Modelos generativos

GANs y VAEs

GAN: Generative Adversarial Nets

“Adversarial training is the coolest idea in Machine Learning in the last 20 years”

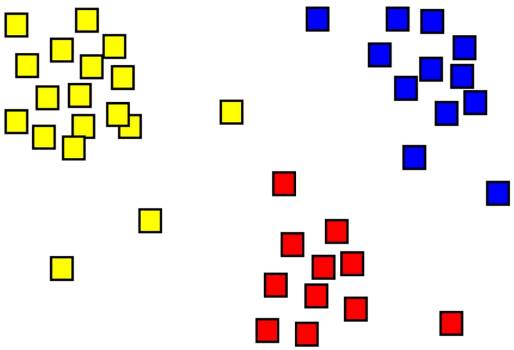
Yann Lecun
Vice President, Chief AI Scientist en Facebook
Professor at New York University
Founding director of the NYU Center for Data Science

Real or Fake?

Real or Fake?

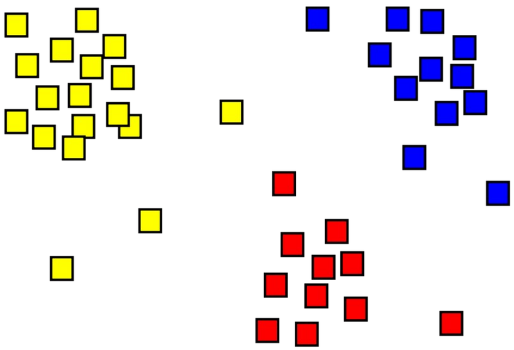
Aprendizaje no supervisado

Clustering: encontrar grupos en los datos (colores)



Aprendizaje no supervisado

Clustering: encontrar grupos en los datos (colores)



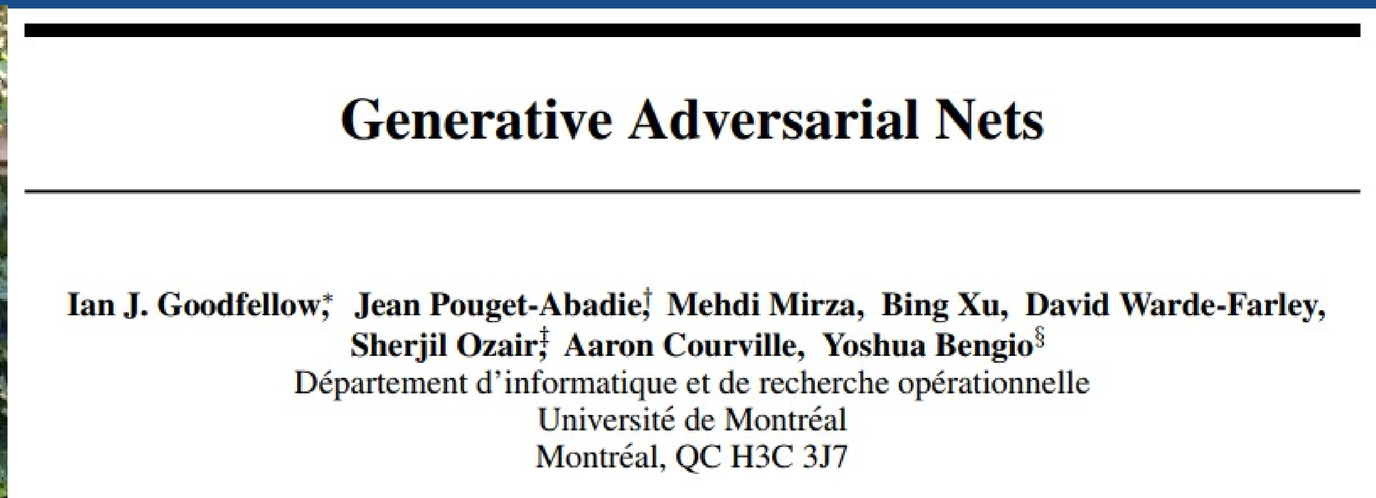
Modelos generativos: encontrar la función ***P(X)*** que generó los datos

Dos tipos: Explícitos e Implícitos

"What I cannot create, I do not understand."

—Richard Feynman

2014



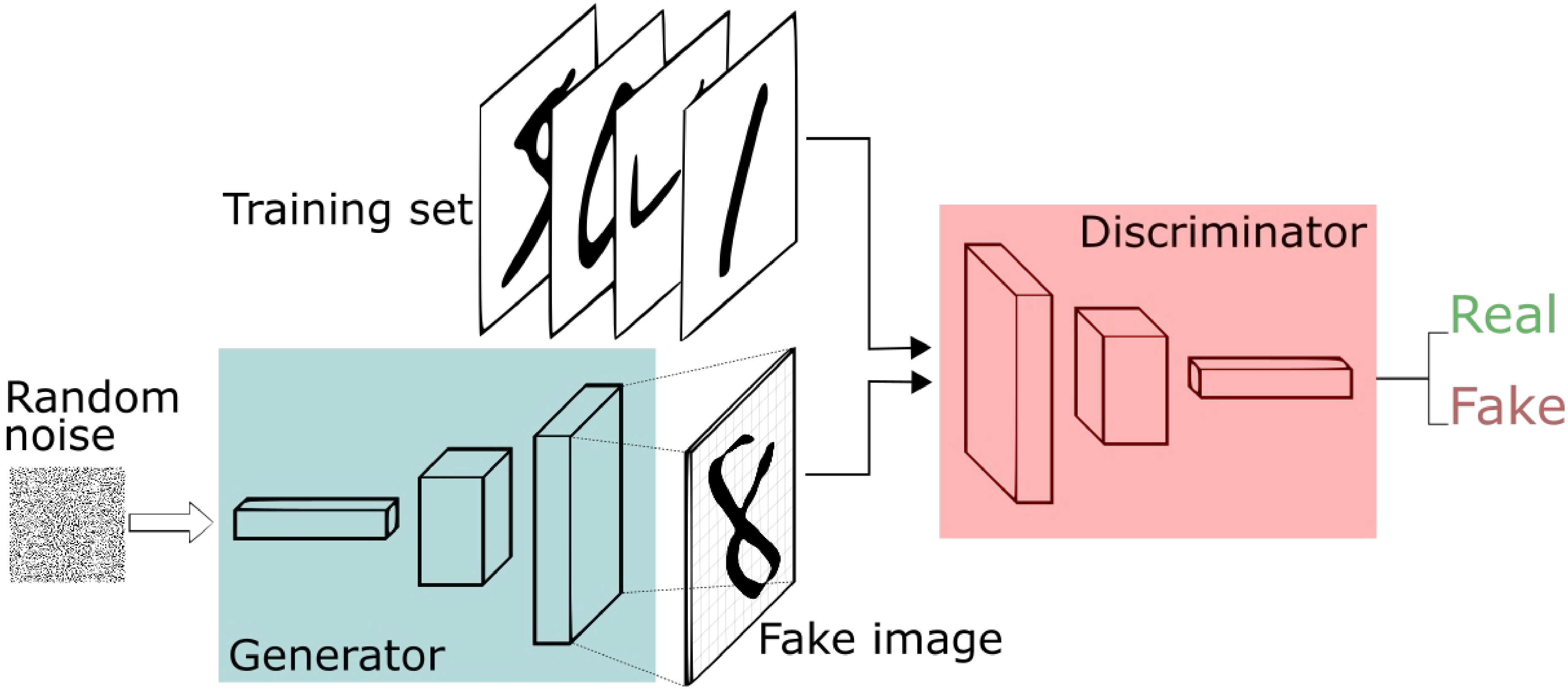
Generative Adversarial Nets

Ian J. Goodfellow[*], Jean Pouget-Abadie[†], Mehdi Mirza, Bing Xu, David Warde-Farley,
Sherjil Ozair[‡], Aaron Courville, Yoshua Bengio[§]
Département d'informatique et de recherche opérationnelle
Université de Montréal
Montréal, QC H3C 3J7

Ian Goodfellow

Deep learner. Inventor of GANs. Lead author of http://www.deeplearningbook.org

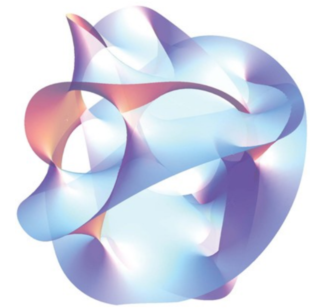
Generative Adversarial Nets (GAN)

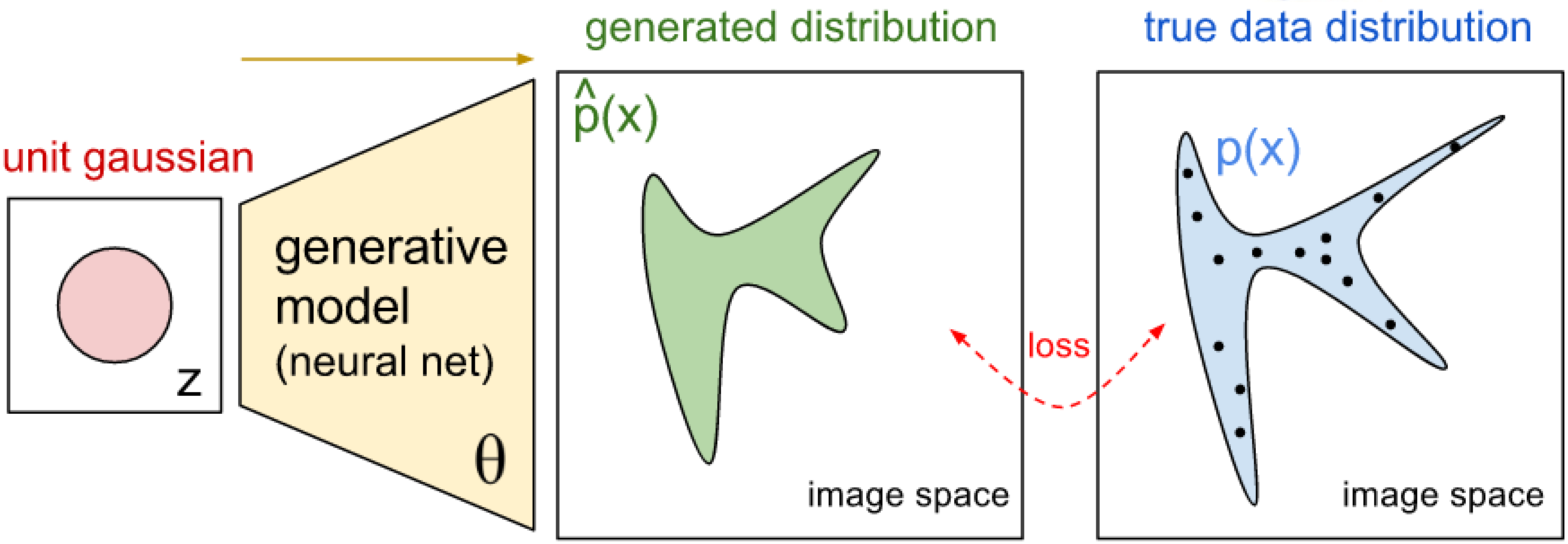


$$\min_G \max_D V(D,G) = \mathbb{E}_{\boldsymbol{x}\sim p_{\text{data}}(\boldsymbol{x})}[\log D(\boldsymbol{x})] + \mathbb{E}_{\boldsymbol{z}\sim p_{\boldsymbol{z}}(\boldsymbol{z})}[\log(1 - D(G(\boldsymbol{z})))]$$

https://sthalles.github.io/intro-to-gans/

Generative Adversarial Nets (GAN)





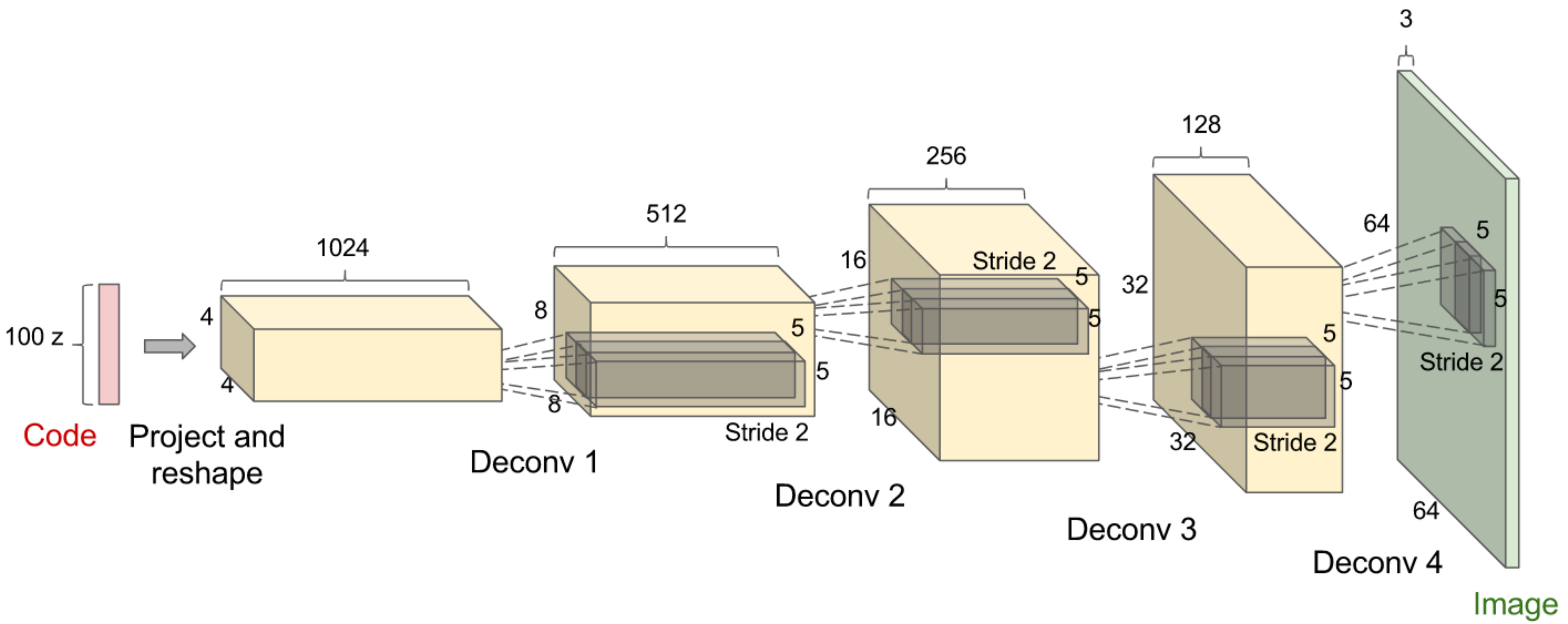
Kullback–Leibler divergence

$$KL(\mathbb{P}_r \| \mathbb{P}_g) = \int \log\left(\frac{P_r(x)}{P_g(x)}\right) P_r(x) d\mu(x)$$

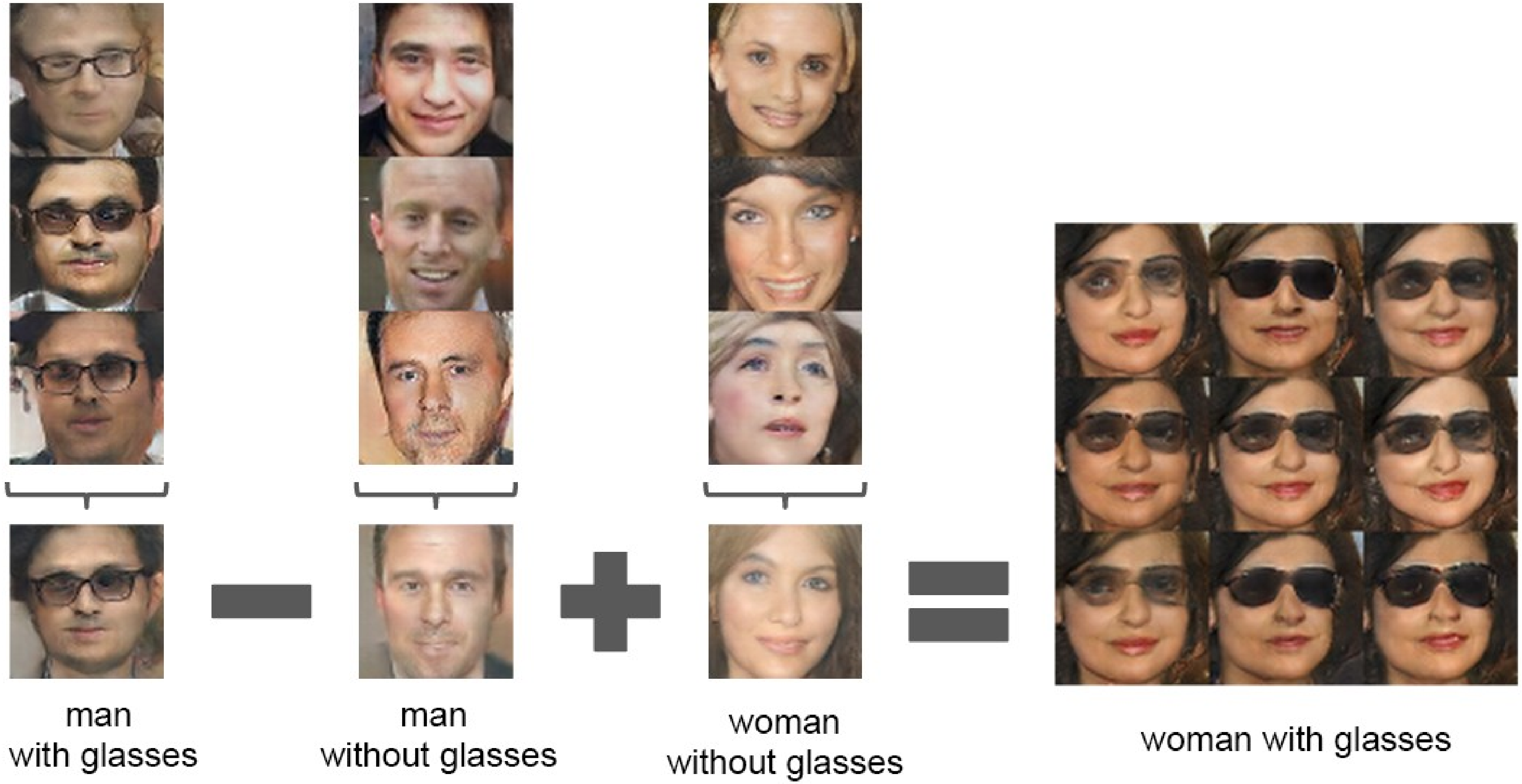
https://blog.openai.com/generative-models/

Deep Convolutional GAN (dcgan, 2015)

Radford, A., Metz, L., & Chintala, S. (2015). Unsupervised representation learning with deep convolutional generative adversarial networks. *arXiv preprint arXiv:1511.06434*.

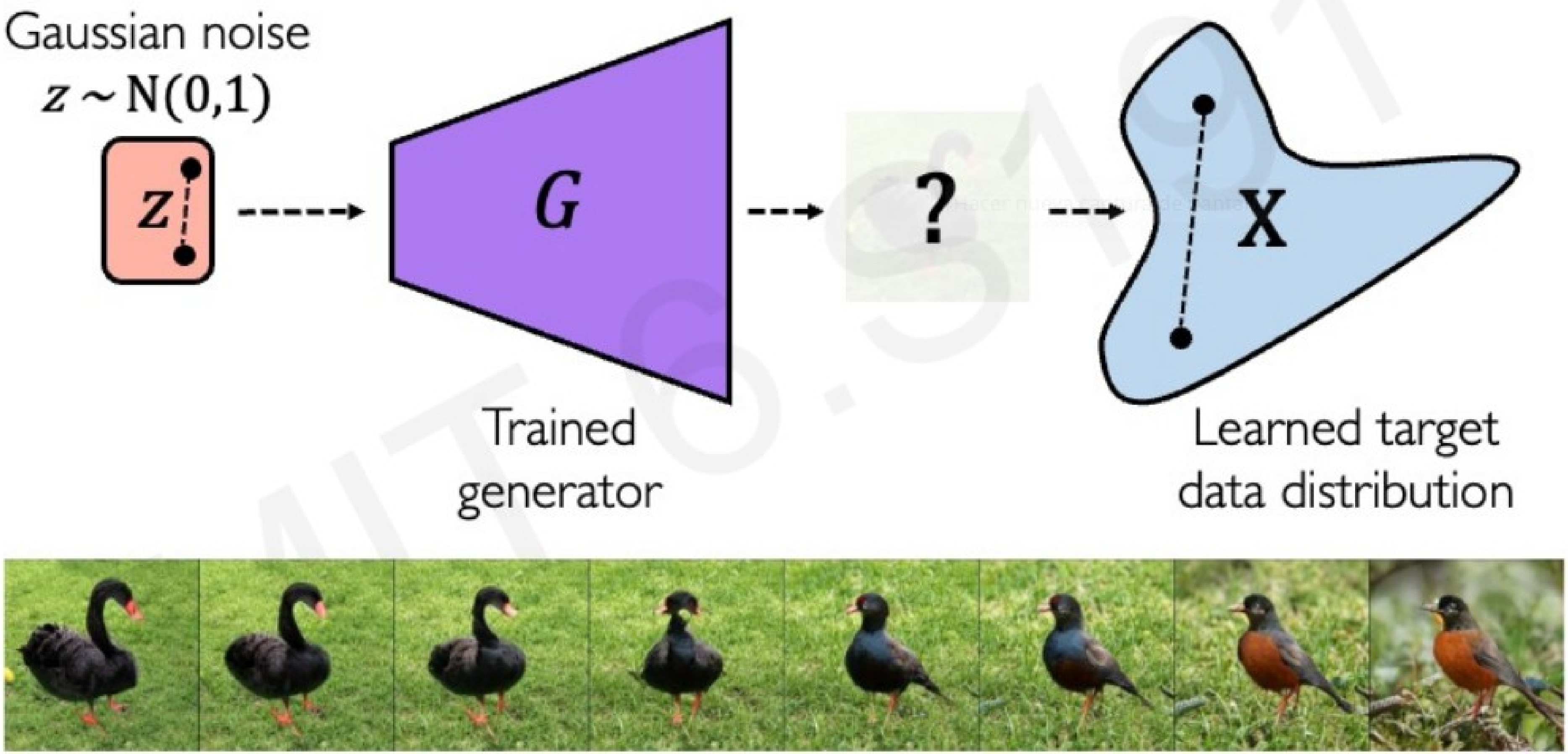


Aritmética de caras

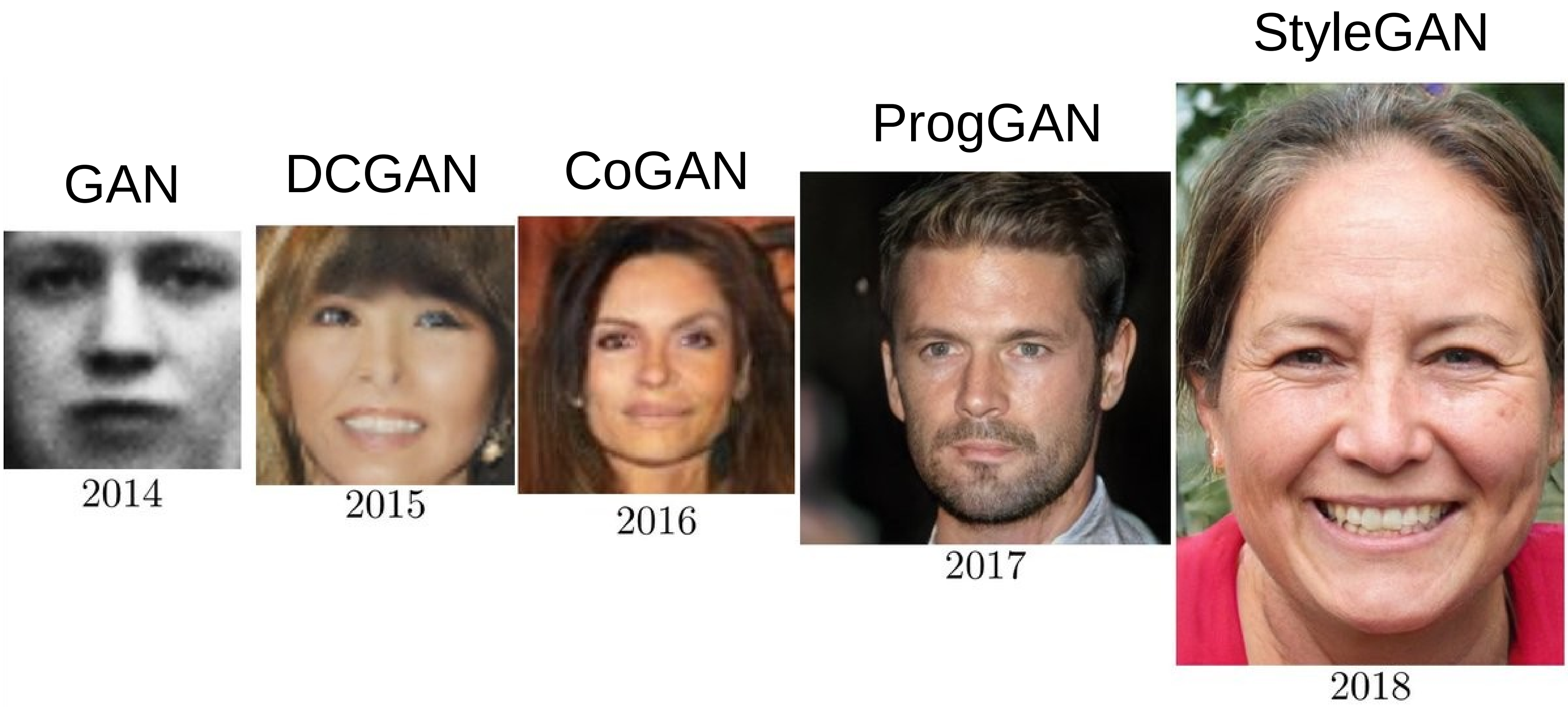


Radford, A., Metz, L., & Chintala, S. (2015). Unsupervised representation learning with deep convolutional generative adversarial networks. arXiv preprint arXiv:1511.06434.

Interpolación



La evolución de GAN (rostros)



https://twitter.com/goodfellow_ian/status/1084973596236144640

La evolución de GAN (imágenes naturales)

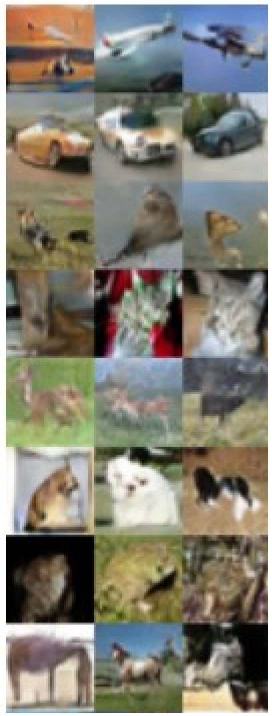
2014

GAN

Université de Montréal

Ene. 2017

WGAN

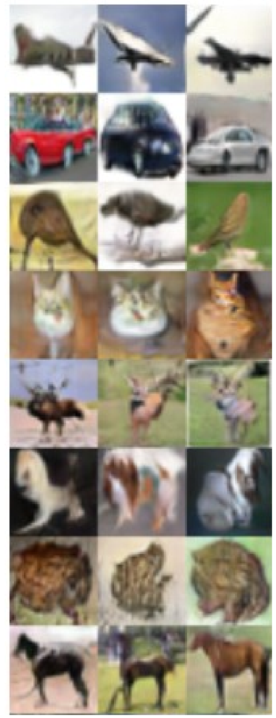


NYU

facebook

Sep. 2017

SplittingGAN



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Universidad Nacional de Rosario

CIFASIS

Oct. 2017

ProgGAN

NVIDIA

2018

BigGAN

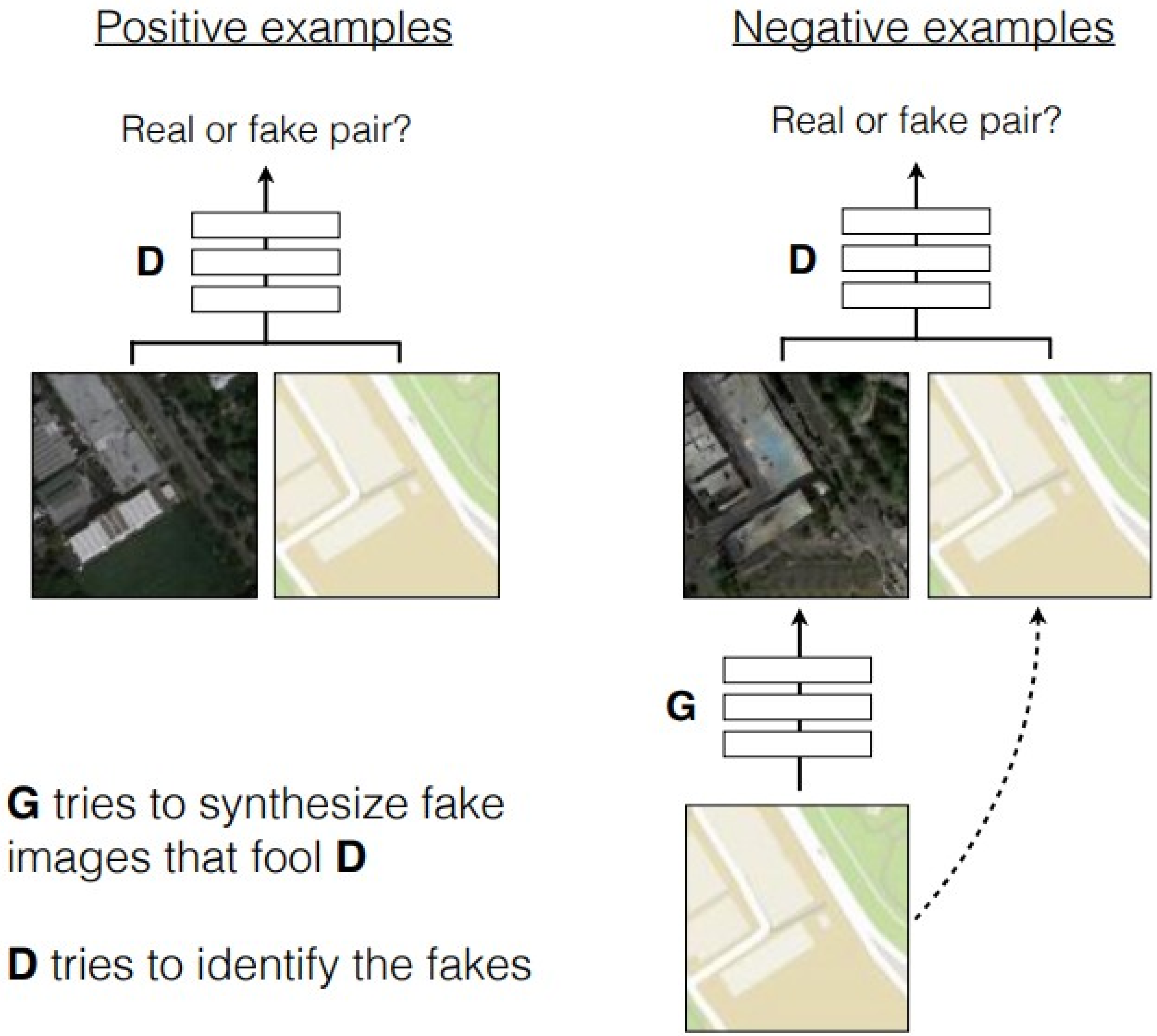
Google DeepMind

BigGAN

Brock, A., Donahue, J., & Simonyan, K. (2018). Large scale gan training for high fidelity natural image synthesis. arXiv preprint arXiv:1809.11096.

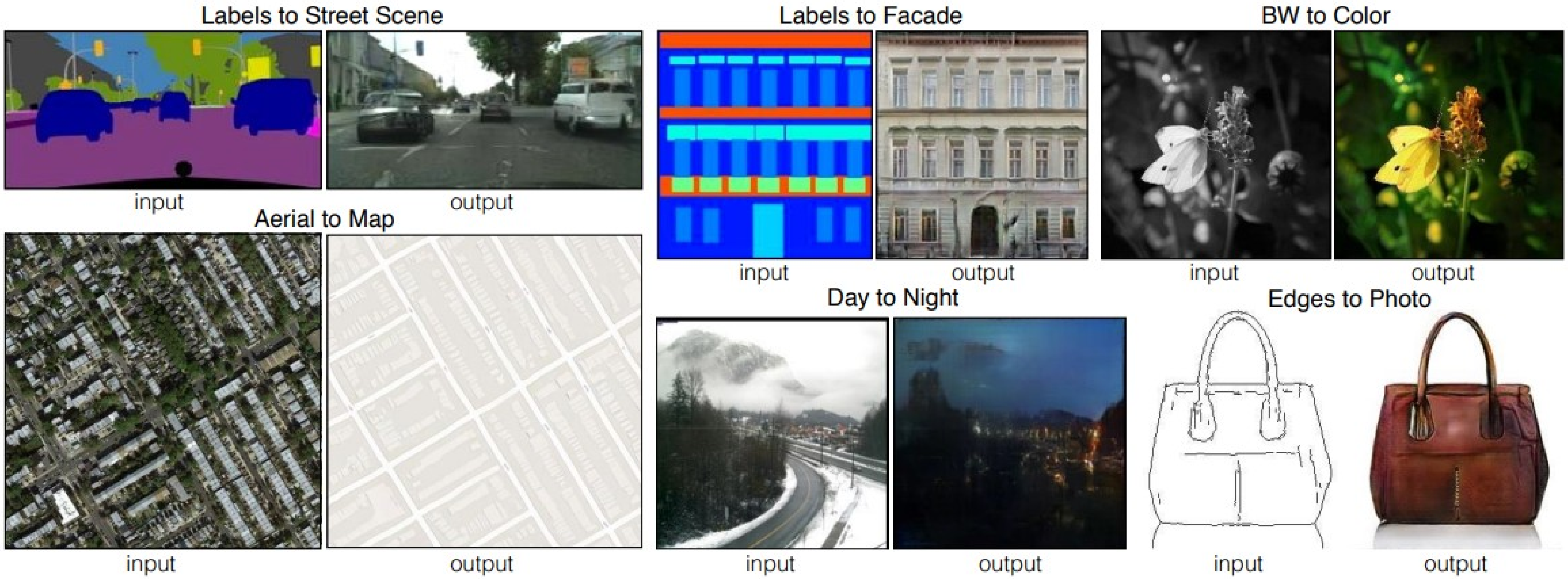
Algunas aplicaciones

Image-to-Image Translation



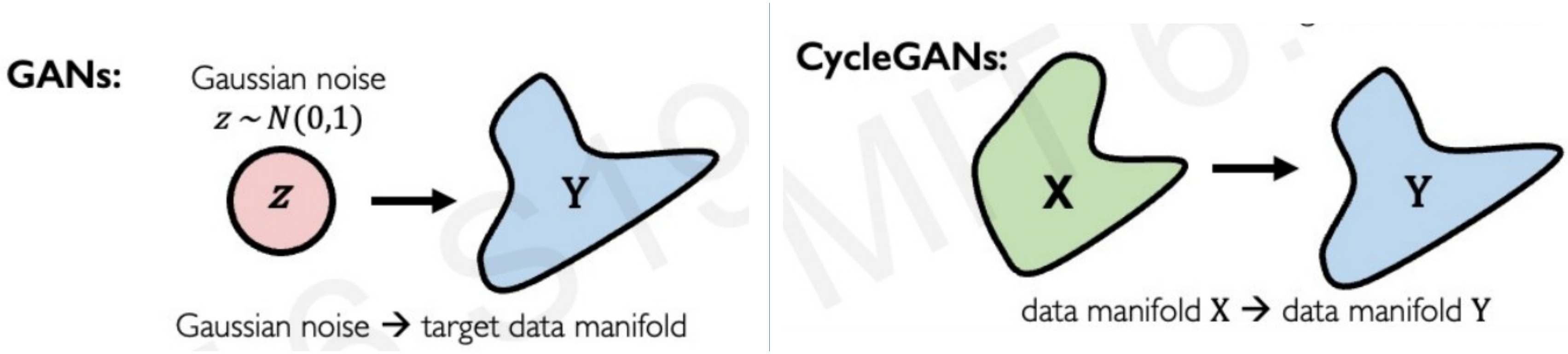
Isola, Phillip, et al. "Image-to-image translation with conditional adversarial networks." arXiv preprint arXiv:1611.07004 (2016).

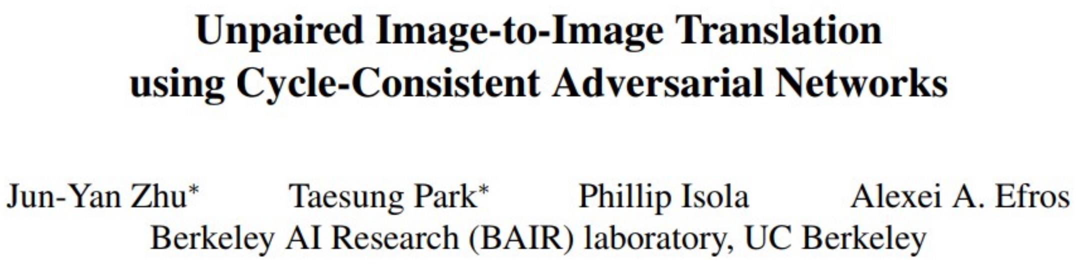
Image-to-Image Translation



Isola, Phillip, et al. "Image-to-image translation with conditional adversarial networks." arXiv preprint arXiv:1611.07004 (2016).

CycleGAN (2017)





https://junyanz.github.io/CycleGAN/

CycleGAN

Cats ↔ Dogs

itok_msi produced cats ↔ dogs CycleGAN results with a local+global discriminator and a smaller cycle loss.

Animal Transfiguration

Tatsuya Hatanaka trained our method to translate black bears to pandas. See more examples and download the models at the **website**. **Matt Powell** performed transfiguration between different species of birds

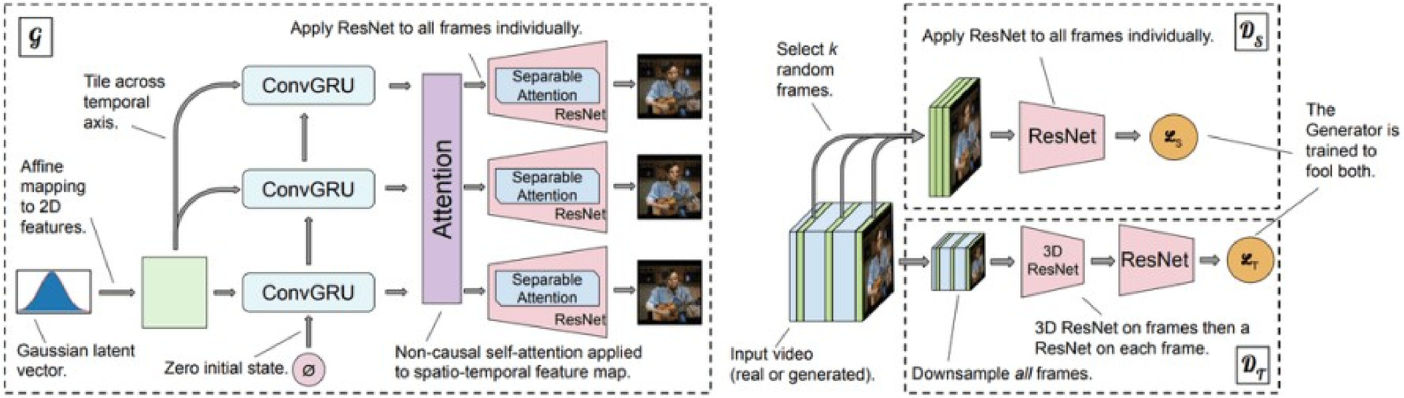
orange → apple

https://junyanz.github.io/CycleGAN/

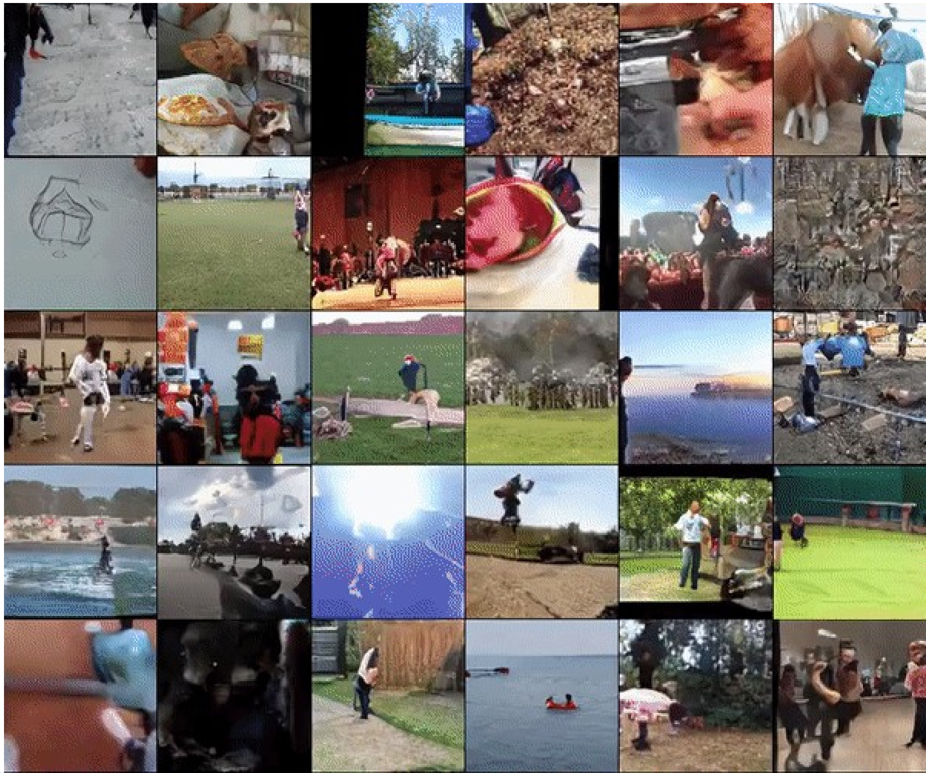
Turning Fortnite into PUBG with CycleGAN

https://towardsdatascience.com/turning-fortnite-into-pubg-with-deep-learning-cyclegan-2f9d339dcdb0

Video: DVD-GAN (2019)

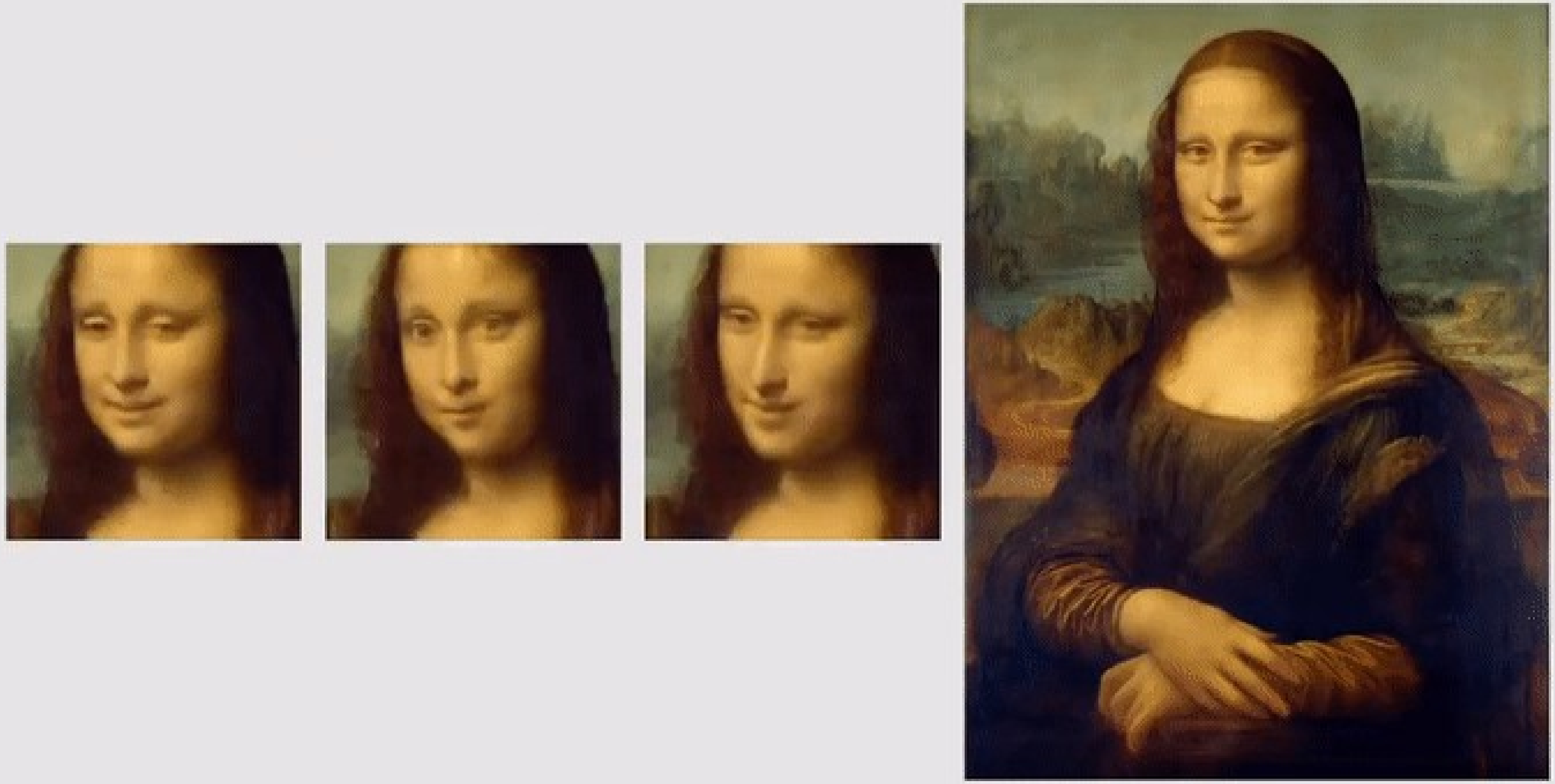


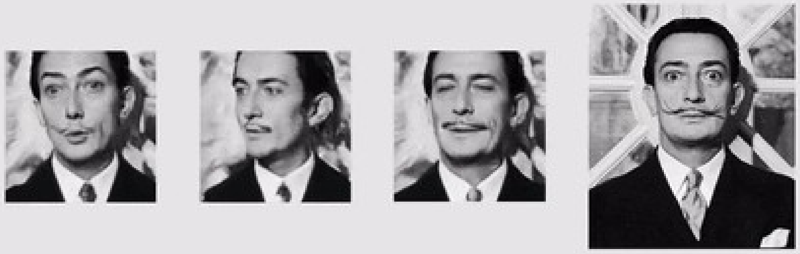
Big-GAN + Youtube +
Discriminar en tiempo y espacio



https://arxiv.org/pdf/1907.06571.pdf

Living portraits





Análisis Semántico en Rostros

Ejemplos de imágenes a clasificar

Caras generadas con GAN

Inteligencia Artificial
Iberoamerican Journal of Artificial Intelligence. Edited by Iberamia.

Semantic analysis on faces using deep neural networks

Nicolás Federico Pellejero
Guillermo Grinblat
Lucas Uzal

DOI: https://doi.org/10.4114/intartif.vol21iss61pp14-29

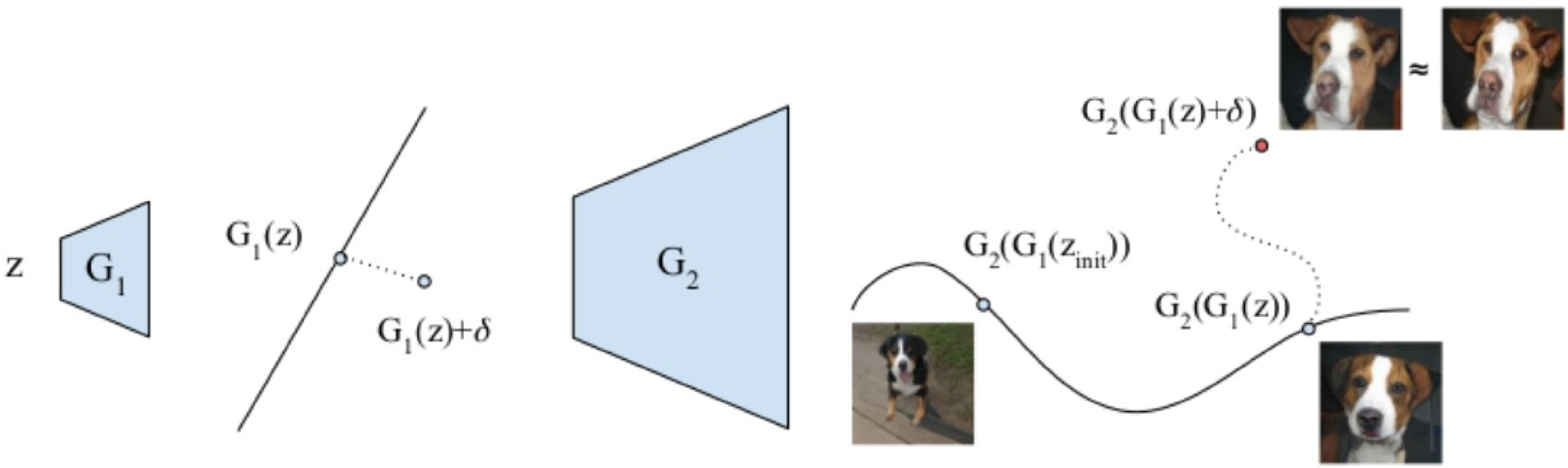
Keywords: Deep, Learning, Emotion, Recognition.

Exploiting GAN Internal Capacity for High-Quality Reconstruction of Natural Images

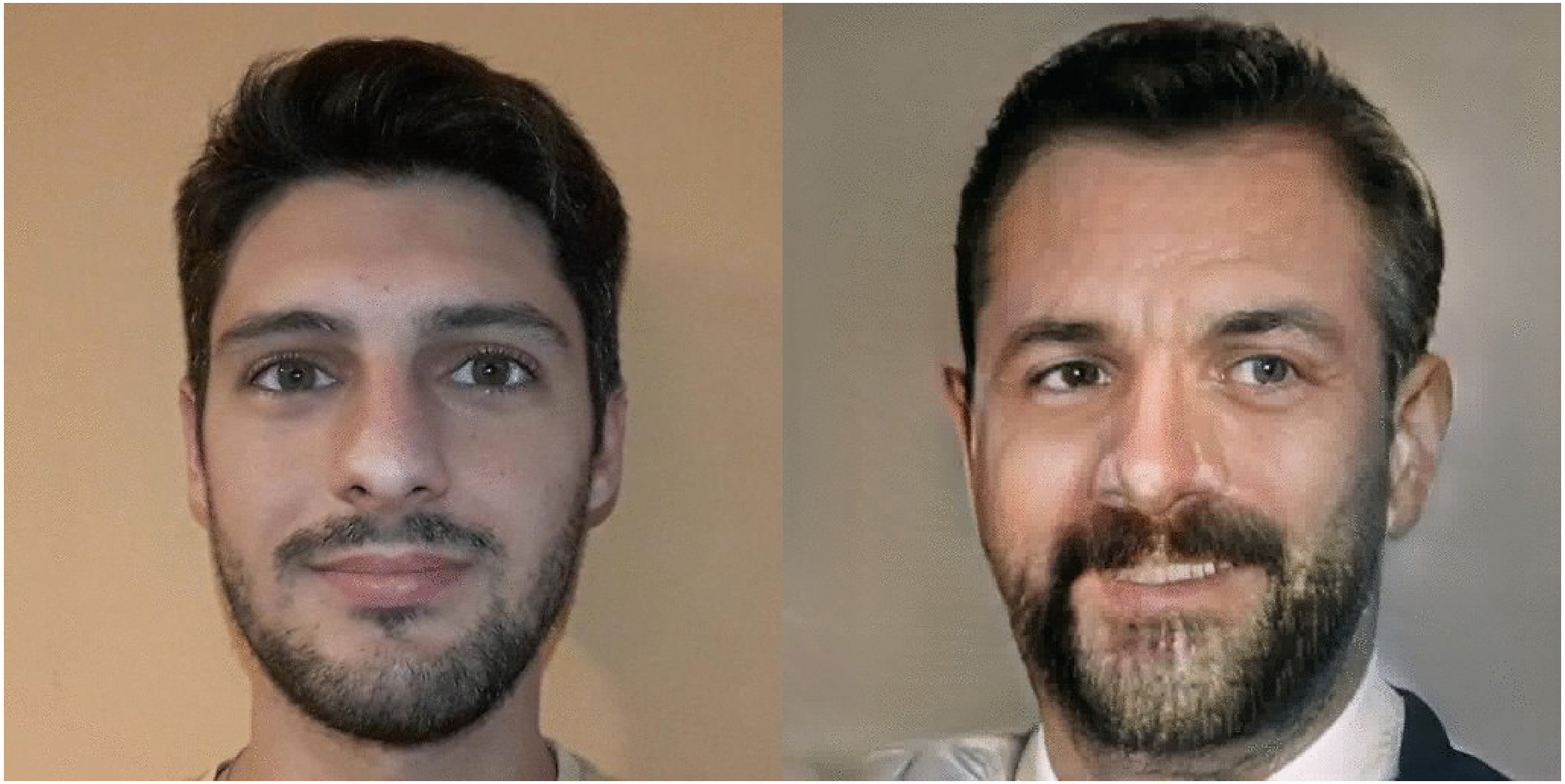
CONICET

C I F A S I S

Marcos Pividori
Guillermo Grinblat
Lucas Uzal



Generación de rostros y manipulación de expresiones



Autoencoders y VAEs

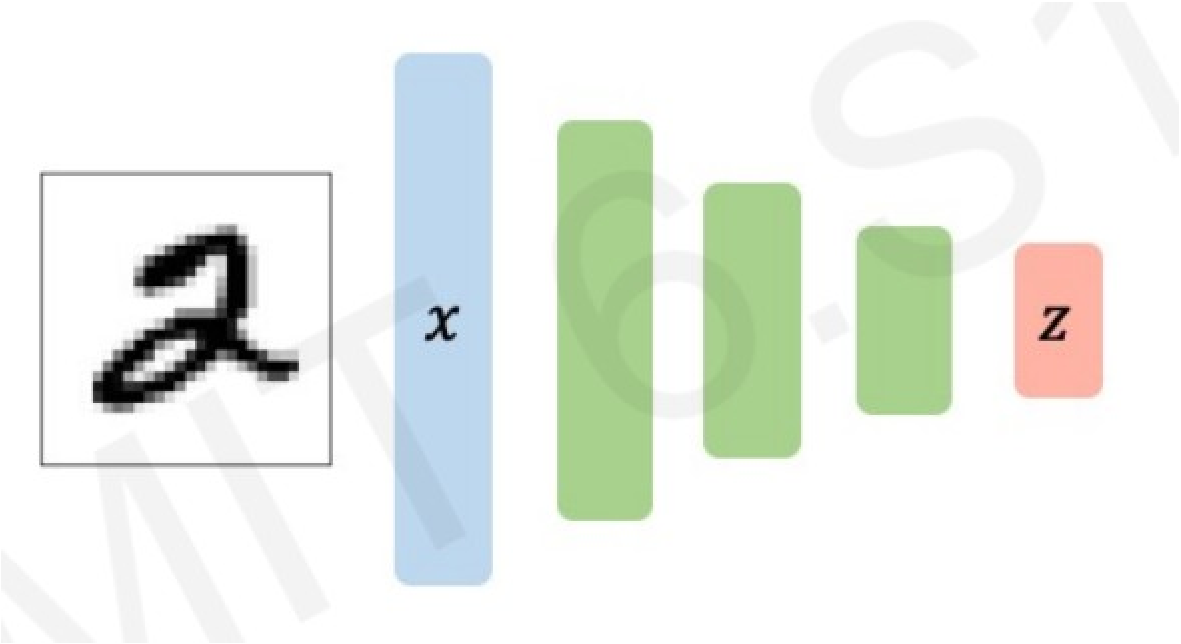
Autoencoders

Variables latentes: Verdaderos factores de variación que explican un fenómeno observable.

Myth of the Cave

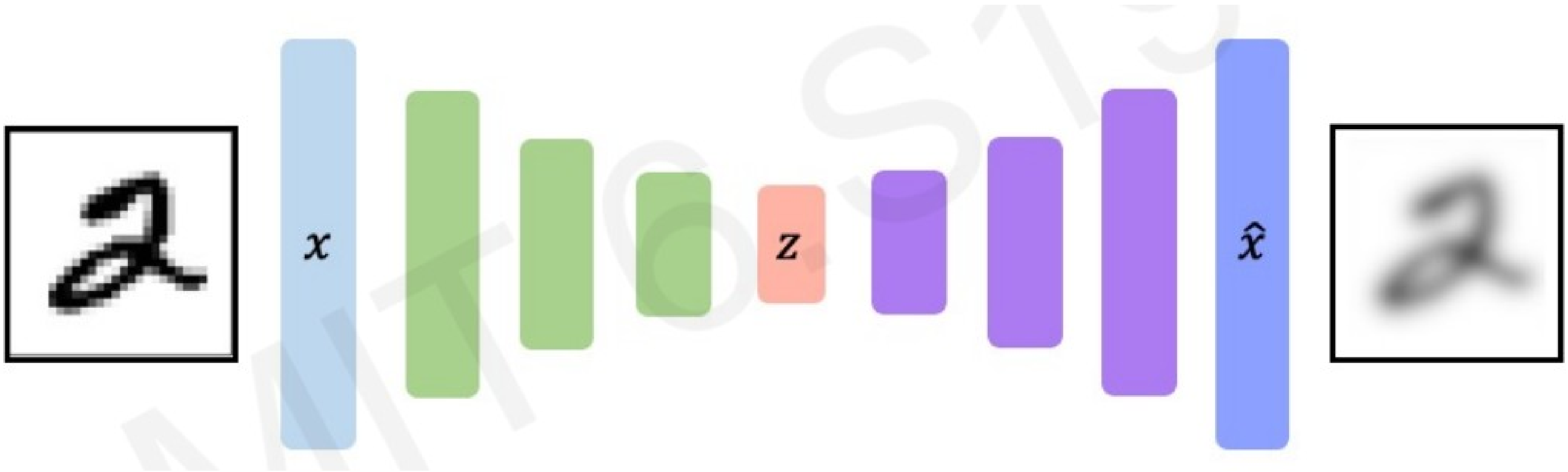
Autoencoders

Encoder: modelo que transforma datos a vectores en un espacio de baja dimensión (espacio latente)



Autoencoders

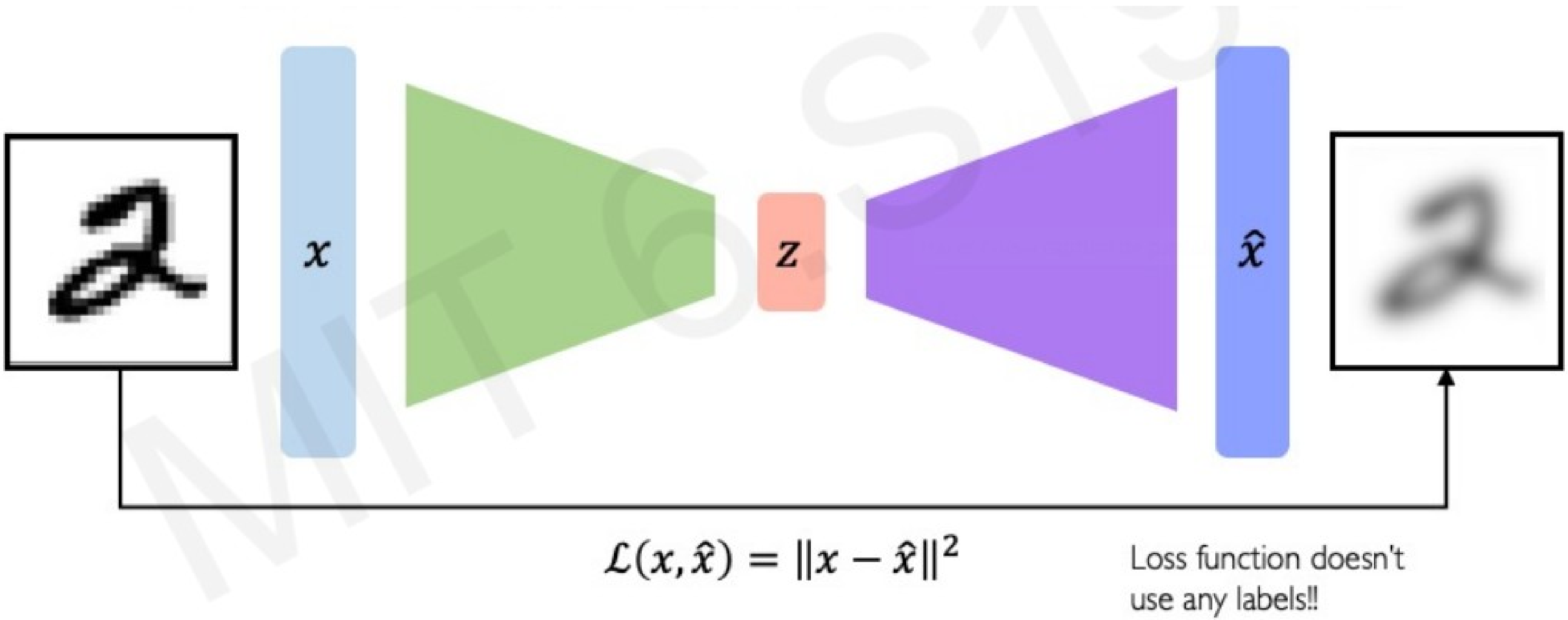
Decoder: modelo que transforma datos del espacio latente al espacio original



Autoencoder: modelo que transforma datos en sí mismos, pasando por un espacio latente.

Autoencoders

Se utiliza una función costo que mide la calidad de la reproducción. No se necesitan datos con etiquetas.

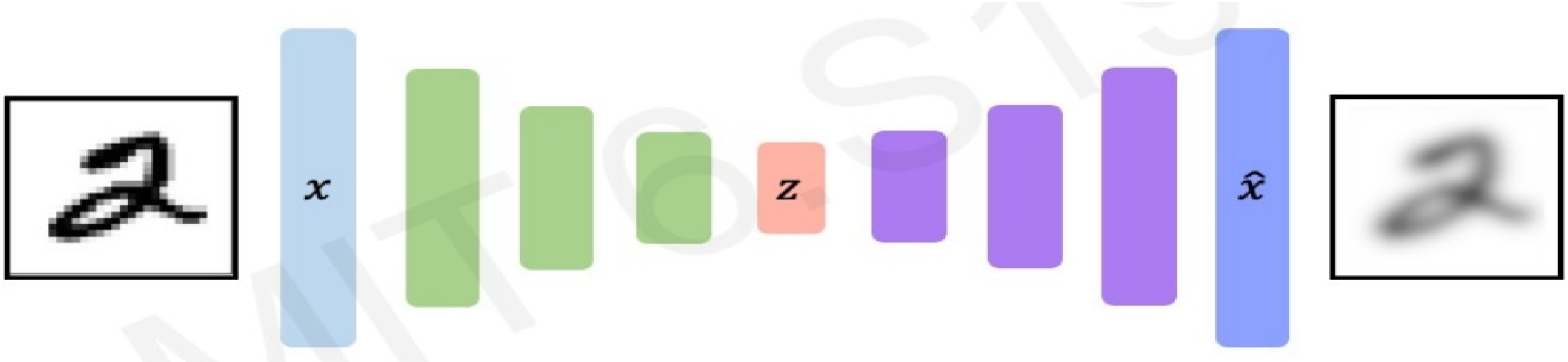


Autoencoders: puntos clave

El cuello de botella en la red obliga a aprender una representación de baja dimensionalidad.

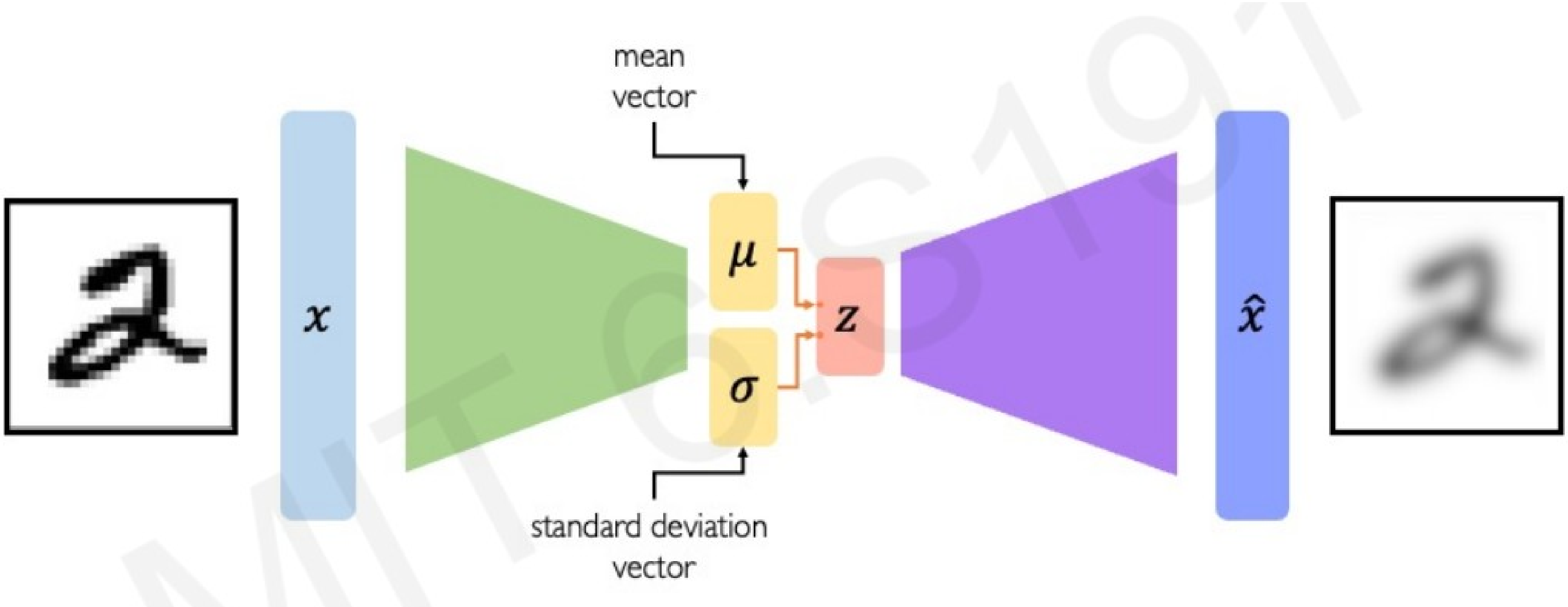
La función costo obliga a reproducir la mayor cantidad posible de información de la entrada

Resultado: proyecciones simples con gran información



Autoencoders variacionales VAE

Autoencoder con mejora: asume que la representación en el espacio latente es sampleada de una distribución.

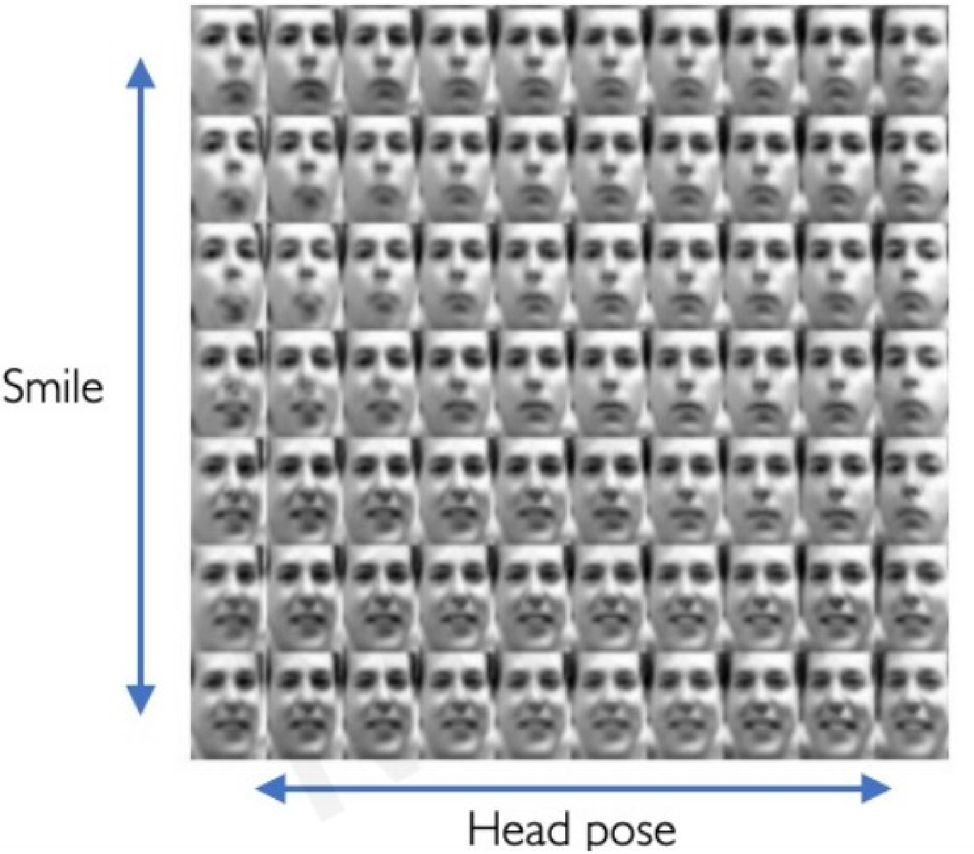


Autoencoder: generación

Se varía lentamente una de las variables latentes con las otras fijas.

Diferentes variables en Z suelen codificar diferentes factores de variación de los datos.

Autoencoder: generación



Queremos variables latentes independientes una de otra.

Se puede forzar al modelo para que aprenda variables “desenredadas”