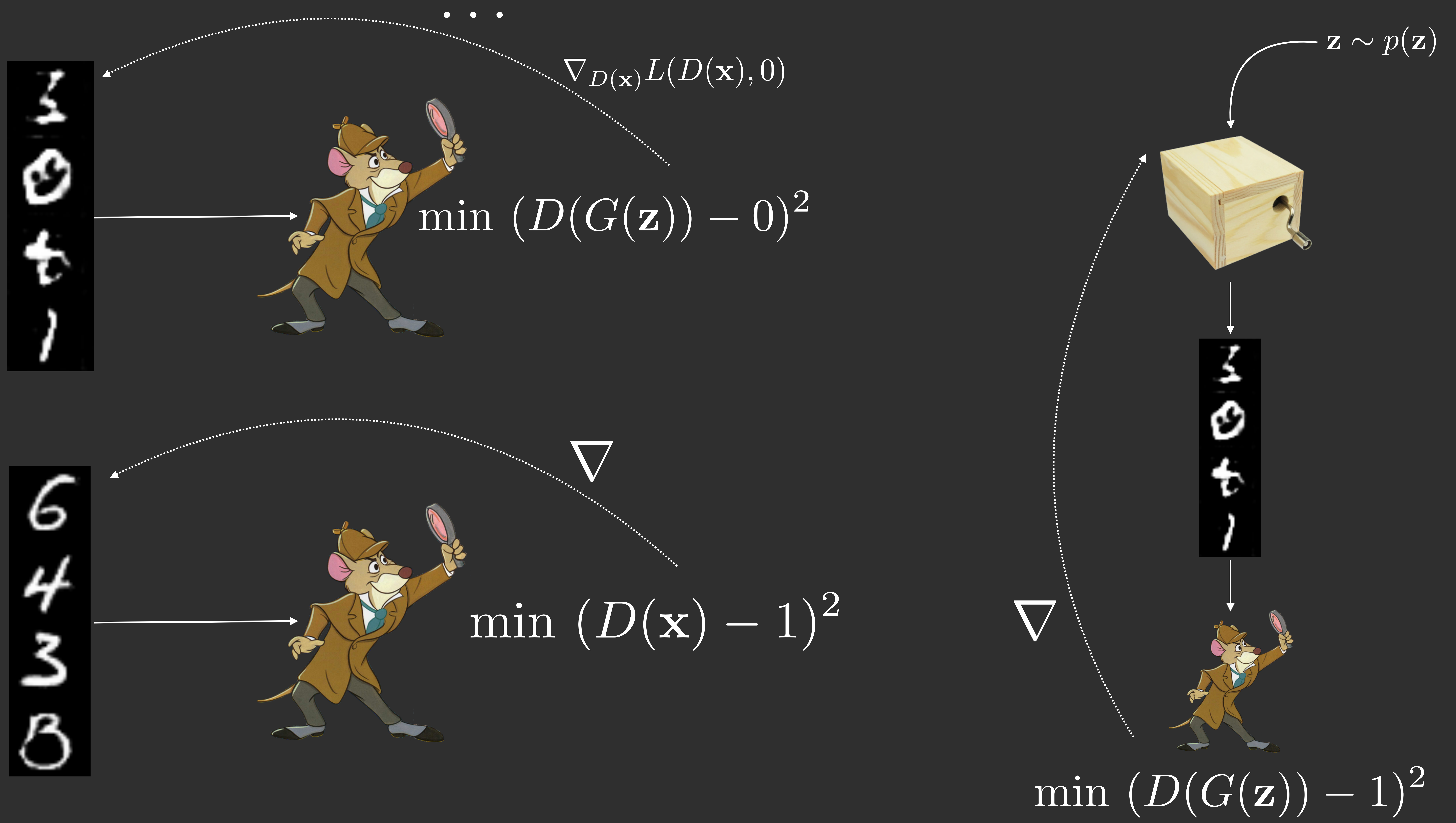

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What’s the use of learning to generate data?

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You may want to actually generate / augment data!

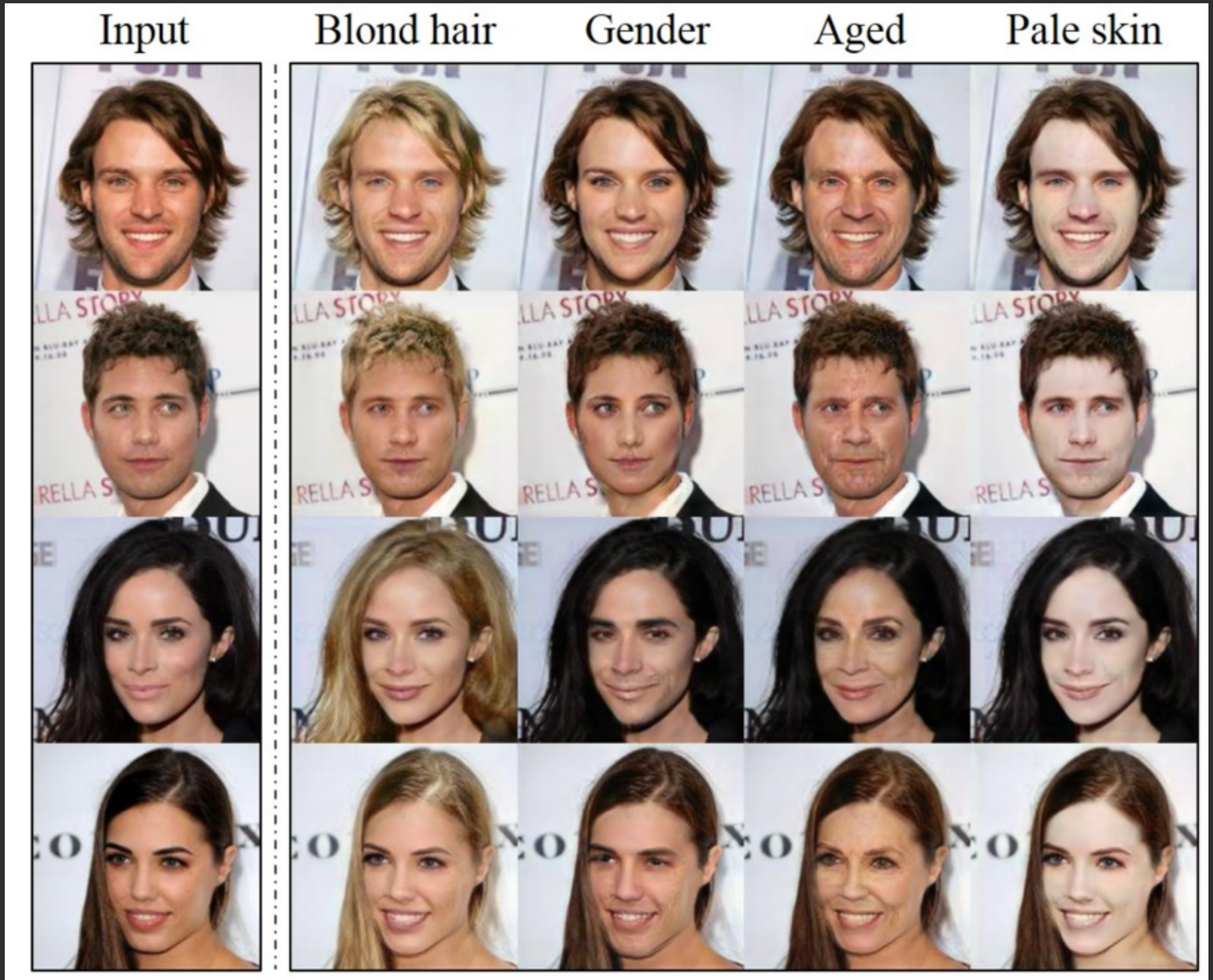
https://towardsdatascience.com/artistic-style-transfer-b7566a216431

GANs to generate / augment data

(a) Input (b) GntIpt (c) PConv(Ours)

Image Inpainting for Irregular Holes Using Partial Convolutions (Liu et al, 2018)

GANs to generate / augment data



StarGAN: unified generative adversarial networks for multi-domain image-to-image translation
(Choi et al, 2017)

What's the use of learning to generate data?

Learning to generate data may help downstream tasks

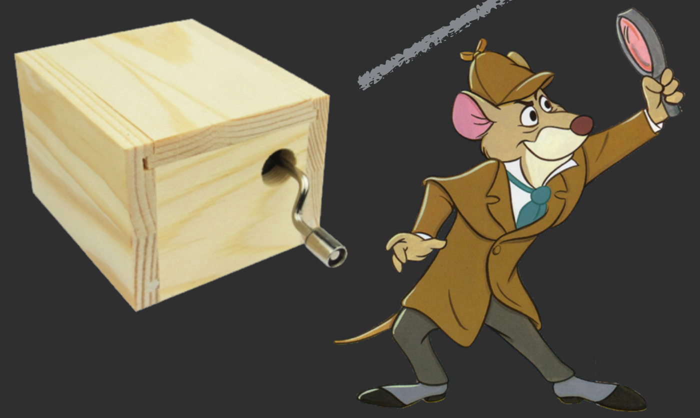
https://en.wikipedia.org/wiki/Richard_Feynman

What I cannot create,
I do not understand

GANs to aid downstream tasks

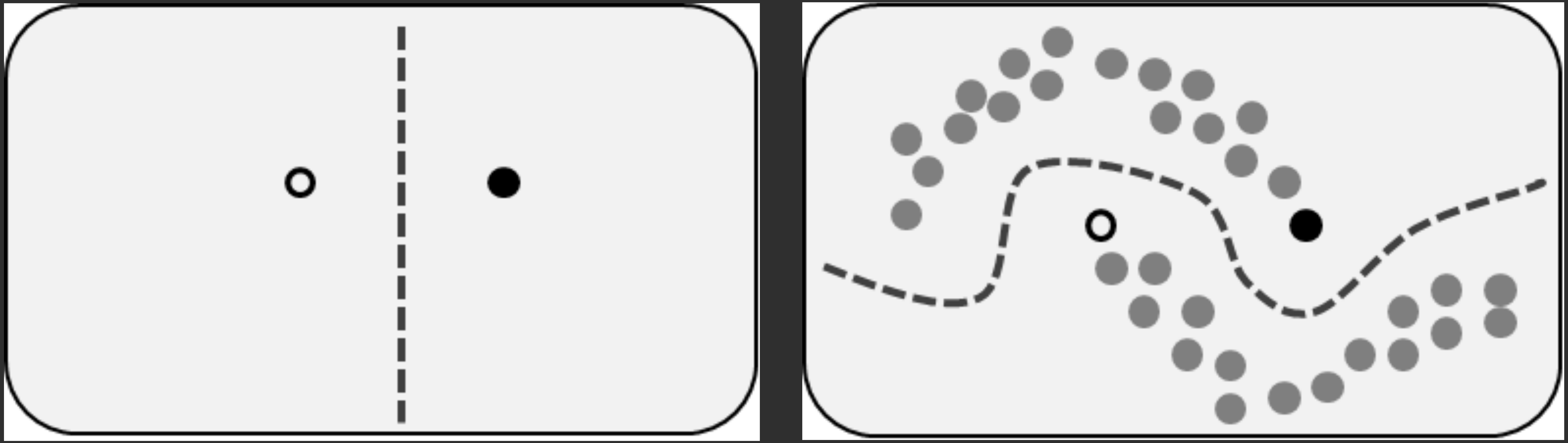
https://media1.fdncms.com/northcoast/imager/u/zoom/3677369/field_notes-579c97c184a67189.jpg

$$p(y|\mathbf{x}) = \frac{p(\mathbf{x}, y)}{p(\mathbf{x})}$$



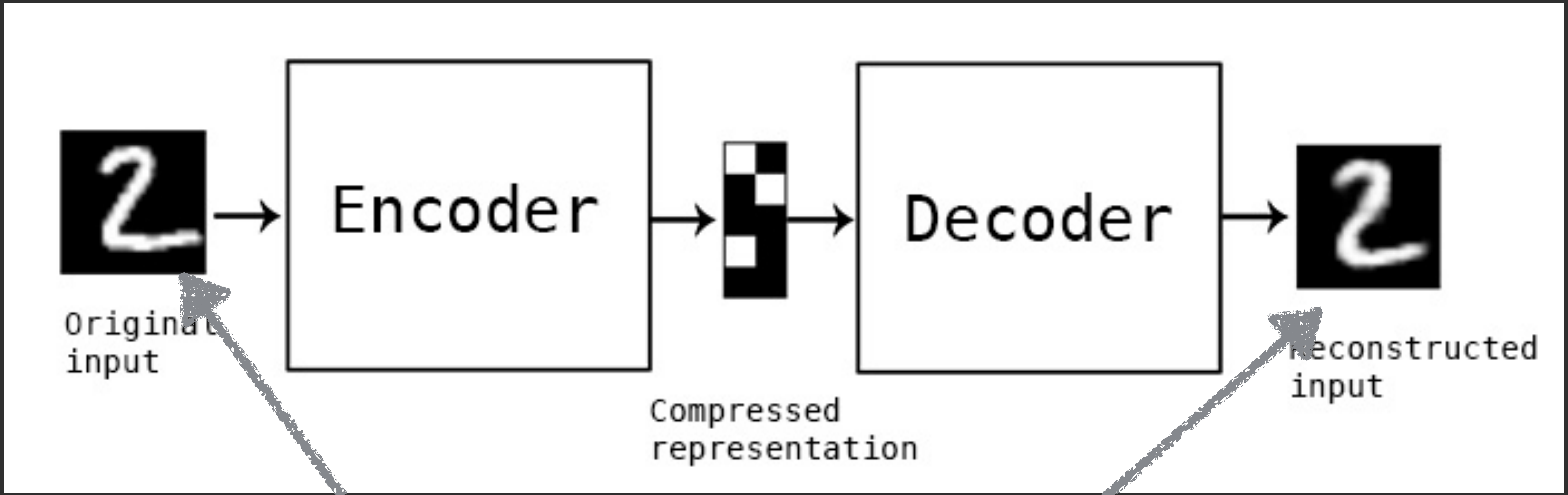
GANs implicitly learn p(x)

GANs in semi-supervised learning



https://en.wikipedia.org/wiki/Semi-supervised_learning#/media/File:Example_of_unlabeled_data_in_semisupervised_learning.png

Autoencoders (cooler than PCA)

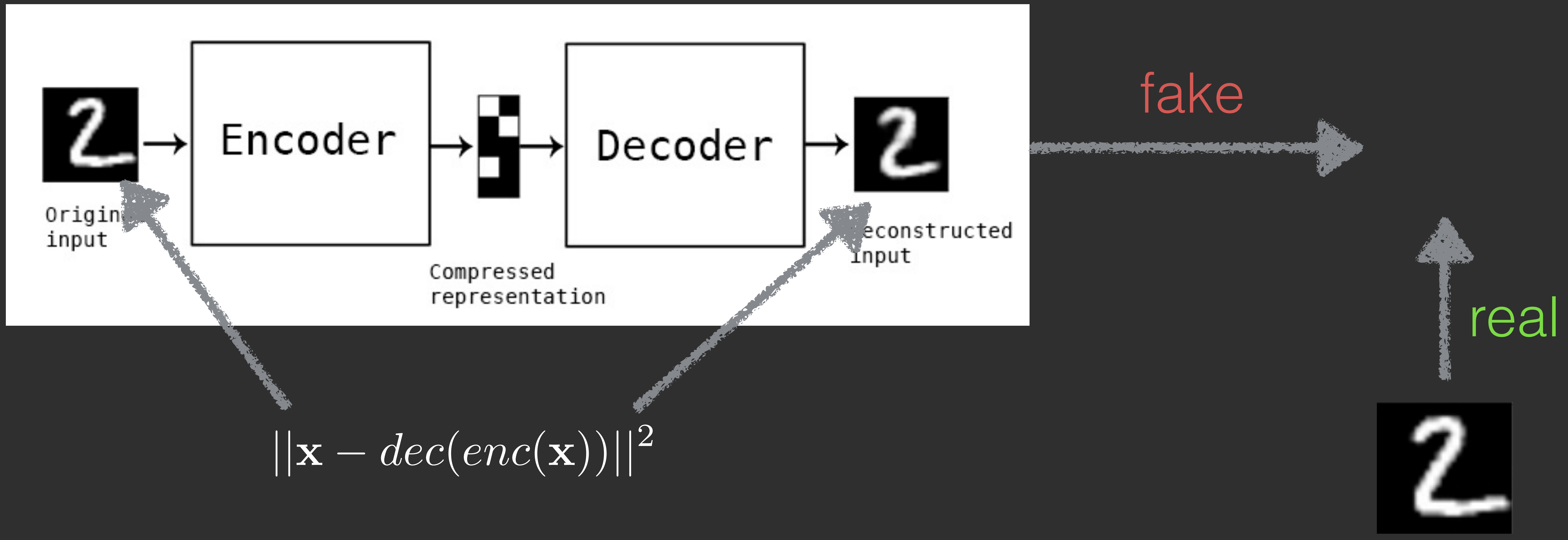


https://blog.keras.io/building-autoencoders-in-keras.html

$$||\mathbf{x} - dec(enc(\mathbf{x}))||^2$$

Euclidean distance is a terrible perceptual similarity metric!

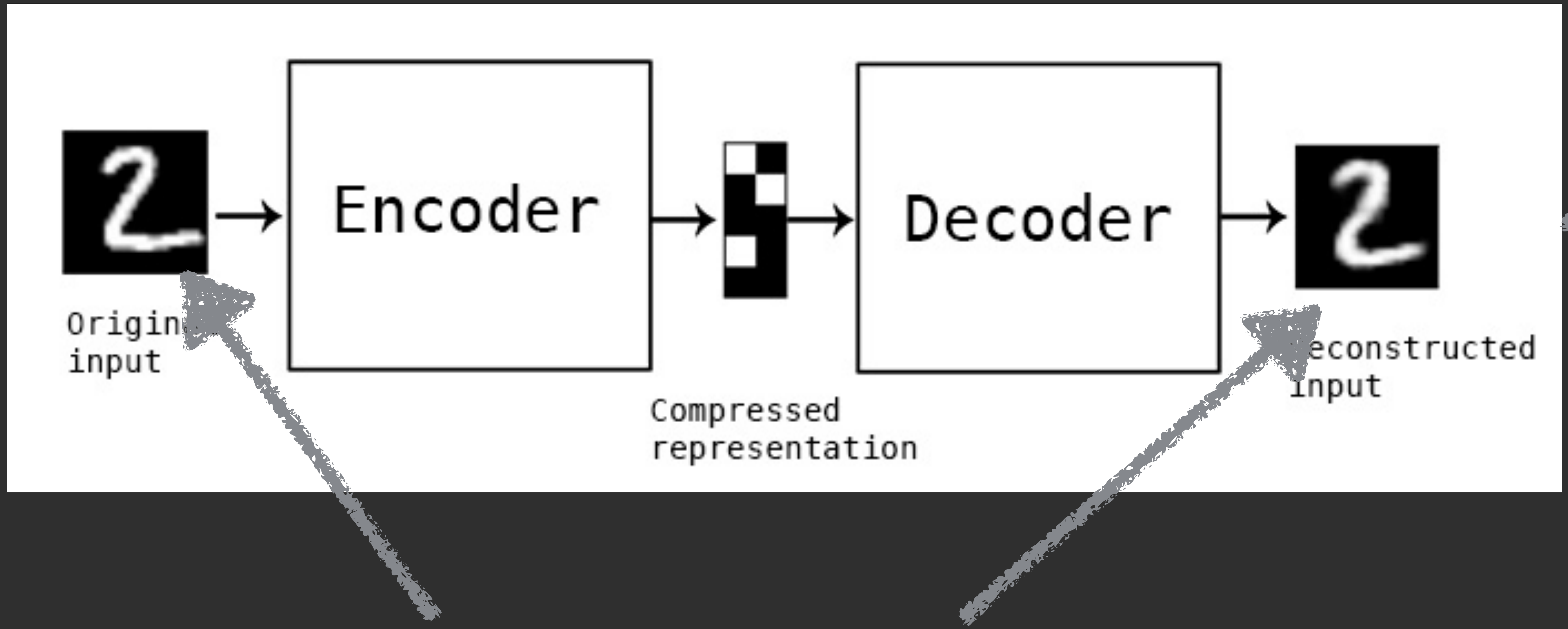
Example: *adversarial* autoencoders



$$||\mathbf{x} - dec(enc(\mathbf{x}))||^2$$

Autoencoder minimises Euclidean distance + tries to fool D

Example: *adversarial* autoencoders



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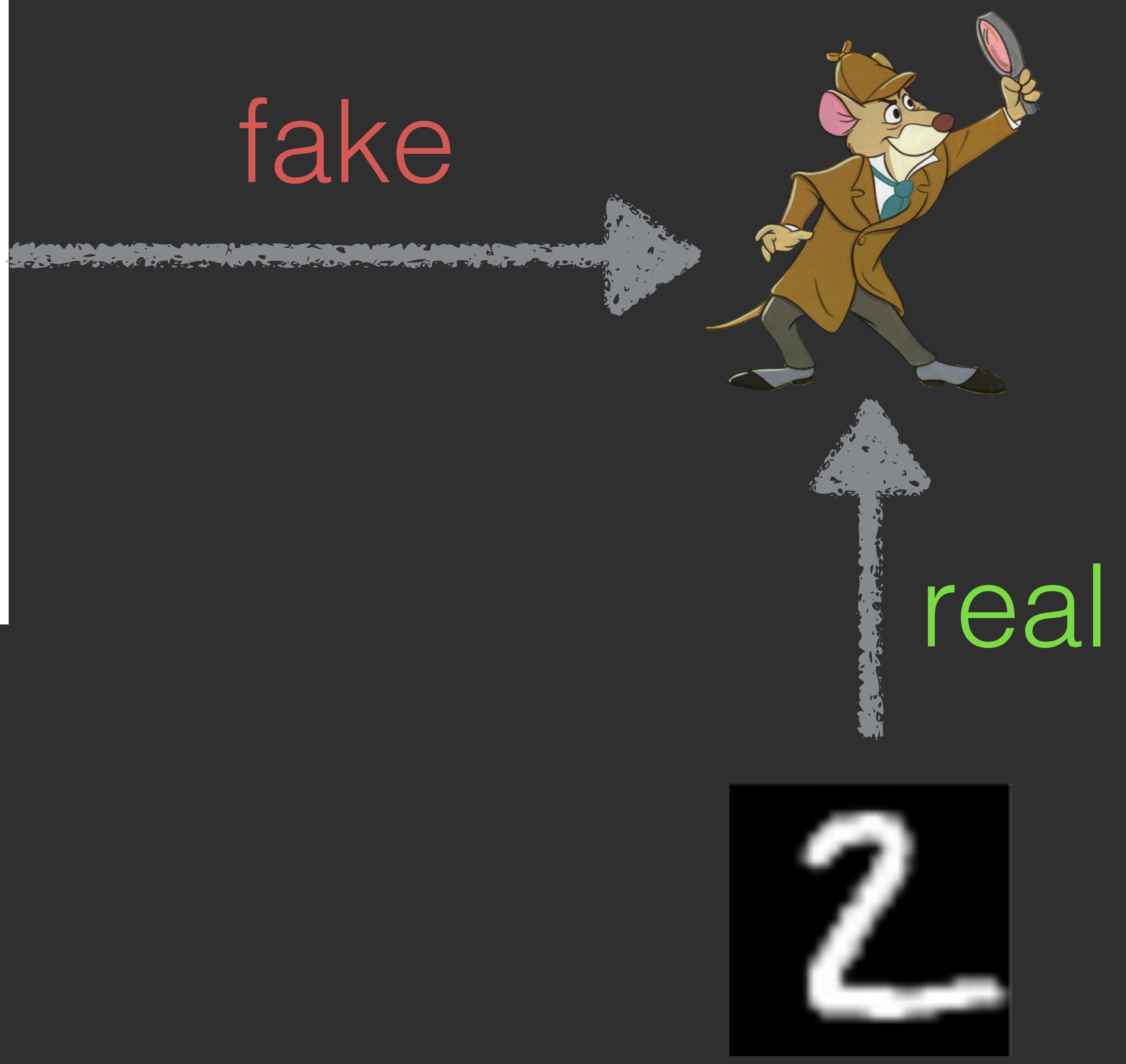
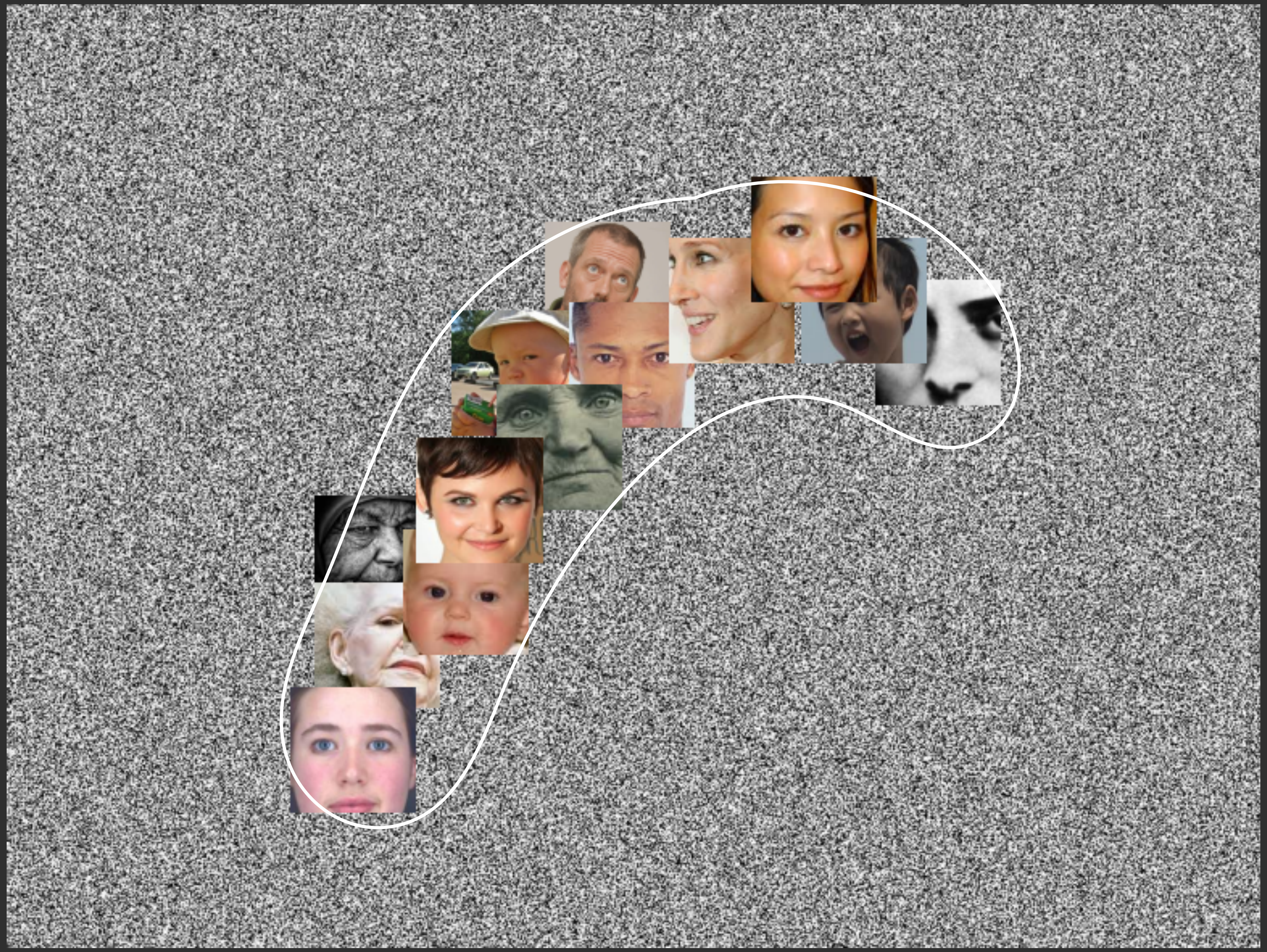


Autoencoder minimises Euclidean distance + tries to fool D

GANs to improve latent representations

Autoencoding beyond pixels using a learned similarity metric (Larsen et al, 2016)

Manifold hypothesis



https://www.iro.umontreal.ca/~bengioy/talks/gss2012-YB3-algorithms-AE-depth.pdf

$$128 \times 128 \times 3 \times 255 = 12.5M$$

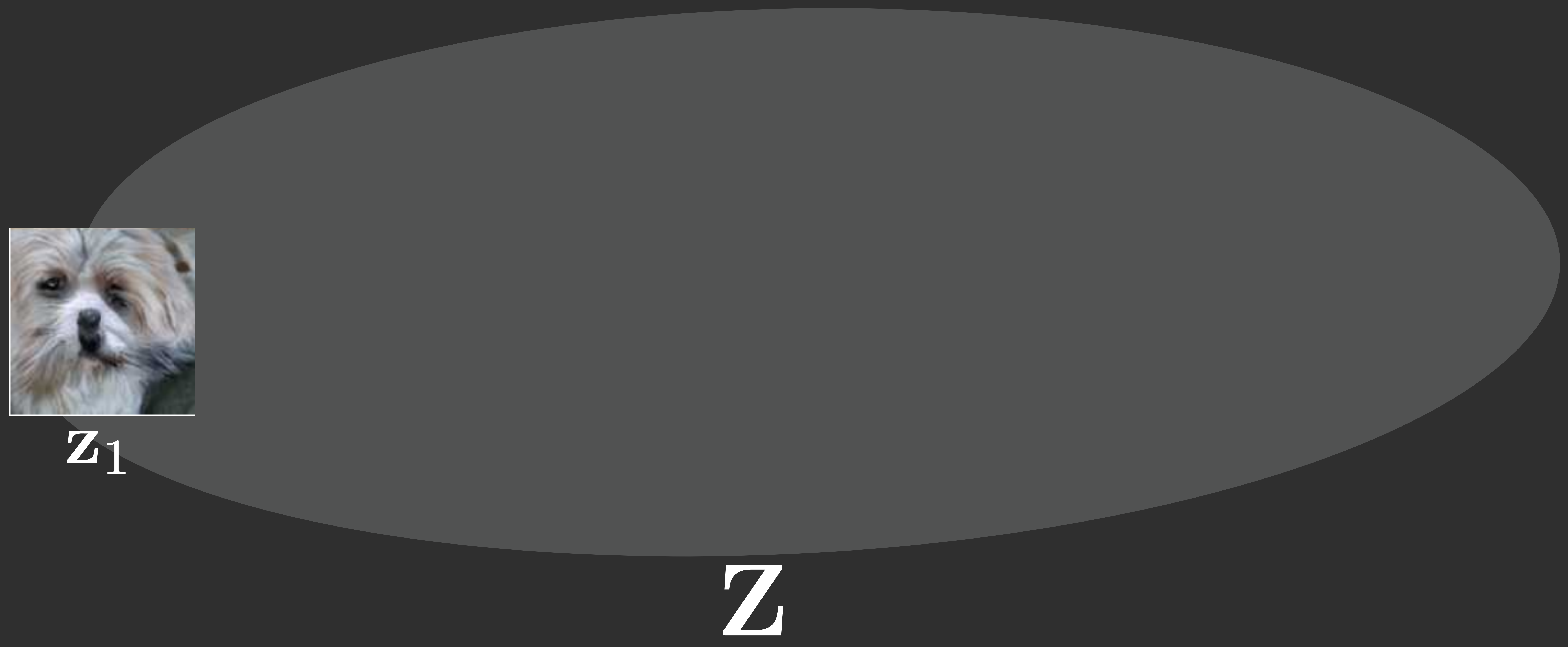
Real data lies on a low dimensional manifold in high dimensional space

Manifold hypothesis

$\mathbf{z}$

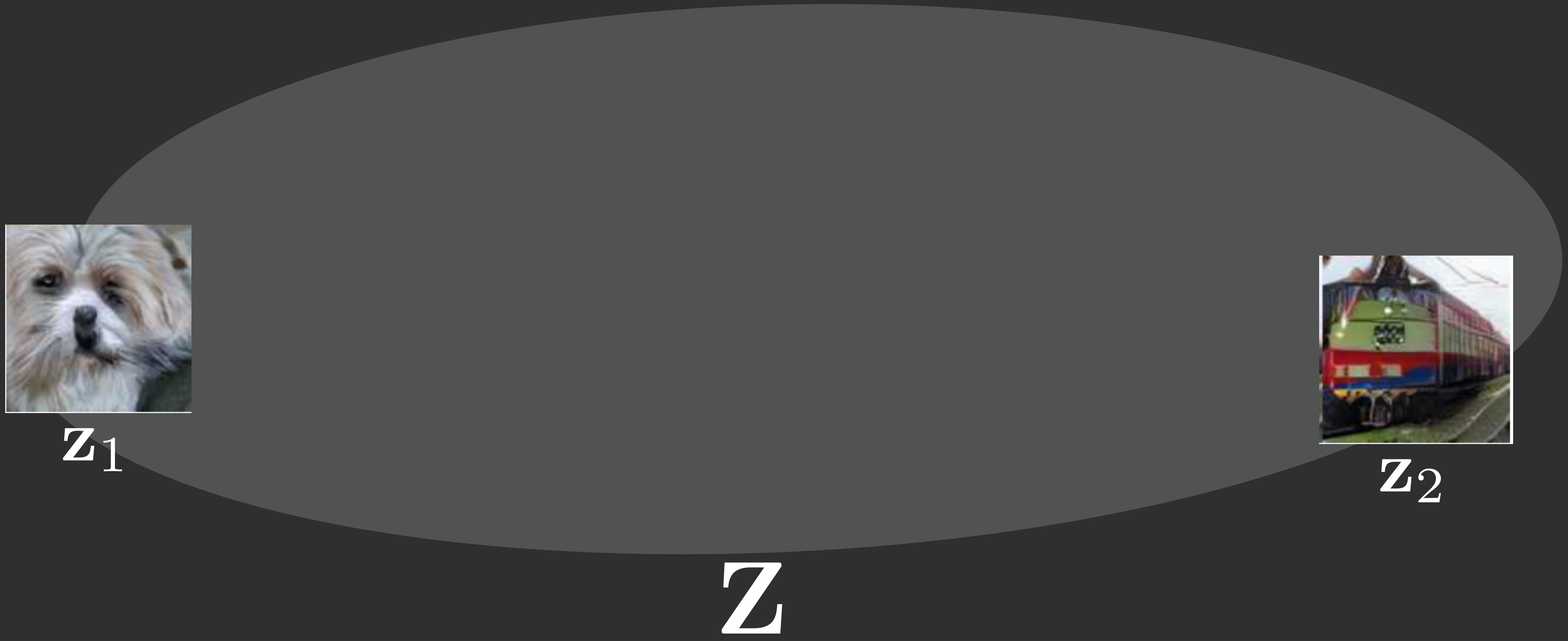
cGANs with projection discriminator (Miyato & Koyama, 2018)

Manifold hypothesis



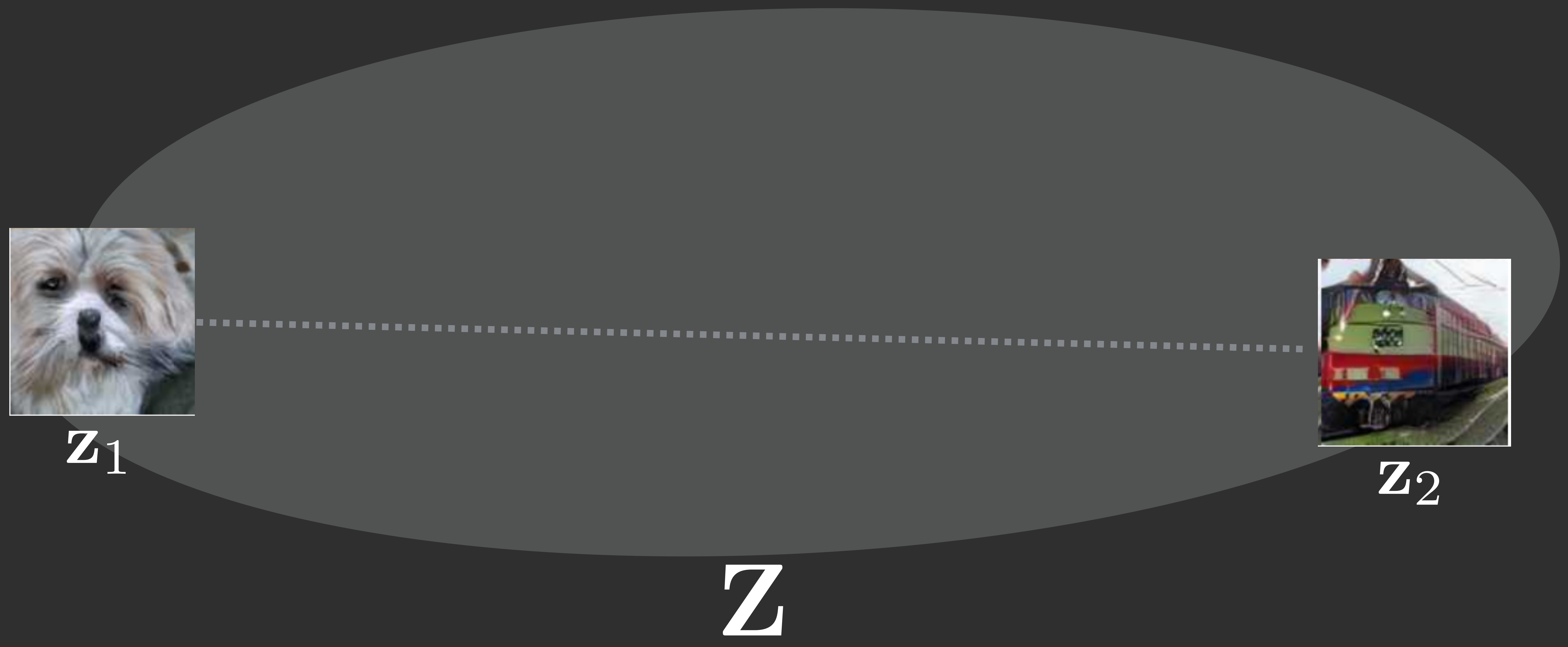
cGANs with projection discriminator (Miyato & Koyama, 2018)

Manifold hypothesis



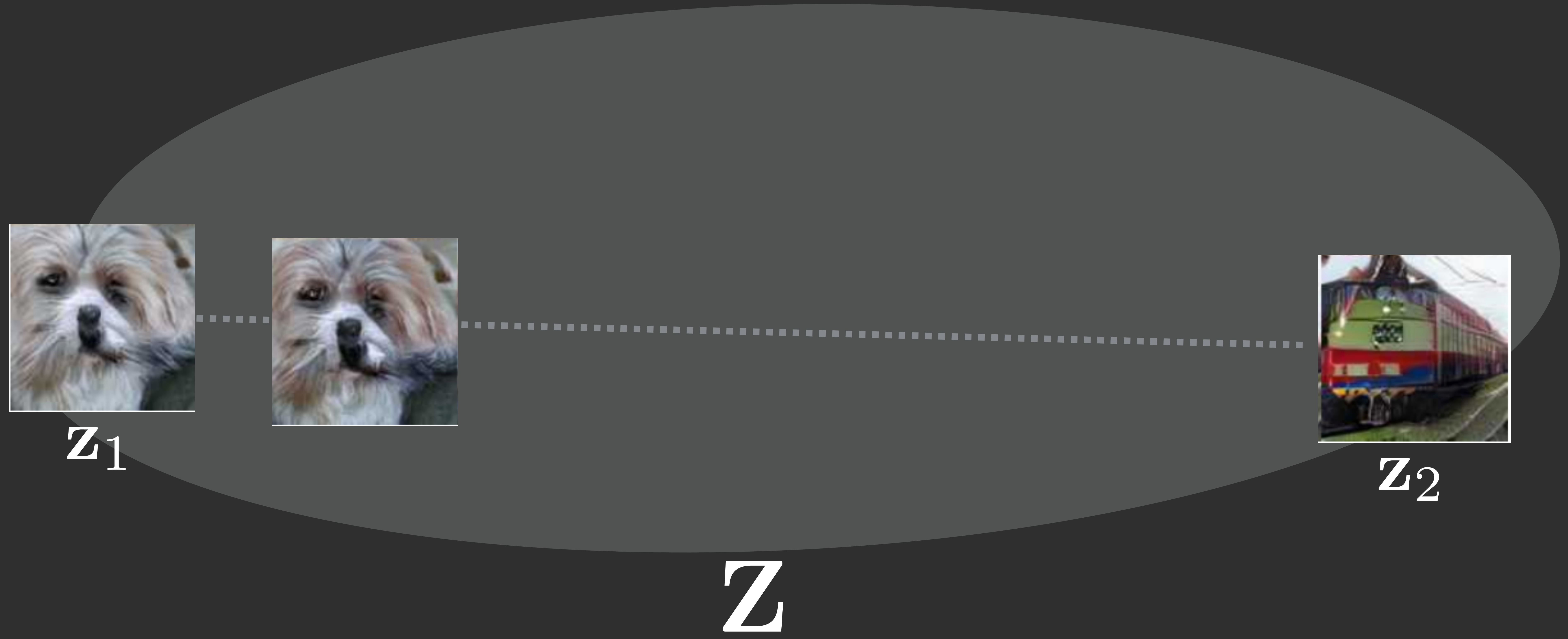
cGANs with projection discriminator (Miyato & Koyama, 2018)

Manifold hypothesis



cGANs with projection discriminator (Miyato & Koyama, 2018)

Manifold hypothesis



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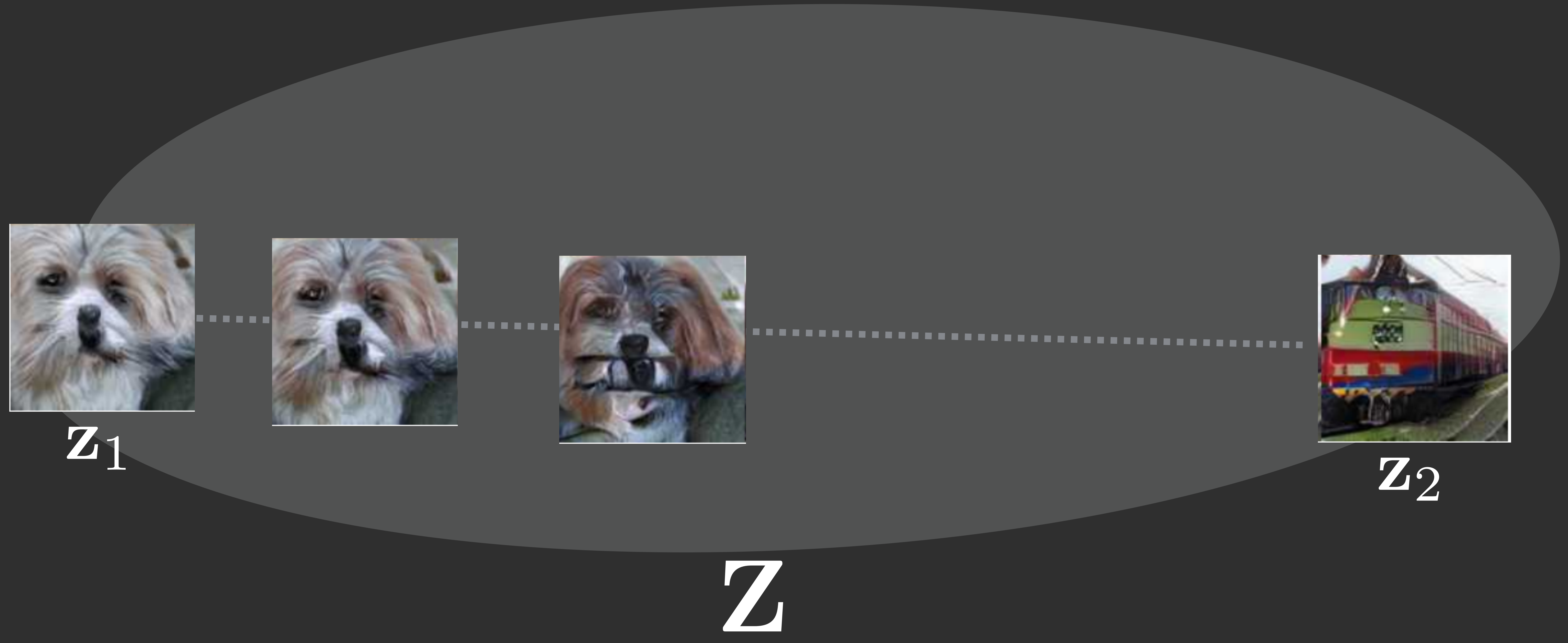
Manifold hypothesis



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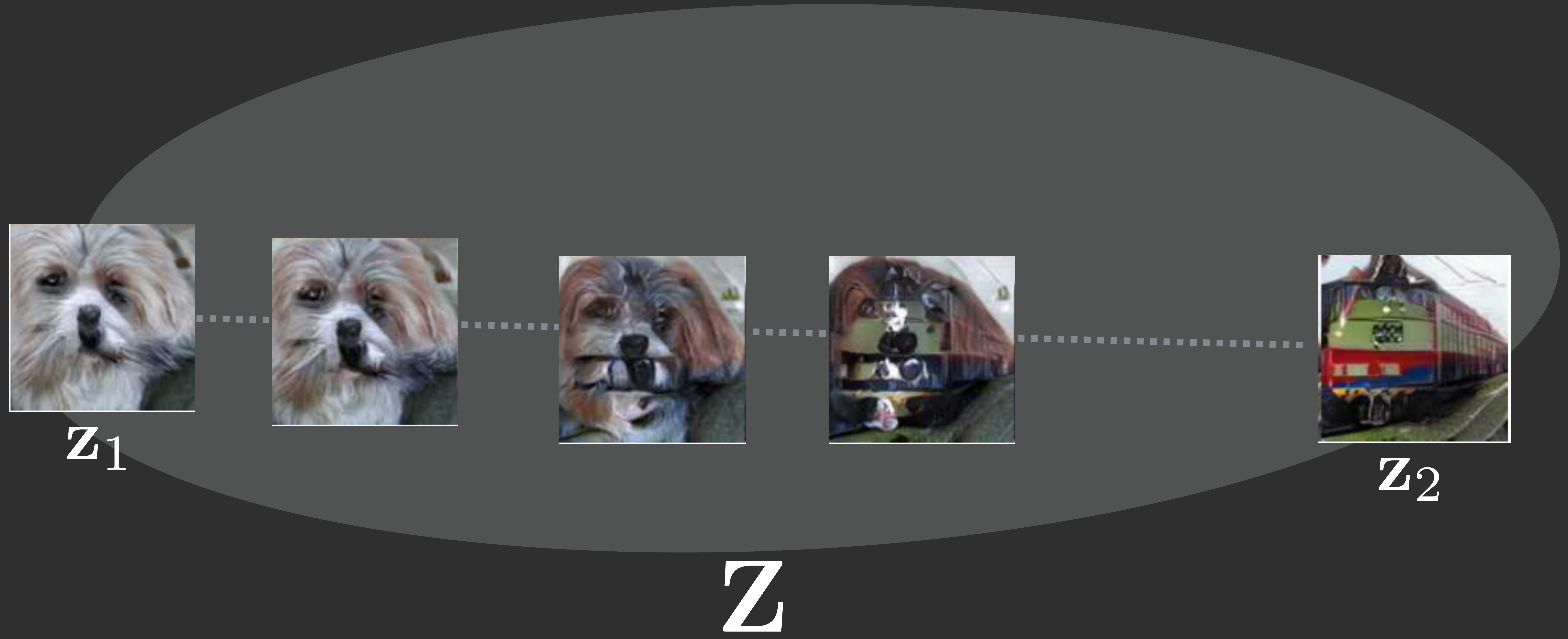

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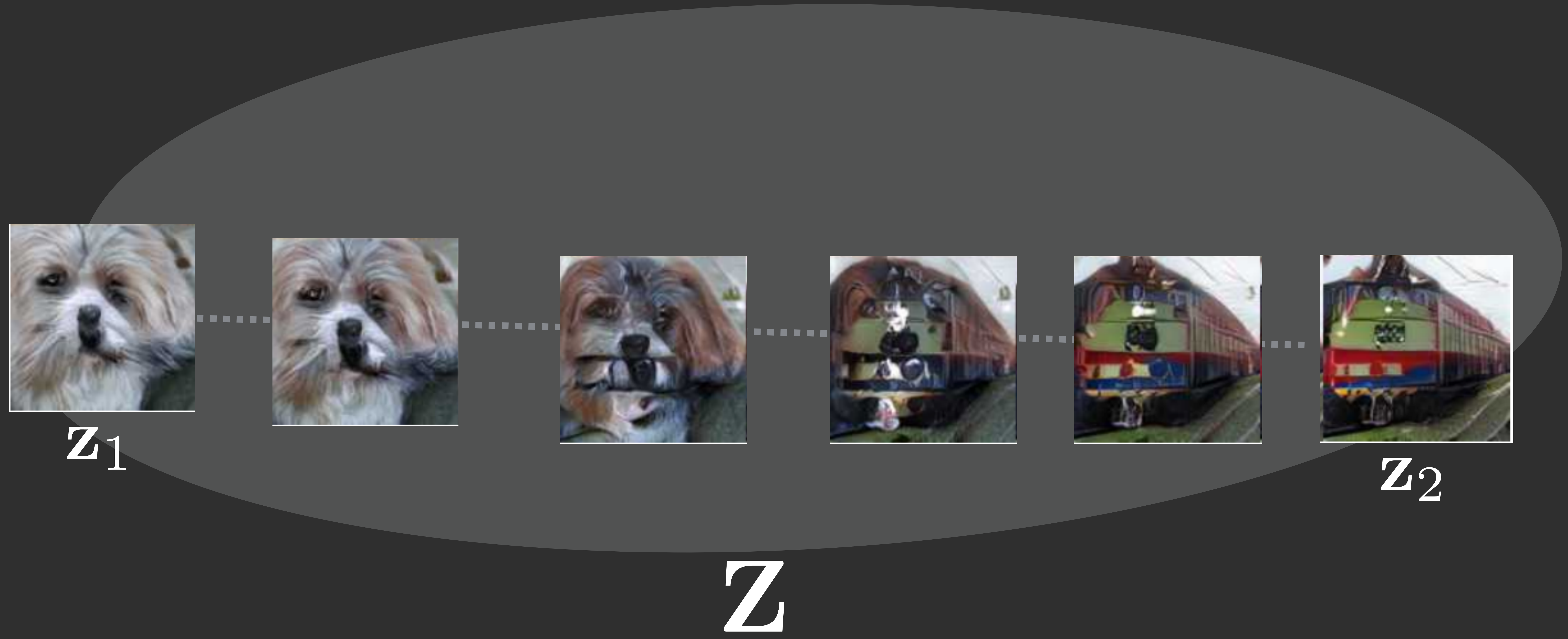

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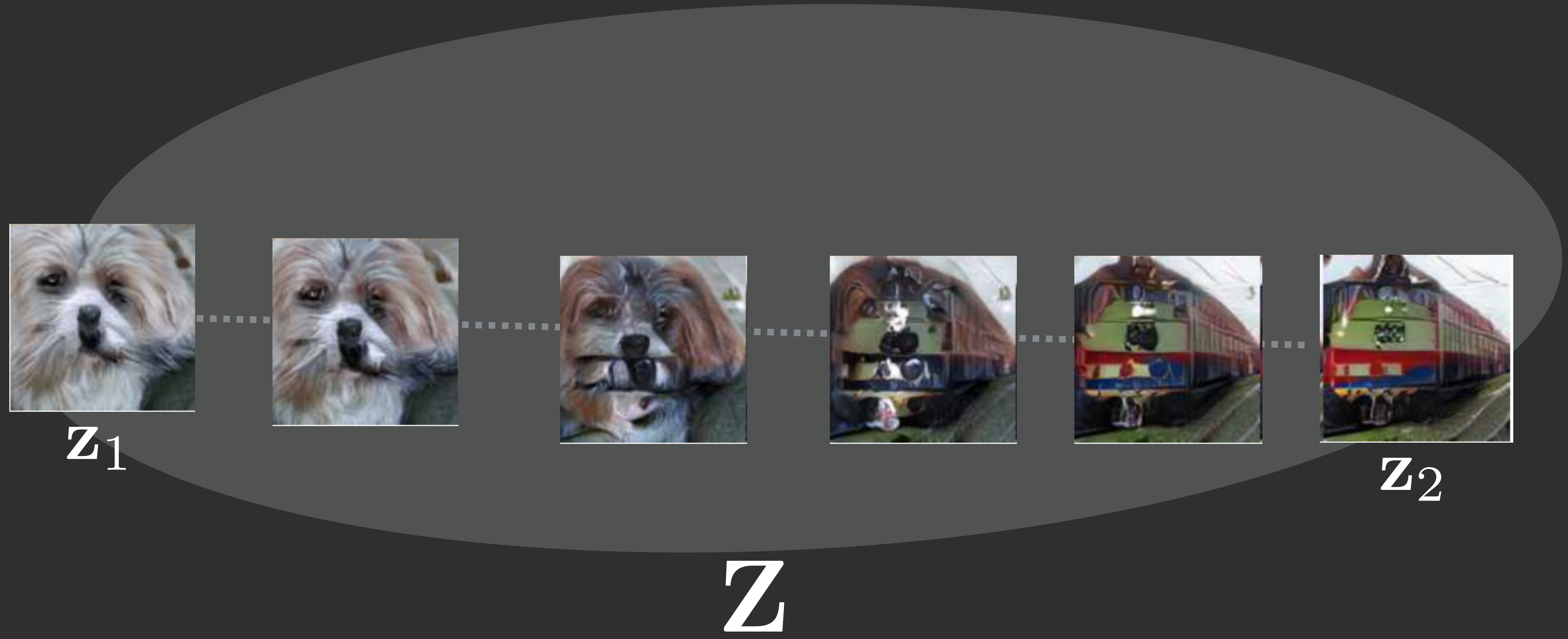

cGANs with projection discriminator (Miyato & Koyama, 2018)

Space of the prior becomes semantically meaningful

Thank you!