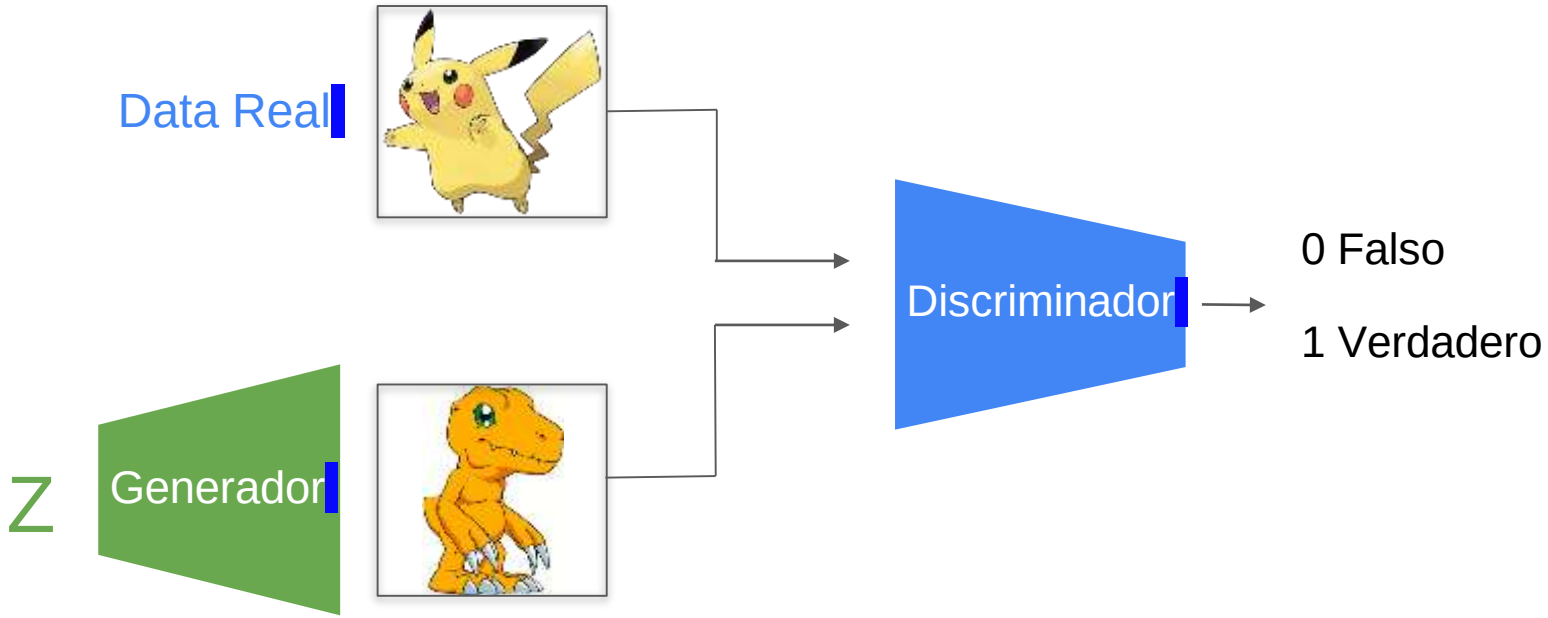
Deep Learning en Imágenes con GANs y Modelos de Difusión - Parte II

Prof. Peter Montalvo

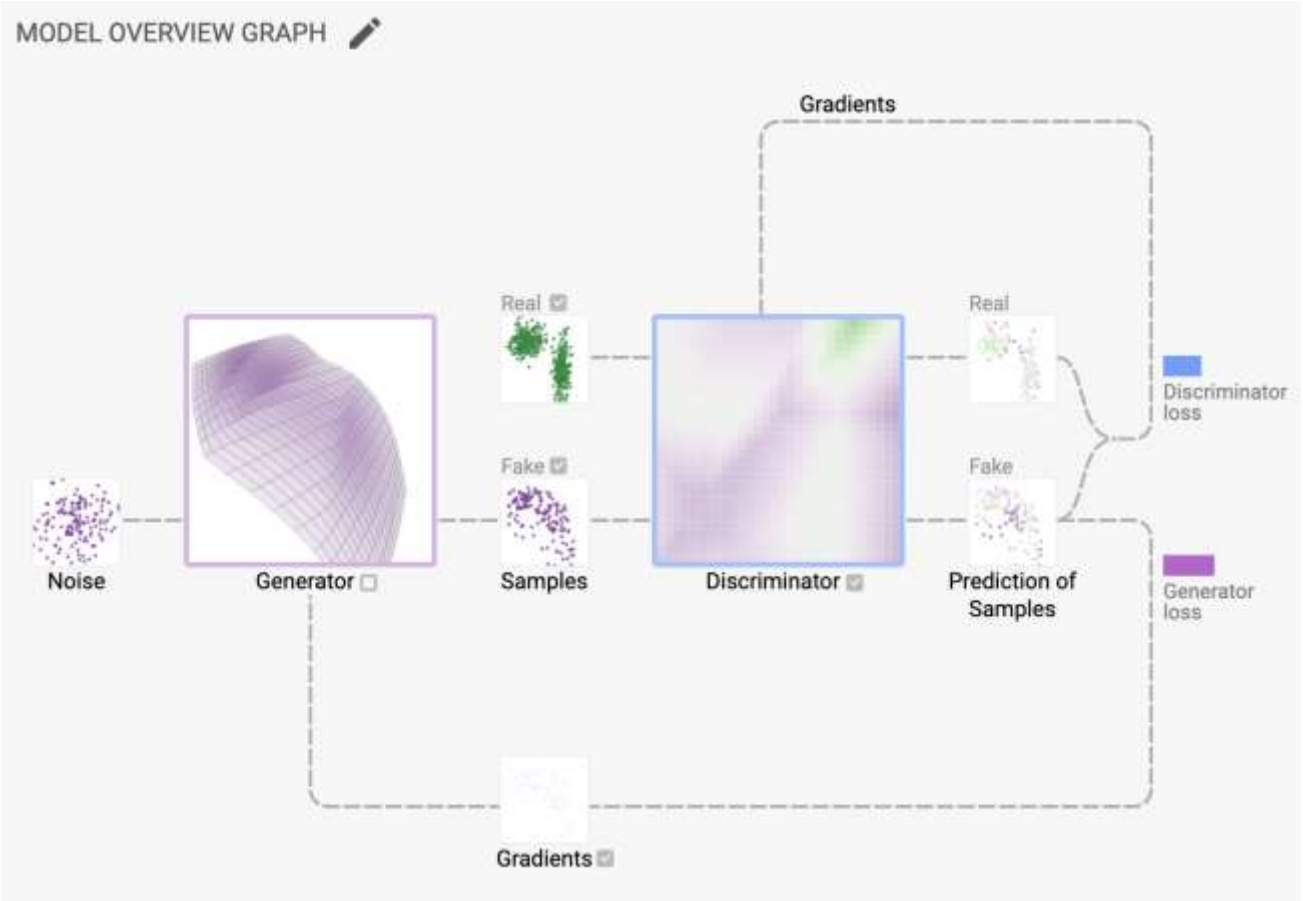
Agenda

- Introducción
- GANs
- Función de Pérdida
- Aplicaciones
- Wasserstein GAN

GAN - Generative Adversarial Nets

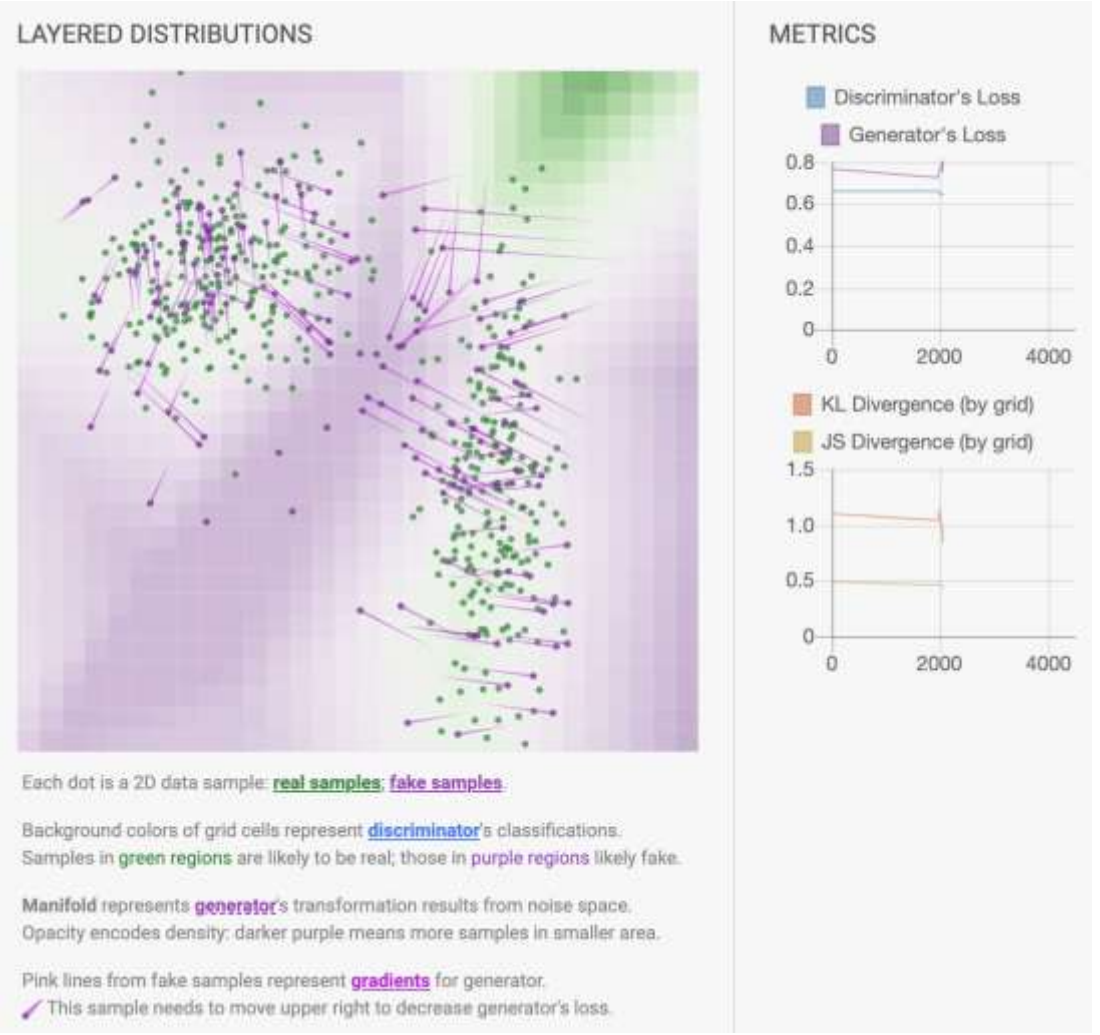


Introducción



https://poloclub.github.io/ganlab/

Introducción



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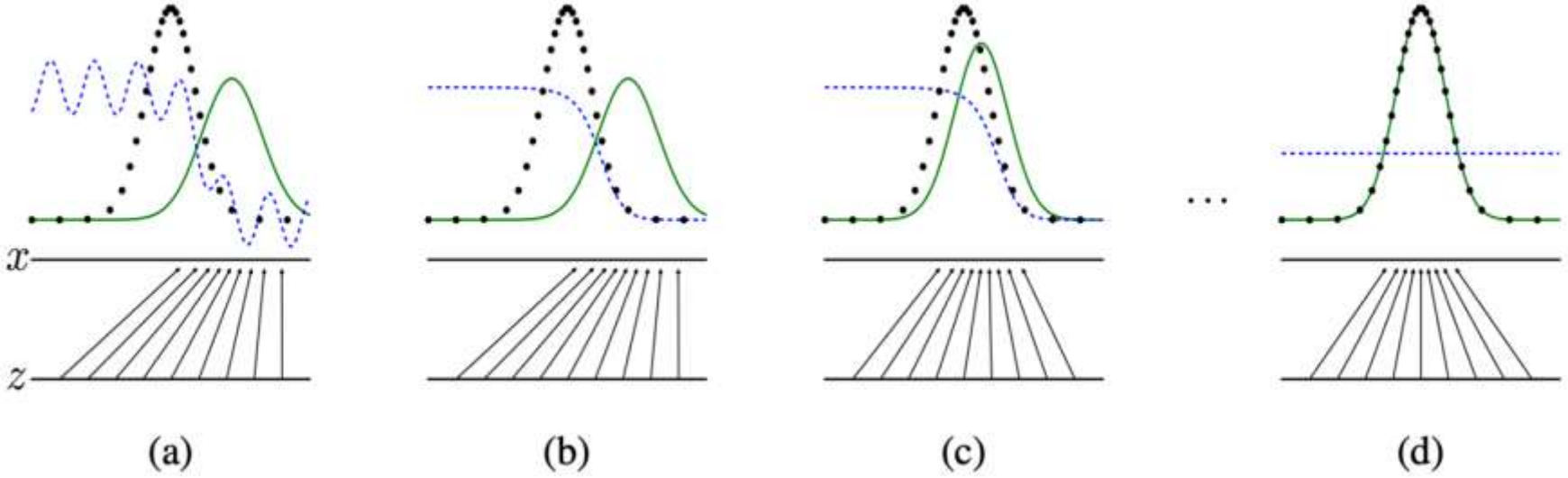
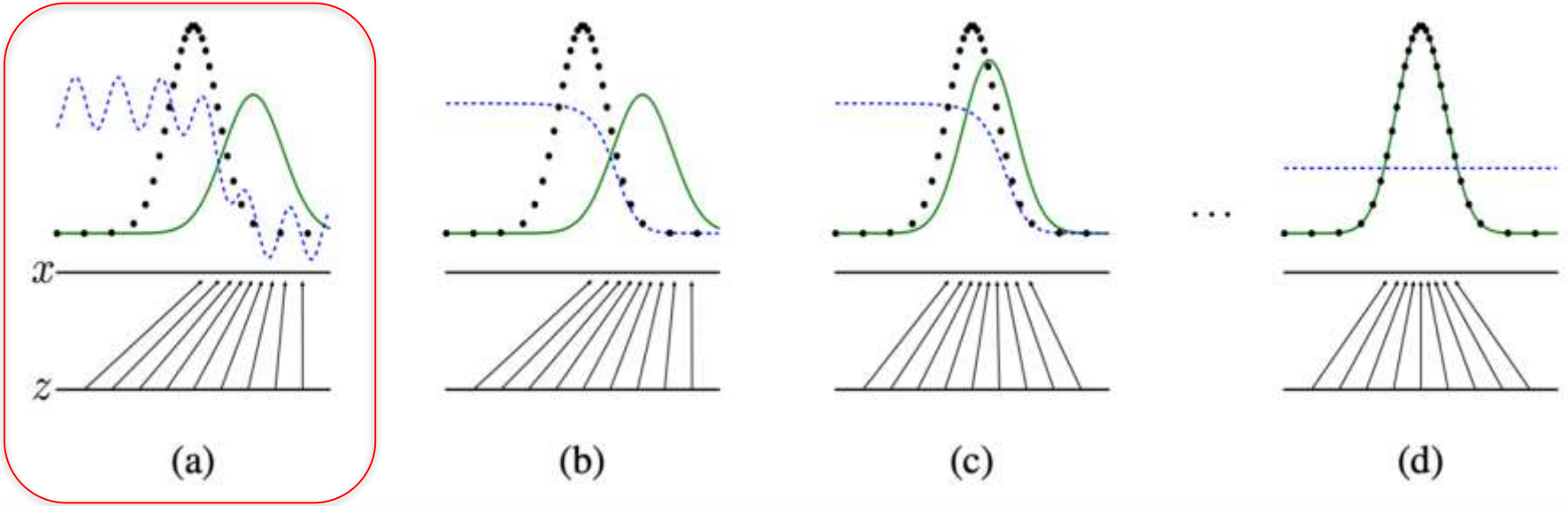
Función de pérdida



Función de pérdida



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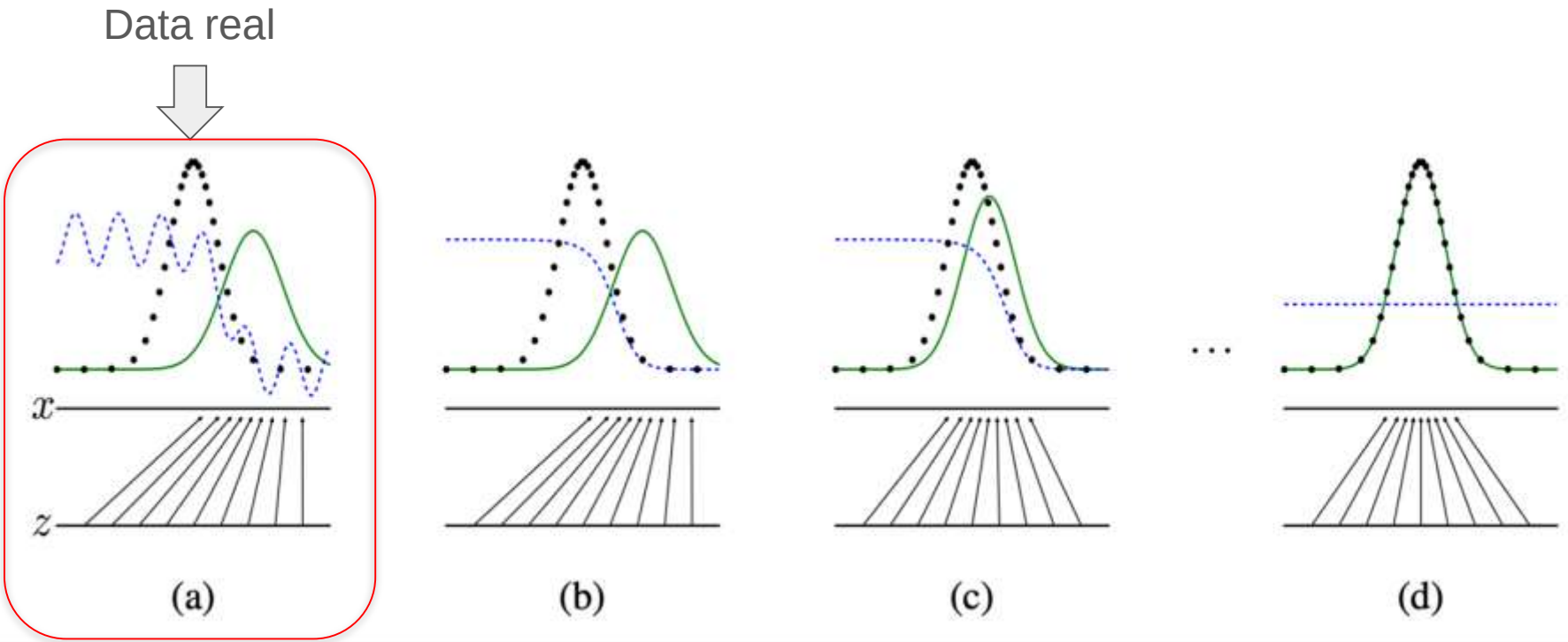

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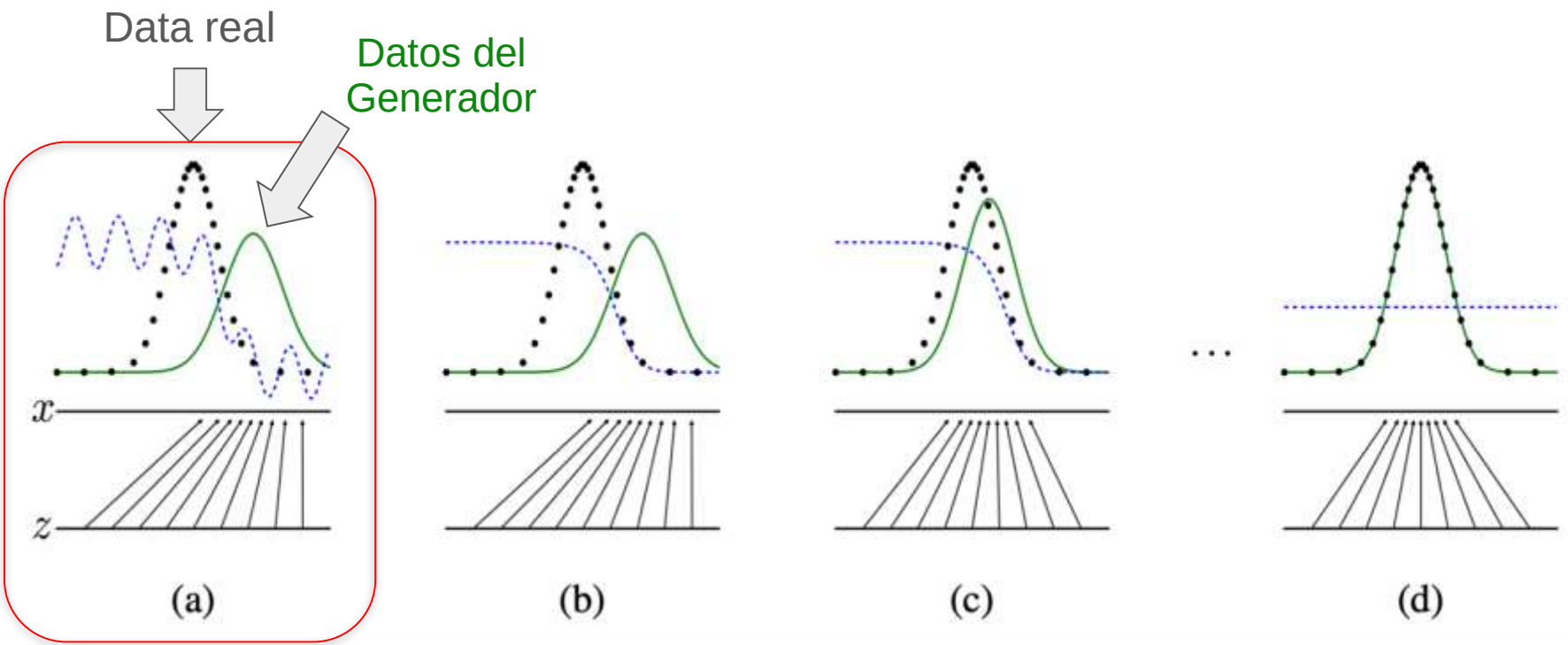
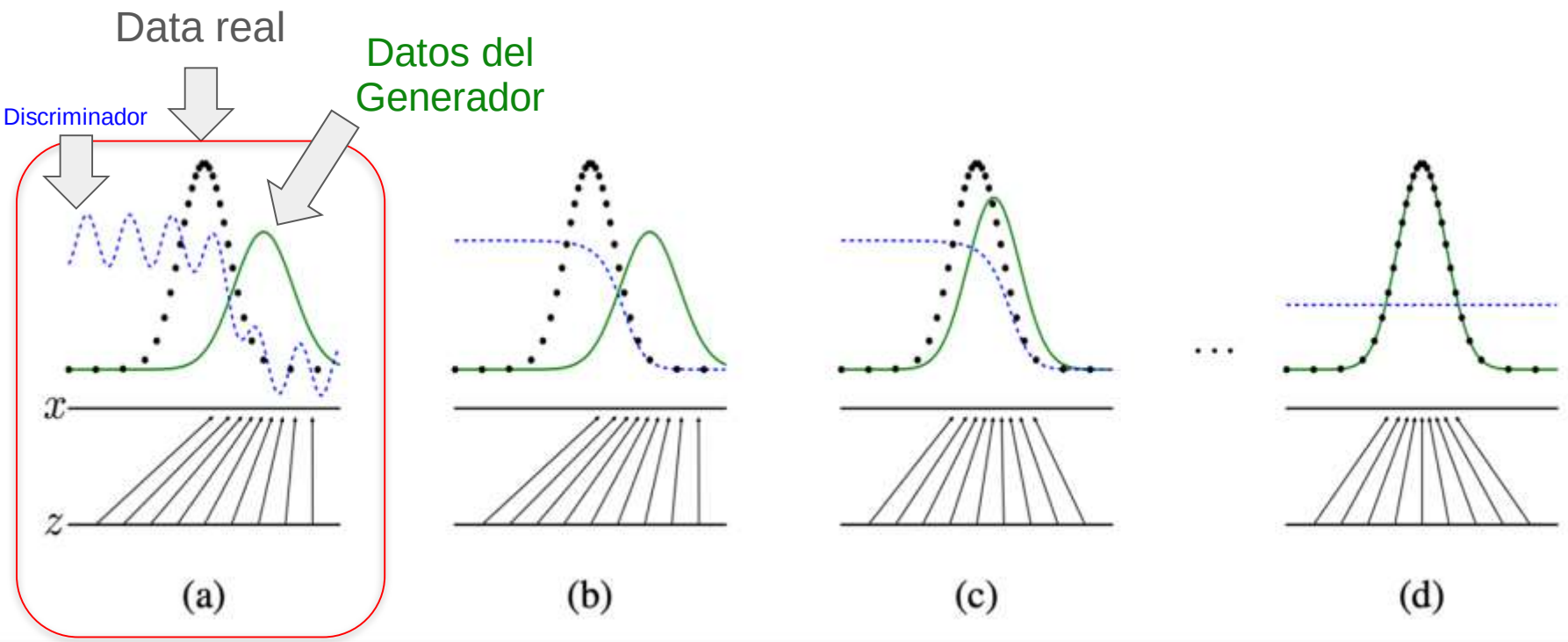
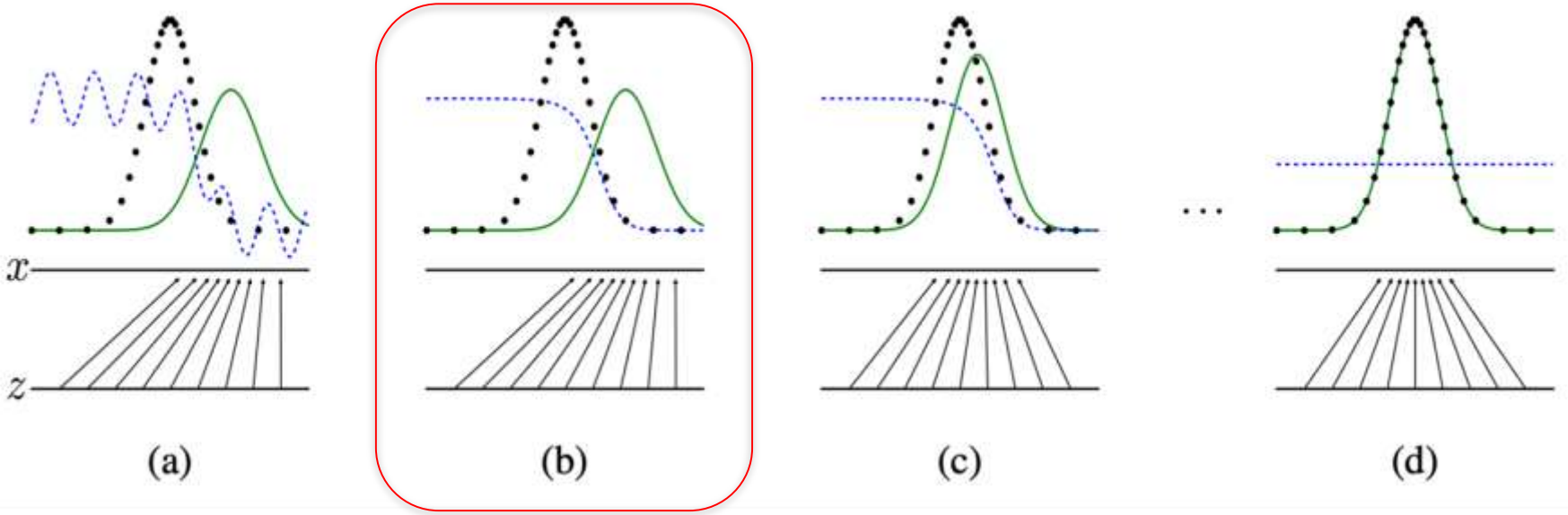


Función de pérdida

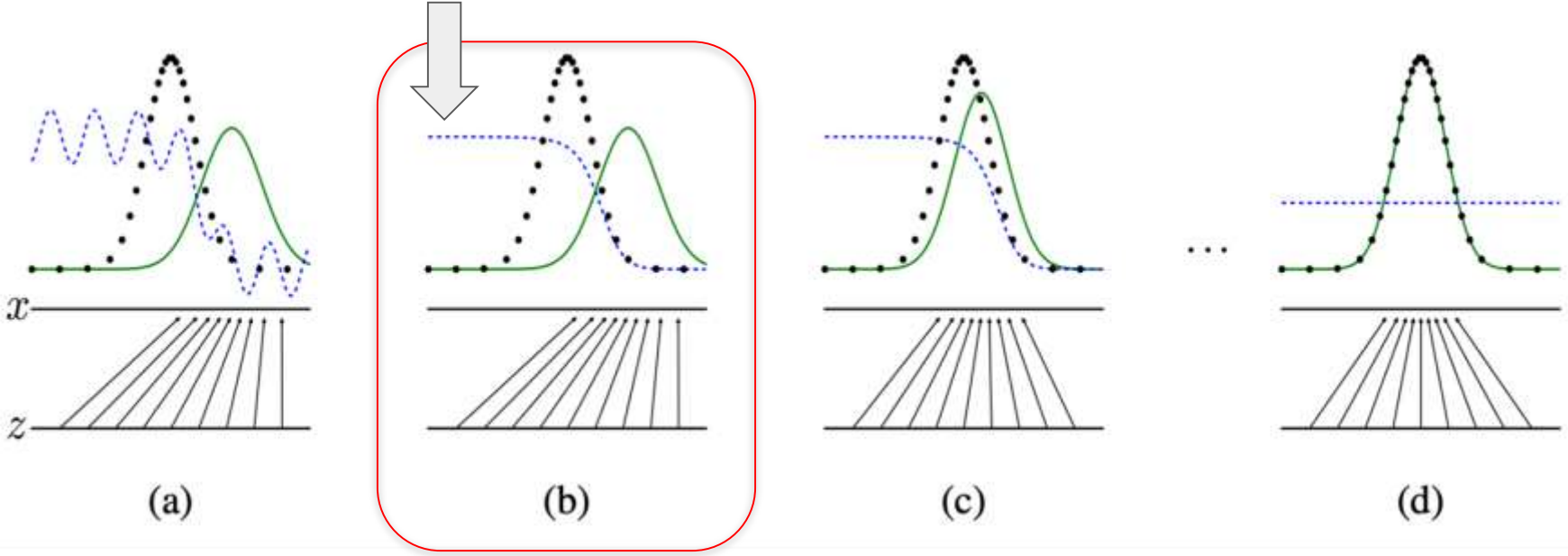


Función de pérdida



Función de pérdida

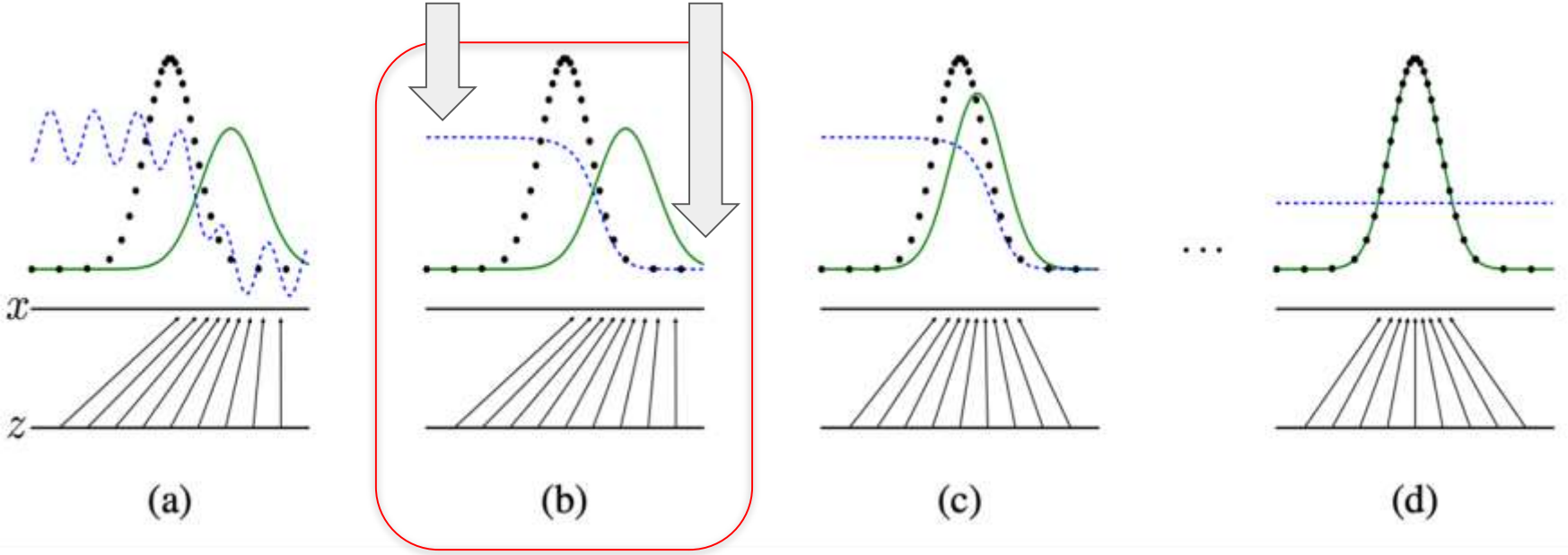
Discriminador da
1 si la data es real



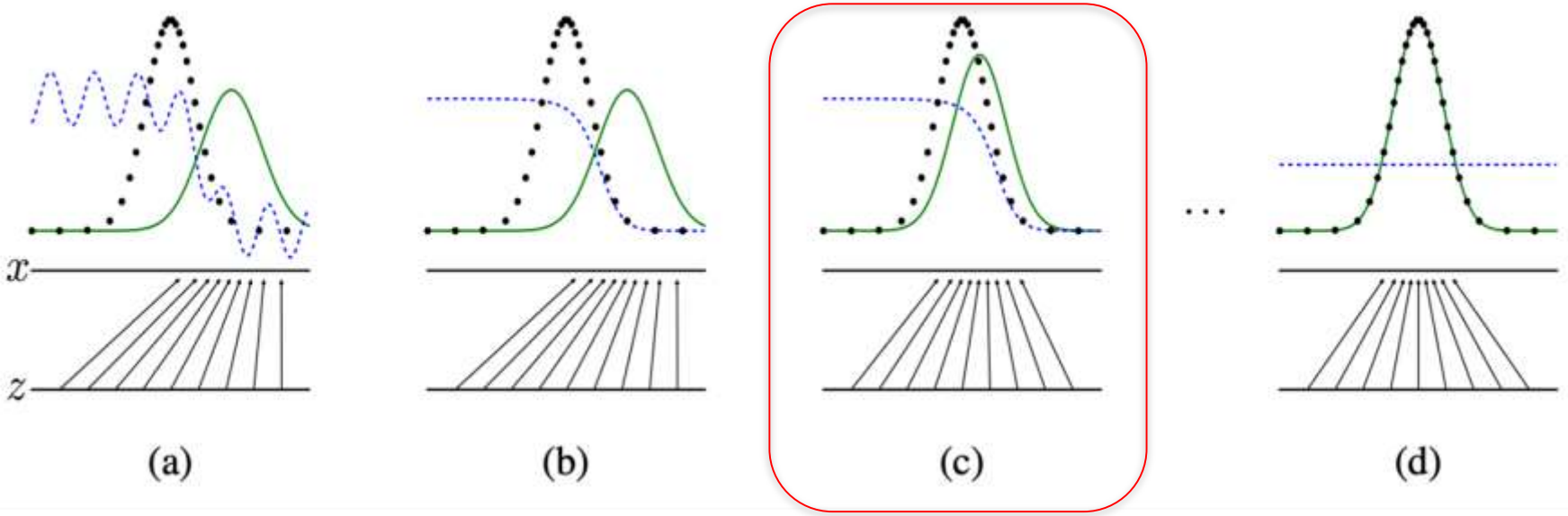
Función de pérdida

Discriminador da 1 si la data es real

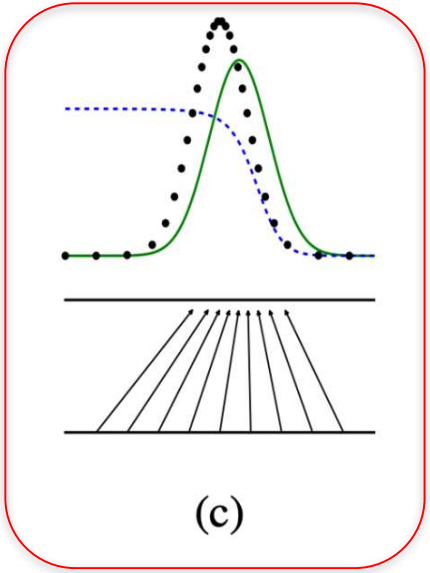
Discriminador da 0 si la data es falsa



Función de pérdida

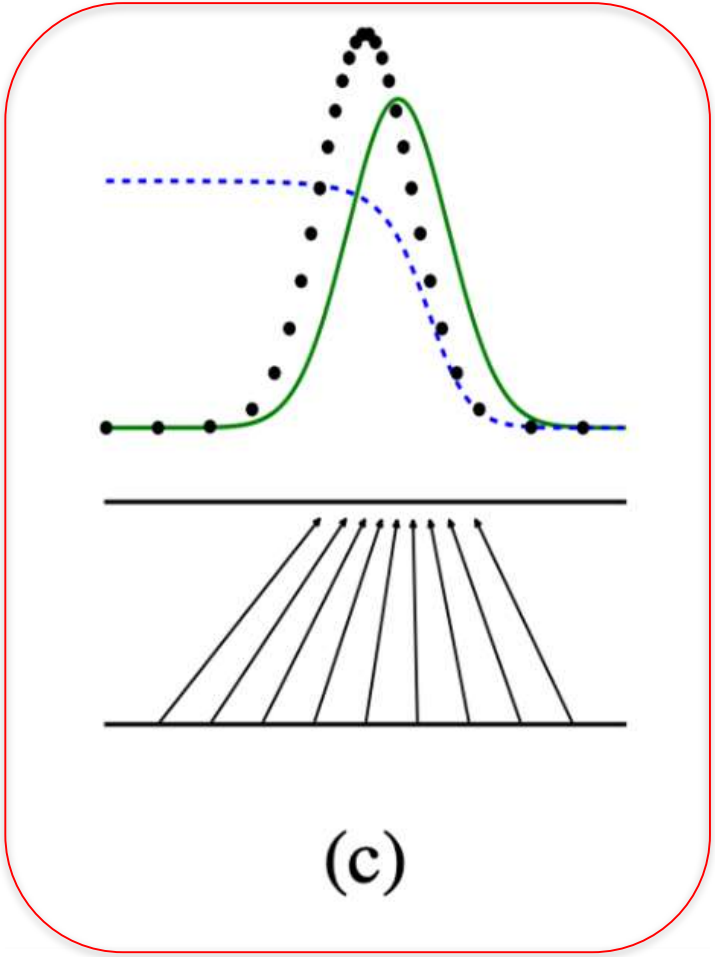


Función de pérdida



Función de pérdida

La distribución de datos falsos se comienza a acercar a la distribución de datos original



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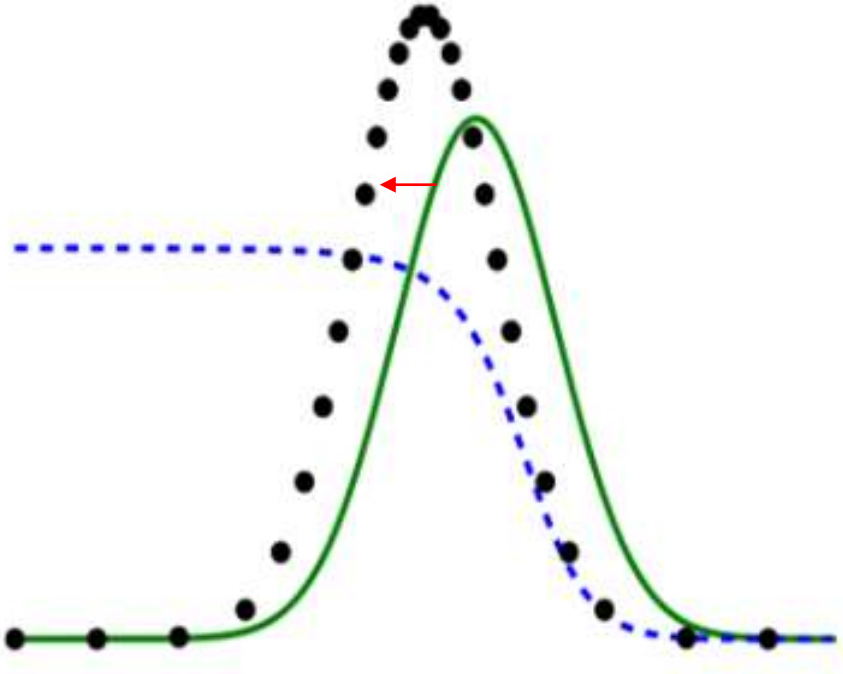
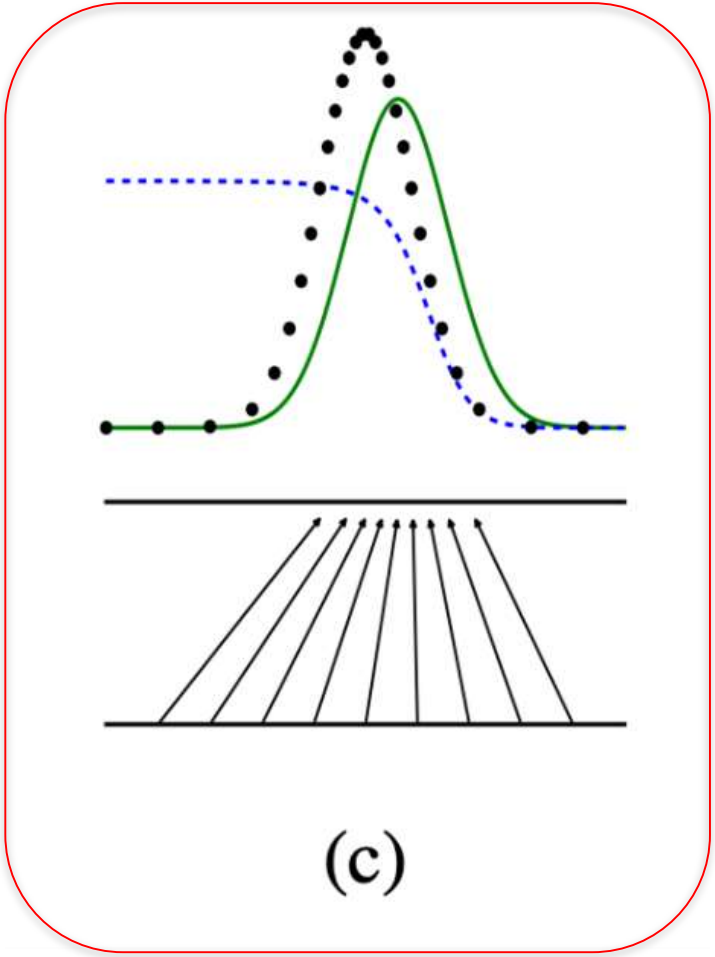


Función de pérdida

El discriminador comienza a clasificar como 1 a la distribución de data falsa.



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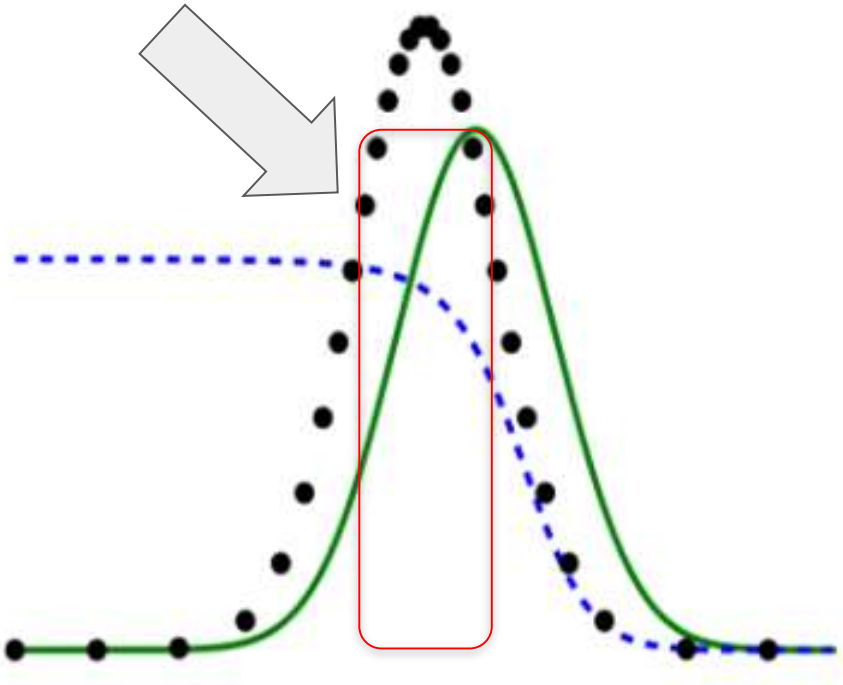

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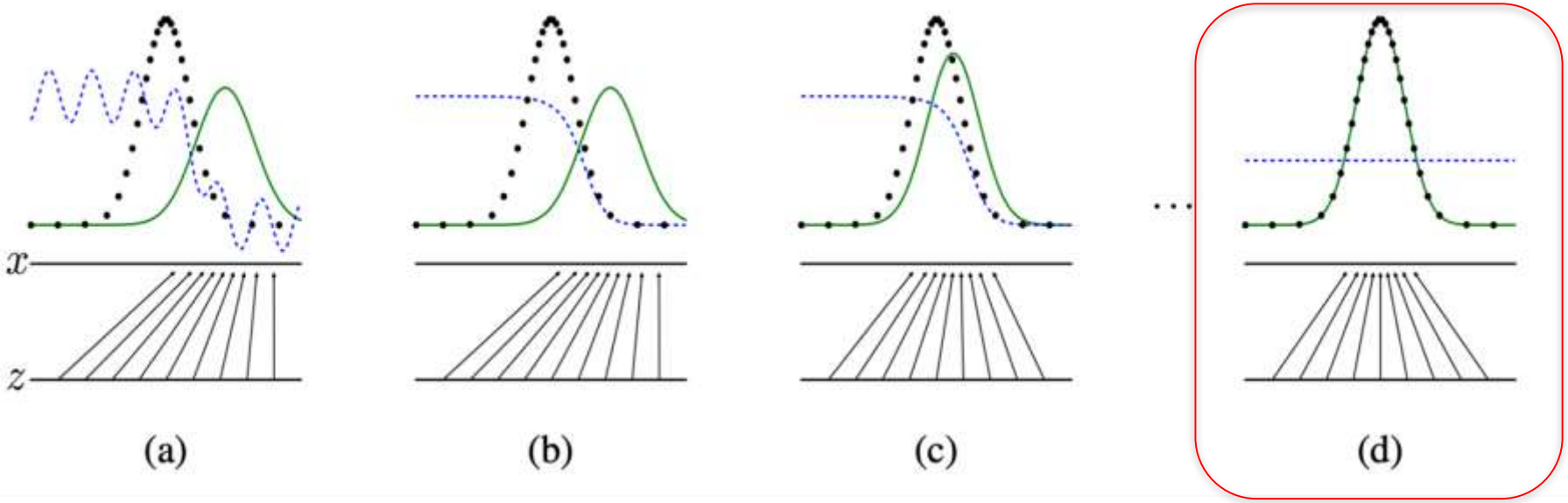

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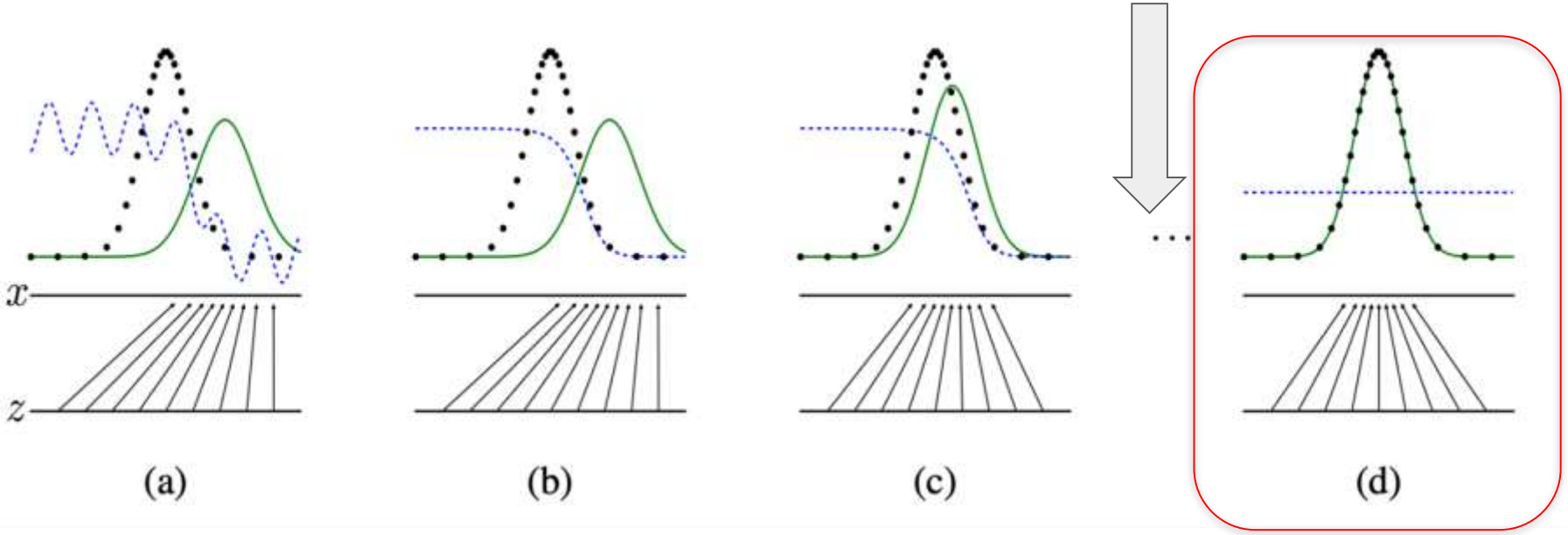
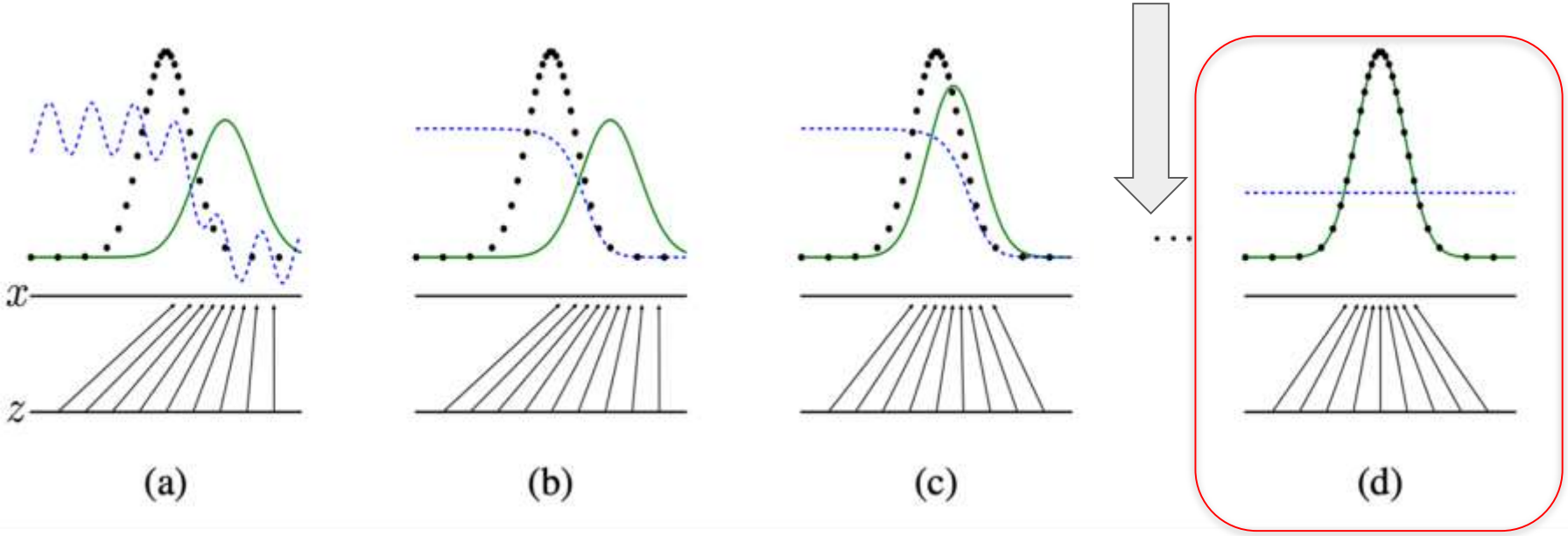


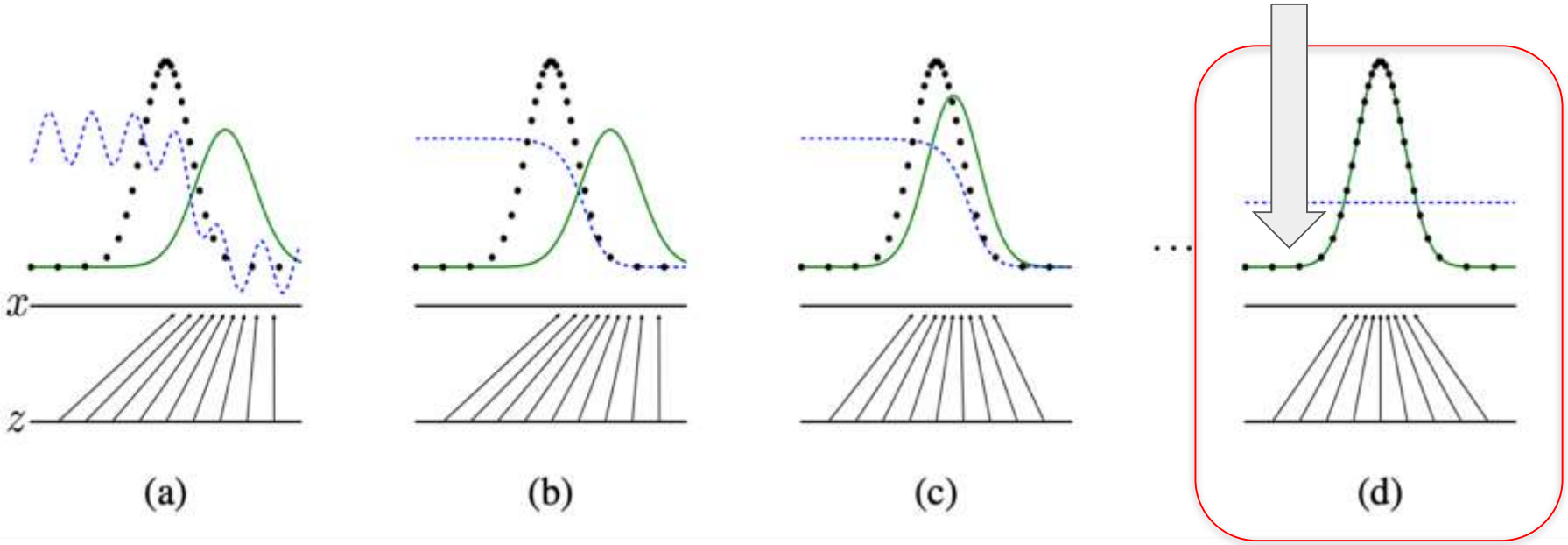
Función de pérdida

Finalmente, luego de algunas iteraciones…



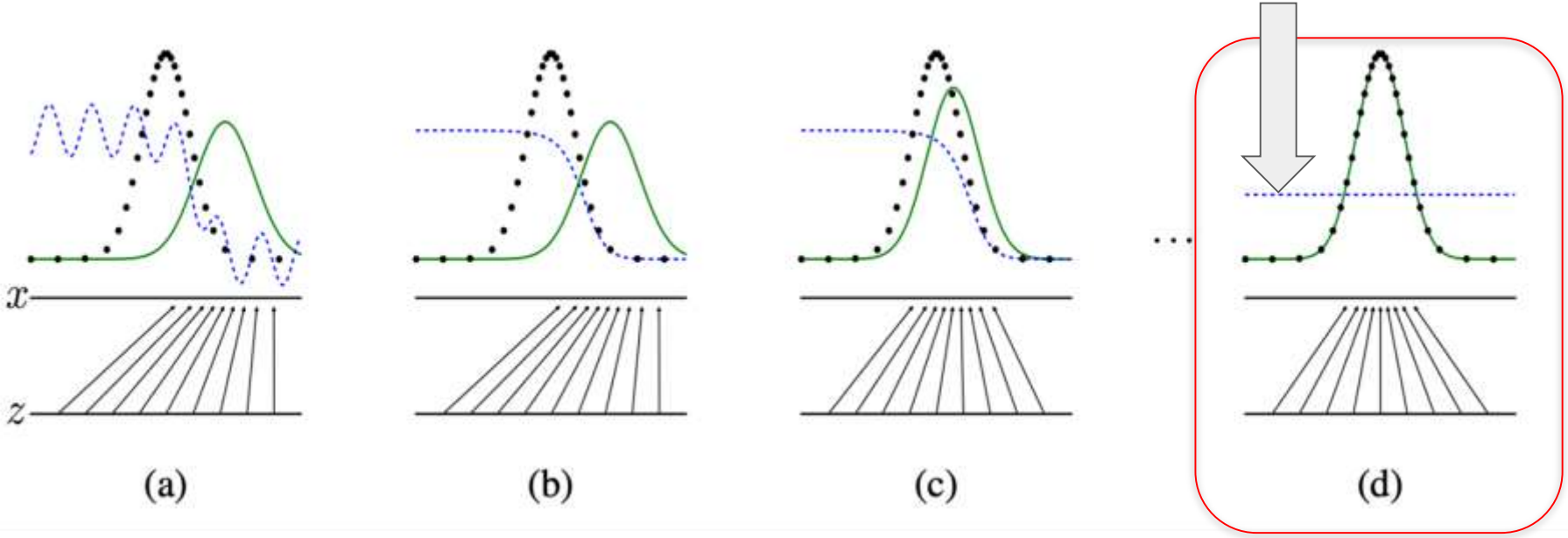
Función de pérdida

El Generador converge generando data similar a la distribución de data real.



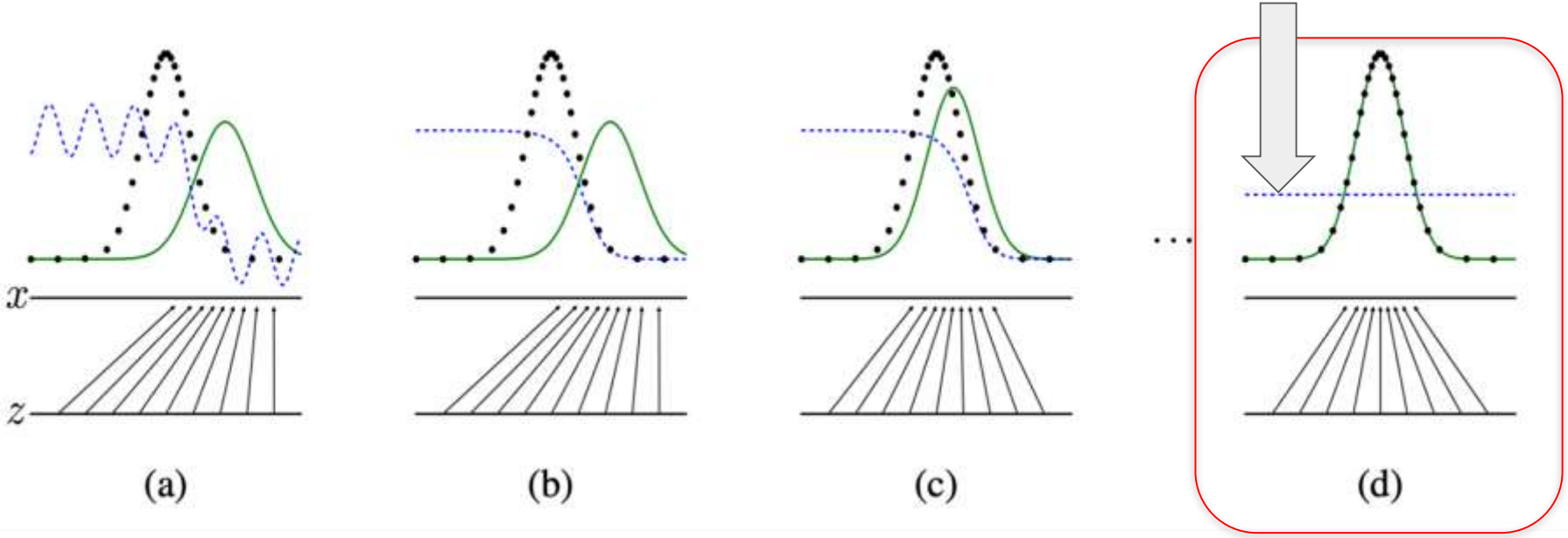
Función de pérdida

El discriminador converge en 0.5



Función de pérdida

El generador converge en 0.5 (No puede diferenciar entre real y falso)



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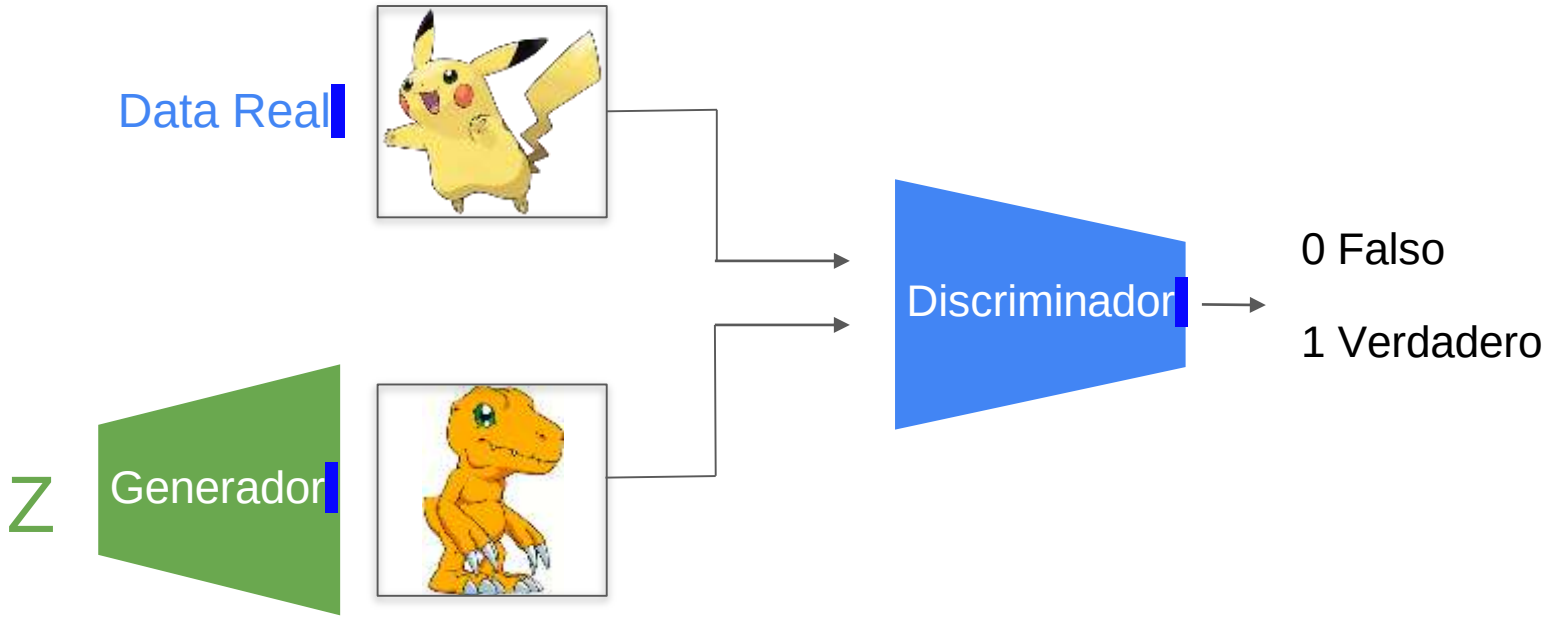

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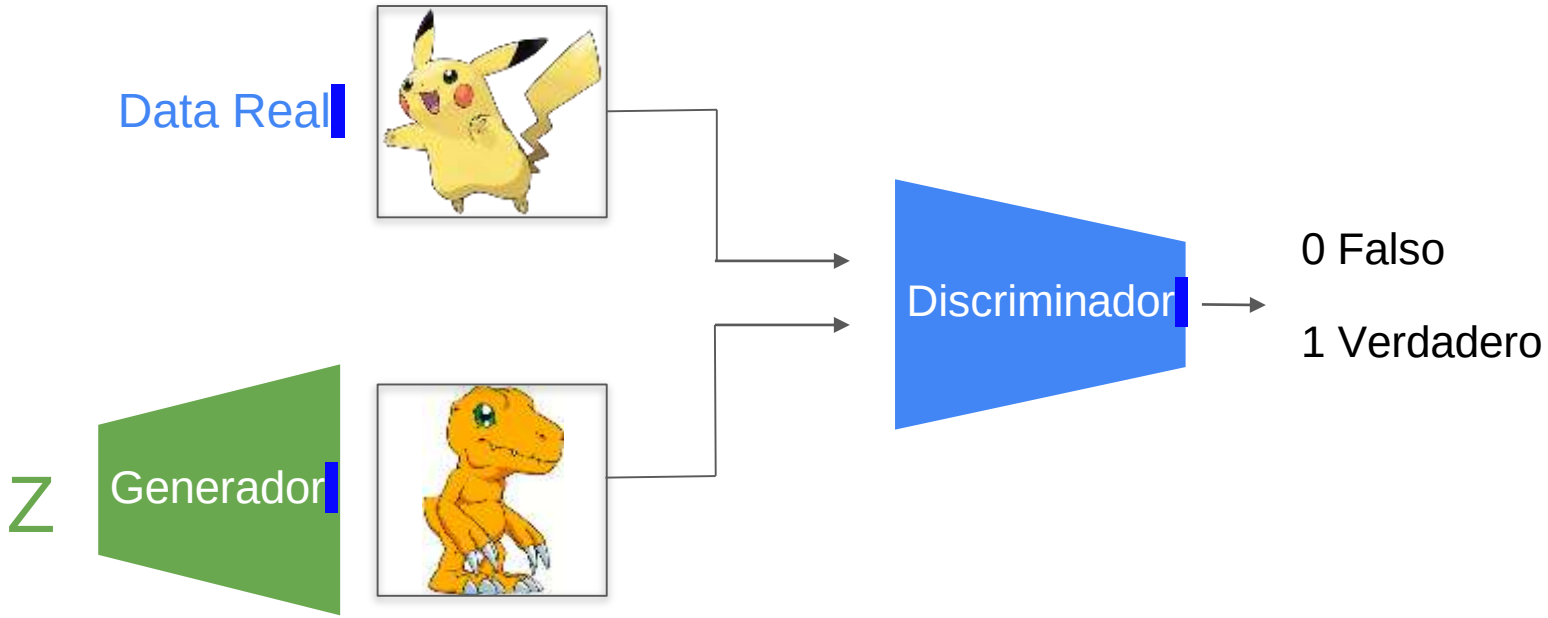
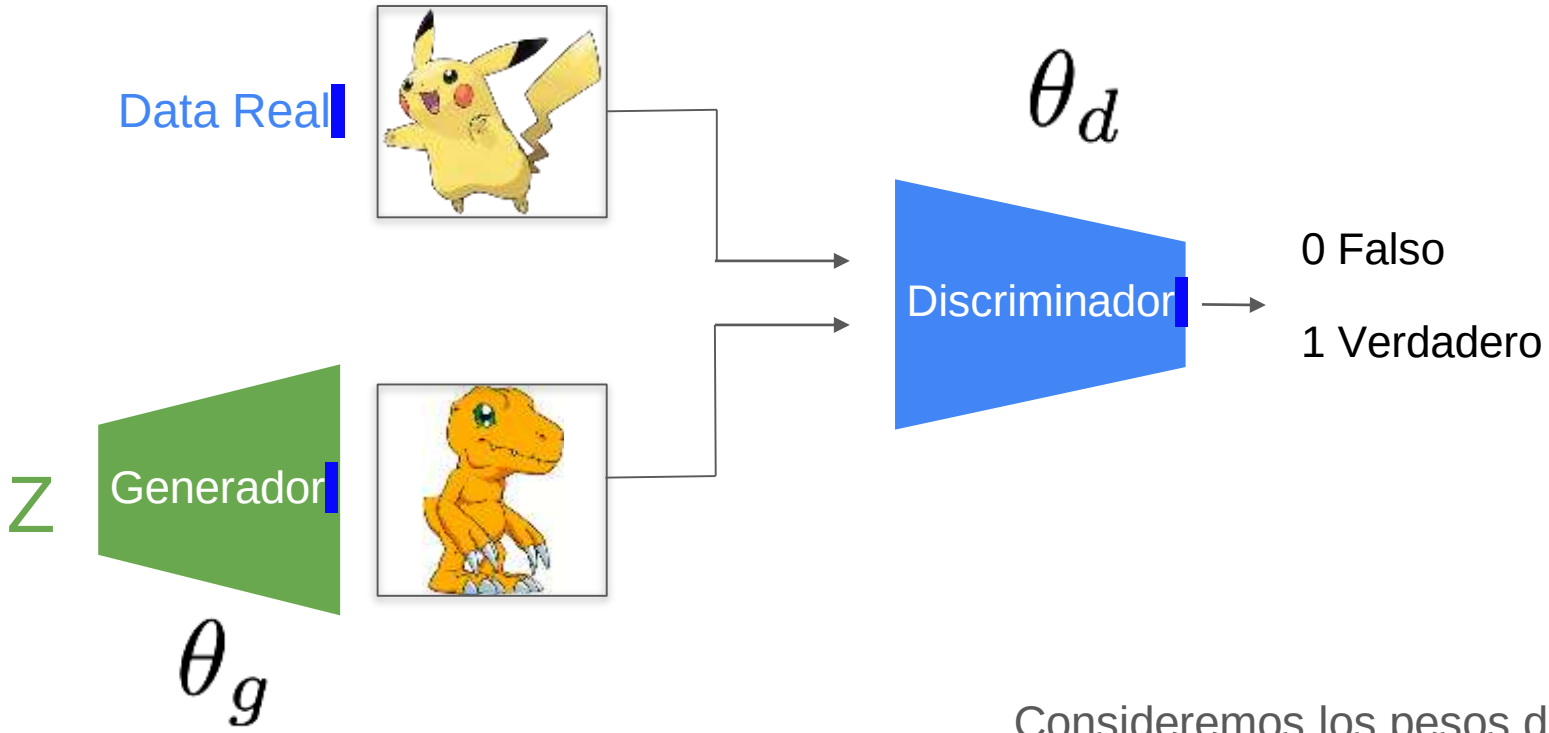


Consideremos los pesos de cada red de la siguiente forma…

Función de pérdida



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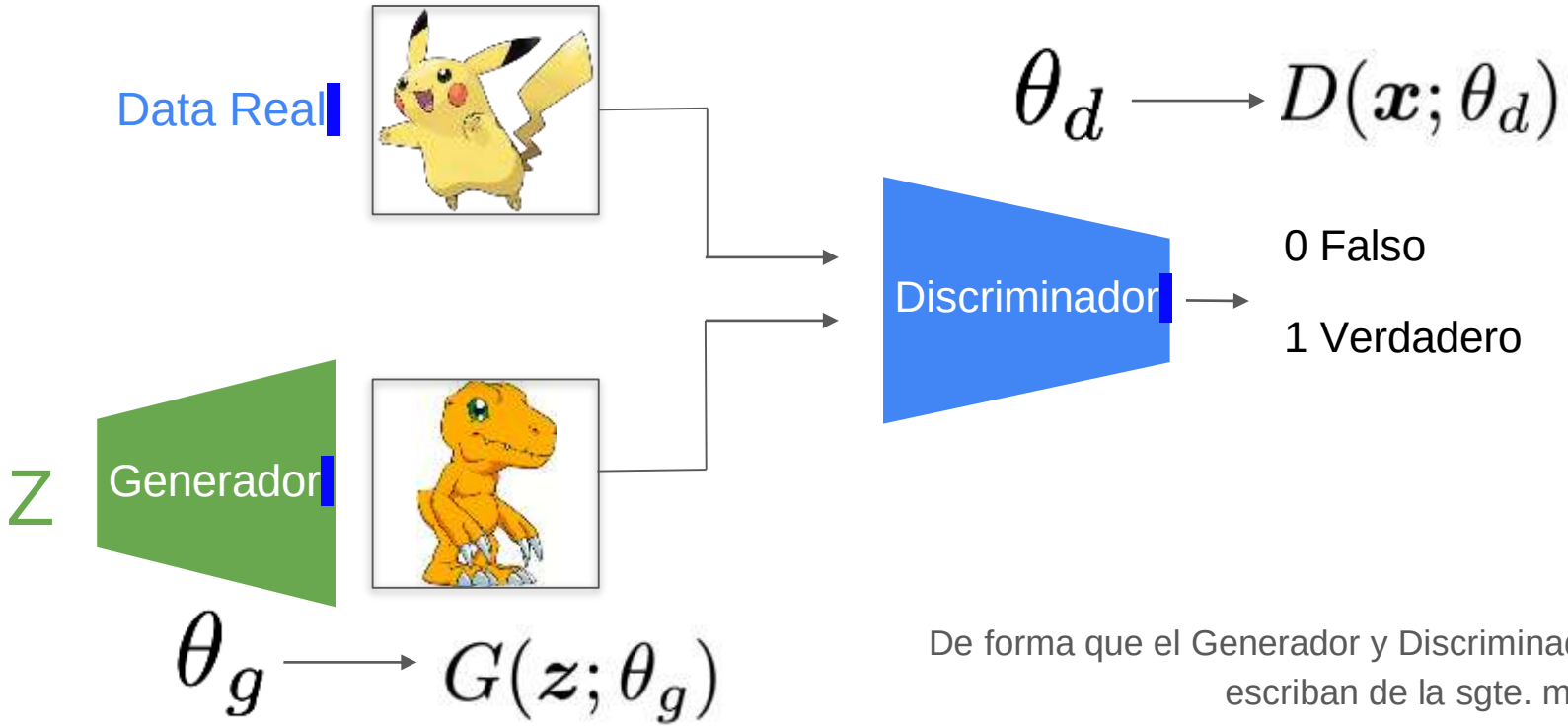
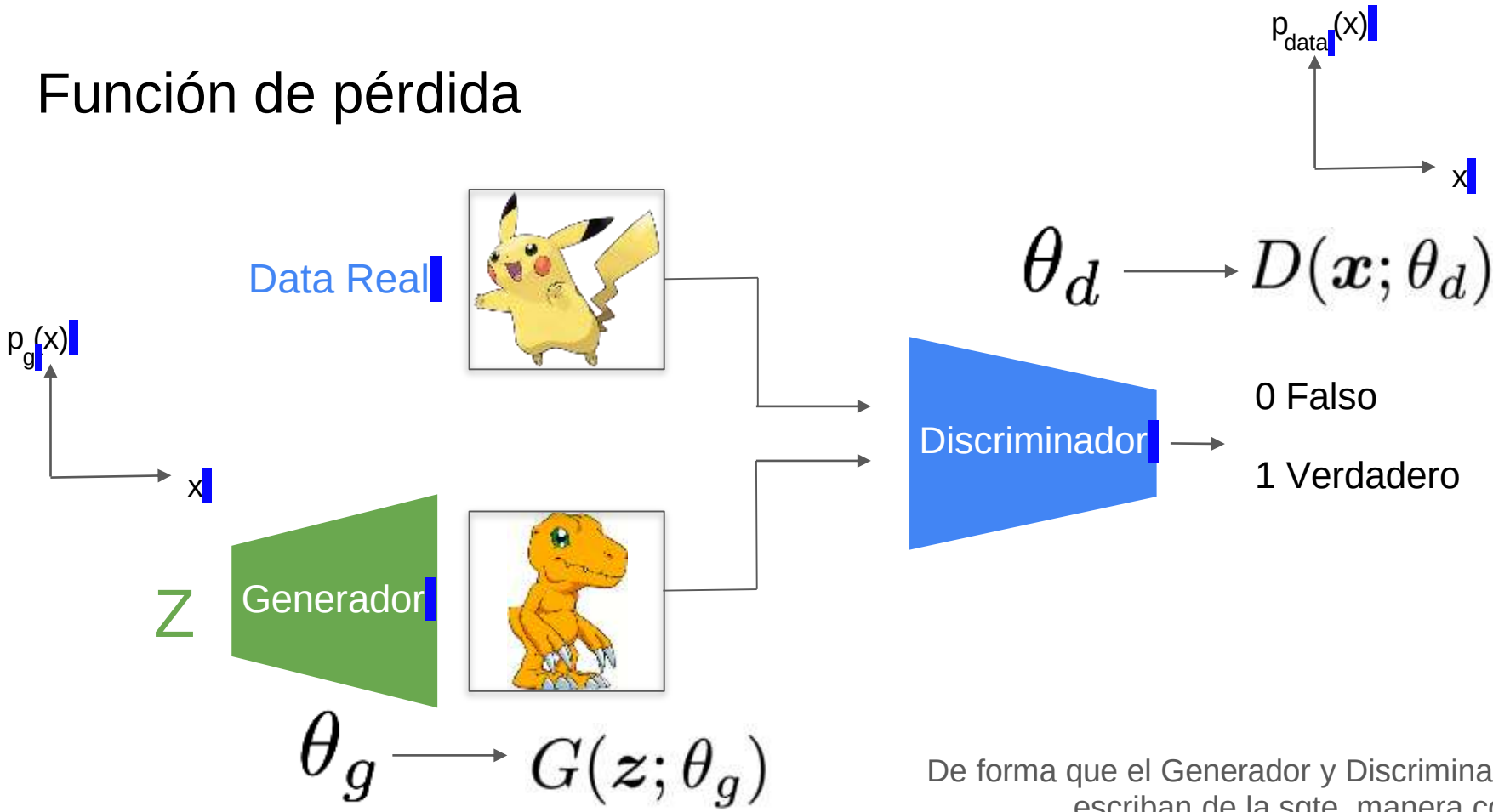


De forma que el Generador y Discriminador se escriban de la sgte. manera

Función de pérdida



De forma que el Generador y Discriminador se escriban de la sgte. manera con sus distribuciones

Función de pérdida

Función de valor

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

De manera que G y D juegan un MinMax de 2 jugadores

Función de pérdida

$$-\frac{1}{N}\sum_{i=1}^{N} y_i \cdot log(p(y_i)) + (1 - y_i) \cdot log(1 - p(y_i))$$

Función de BCE

Esto es similar a la función de

Binary Cross Entropy

Función de pérdida

$$-\frac{1}{N}\sum_{i=1}^{N} y_i \cdot log(p(y_i)) + (1 - y_i) \cdot log(1 - p(y_i))$$

Función de BCE

Cuando $y = 1$ $\quad \hat{y} = D(x) \Rightarrow \mathcal{L} = \ln[Dx]$

Cuando $y = 0$ $\quad \hat{y} = D(G(z)) \Rightarrow \mathcal{L} = \ln[1 - D(G(z))]$

Asimismo, cuando analizamos los valores de y=1 o y=0, vemos que…

Función de pérdida

$$\mathcal{L} = \ln[D(x)] + \ln[1 - D(G(z))]$$

De forma que la función de valor queda de la sgte. forma

Función de pérdida

$$\mathcal{L} = \ln[D(x)] + \ln[1 - D(G(z))]$$

Pero esto es para una única muestra.

Se debe considerar la Esperanza

Función de pérdida

$$E(x) = \sum x p(x) \rightarrow \qquad (1+2+3+4+5+6)$$

La Esperanza…

Función de pérdida

$$E(x) = \sum x p(x) \rightarrow \frac{1}{6}(1+2+3+4+5+6)$$

La Esperanza…

Función de pérdida

$$E(x) = \sum x p(x) \rightarrow 3.5$$

La Esperanza…

Función de pérdida

$$\sum p_{data}(x) \ln[D(x)] + \sum p_z(z) \ln[1 - D(G(z))]$$

Aplicando la Esperanza a nuestra función de valor

Función de pérdida

$$\int p_{data}(x) \ln[D(x)]\,dx + \int p_z(z) \ln[1 - D(G(z))]\,dz$$

Aplicando la Esperanza a nuestra función de valor

Función de pérdida

$$V(G,D) = E_{x \sim p_{data}}[\ln(D(x))] + E_{z \sim p_z}[\ln(1 - D(G(z)))]$$

Aplicando la Esperanza a nuestra función de valor

Función de pérdida

MINIMIZAR
D

$$\frac{\partial}{\partial \theta_d} \frac{1}{m} \cdot \left[\ln\left[1 - D(G(z))\right]\right]$$

MAXIMIZAR
G

$$\frac{\partial}{\partial \theta_g} \frac{1}{m} \left[\ln\left[1 - D(G(z))\right]\right]$$

cant. de muestras

El algoritmo de entrenamiento quedaría de la siguiente forma

Función de pérdida

Algorithm 1 Minibatch stochastic gradient descent training of generative adversarial nets. The number of steps to apply to the discriminator, k, is a hyperparameter. We used $k = 1$, the least expensive option, in our experiments.

for number of training iterations **do**

  for k steps **do**

  - Sample minibatch of m noise samples $\{\boldsymbol{z}^{(1)}, \ldots, \boldsymbol{z}^{(m)}\}$ from noise prior $p_g(\boldsymbol{z})$.
  - Sample minibatch of m examples $\{\boldsymbol{x}^{(1)}, \ldots, \boldsymbol{x}^{(m)}\}$ from data generating distribution $p_{\text{data}}(\boldsymbol{x})$.
  - Update the discriminator by ascending its stochastic gradient:

$$\nabla_{\theta_d} \frac{1}{m} \sum_{i=1}^{m} \left[\log D\left(\boldsymbol{x}^{(i)}\right) + \log\left(1 - D\left(G\left(\boldsymbol{z}^{(i)}\right)\right)\right) \right].$$

  end for

  - Sample minibatch of m noise samples $\{\boldsymbol{z}^{(1)}, \ldots, \boldsymbol{z}^{(m)}\}$ from noise prior $p_g(\boldsymbol{z})$.
  - Update the generator by descending its stochastic gradient:

$$\nabla_{\theta_g} \frac{1}{m} \sum_{i=1}^{m} \log\left(1 - D\left(G\left(\boldsymbol{z}^{(i)}\right)\right)\right).$$

end for

The gradient-based updates can use any standard gradient-based learning rule. We used momentum in our experiments.

El algoritmo de entrenamiento quedaría de la siguiente forma

Aplicaciones

Crear personajes de anime

https://arxiv.org/pdf/1708.05509.pdf

Figure 7: Generated samples

Aplicaciones

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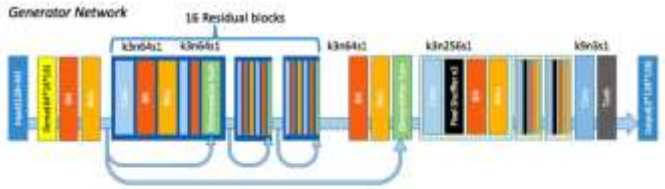


Figure 3: Generator Architecture

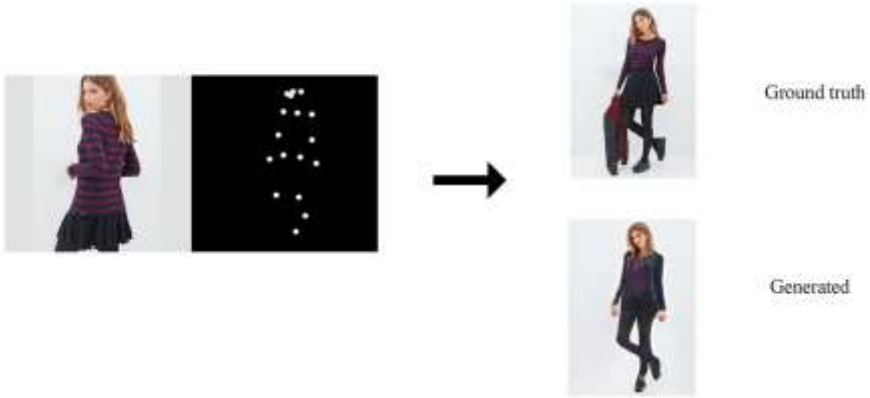
Figure 4: Discriminator Architecture

Figure 7: Generated samples

Aplicaciones

Personas posando

https://arxiv.org/pdf/1705.09368.pdf



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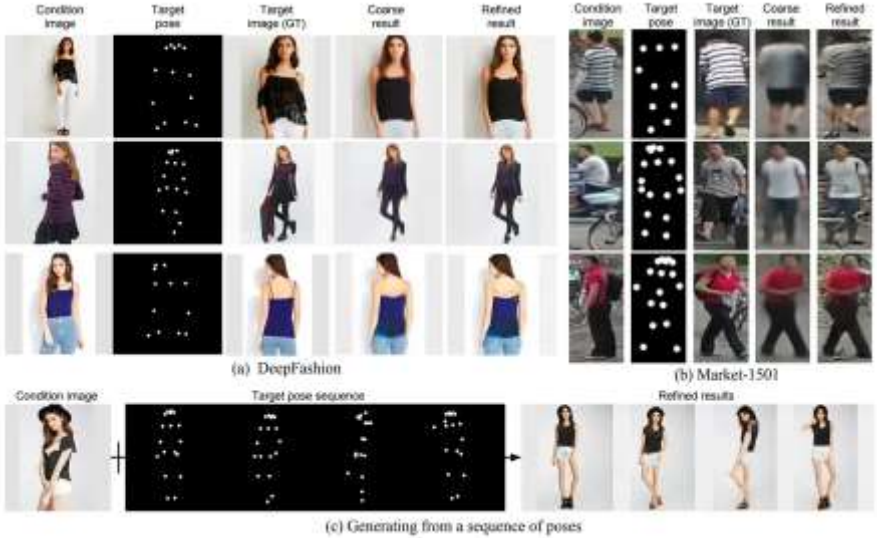

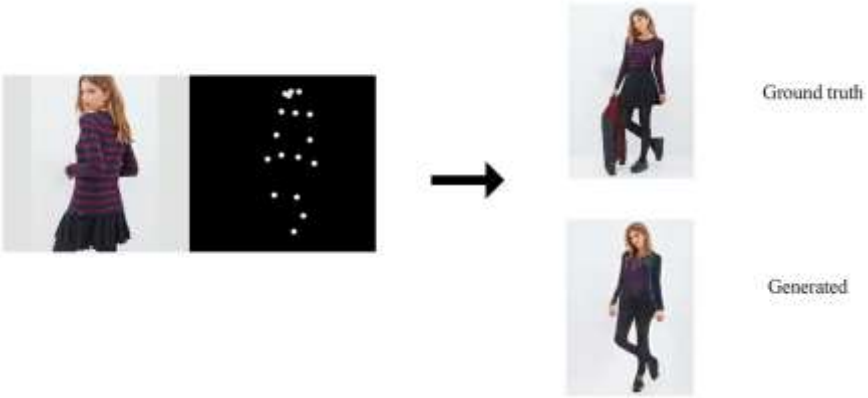

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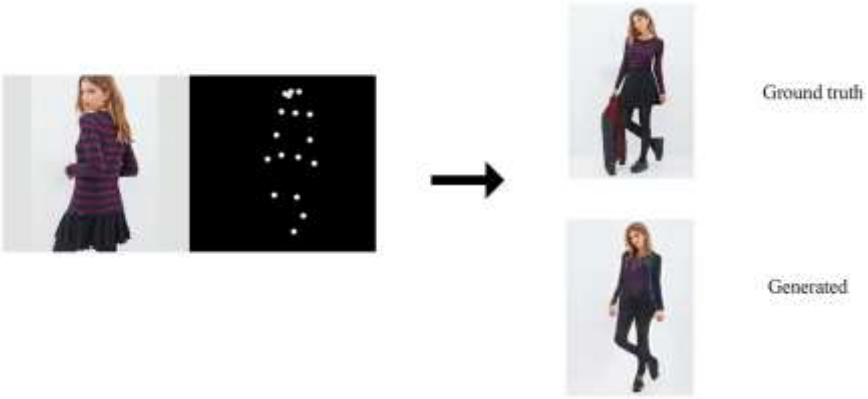
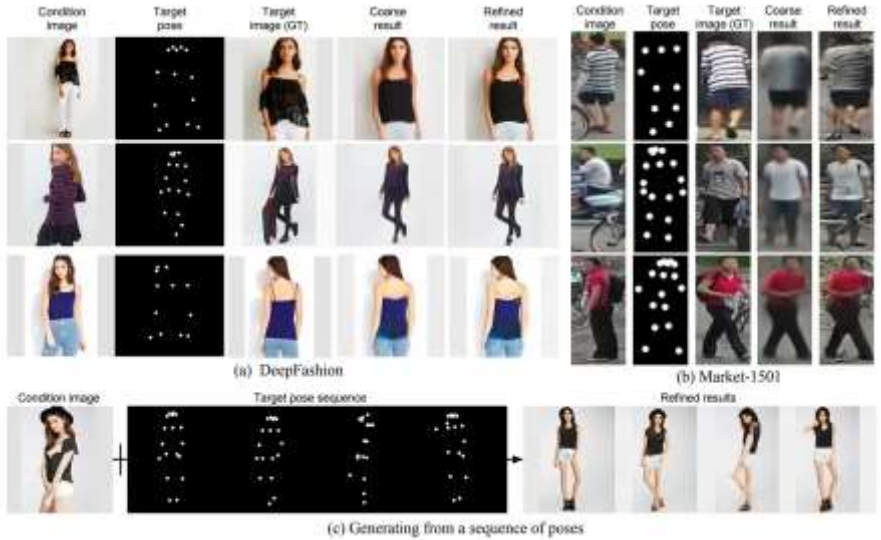
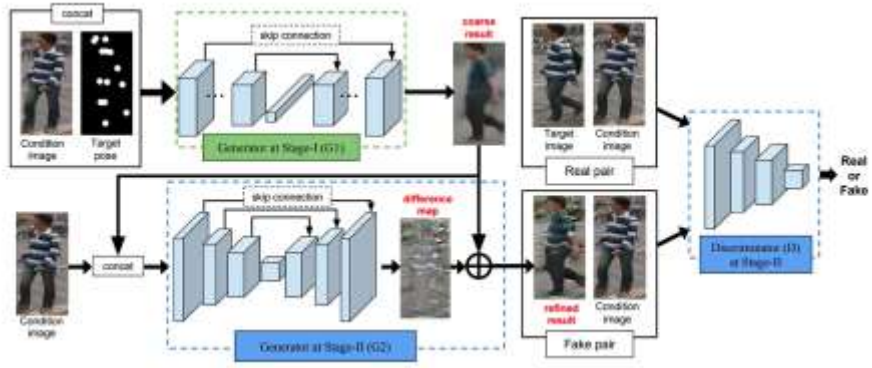


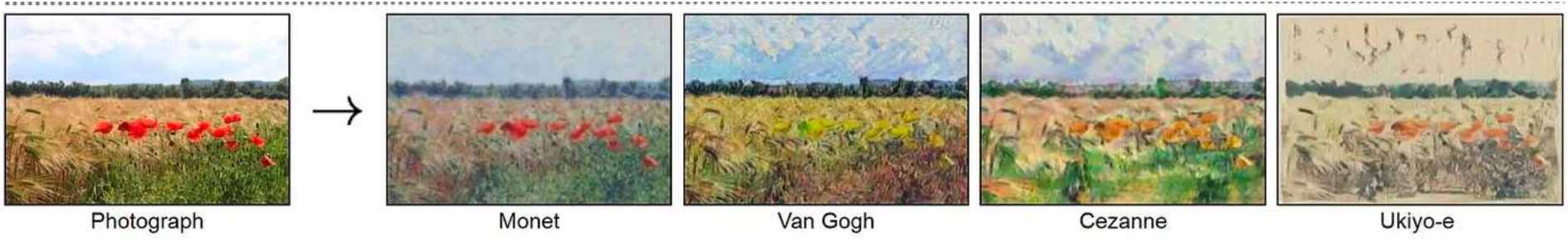




Aplicaciones

CycleGAN

https://github.com/junyanz/CycleGAN



Aplicaciones

CycleGAN

https://github.com/junyanz/CycleGAN

Aplicaciones

StarGAN

https://arxiv.org/pdf/1711.09020.pdf

StarGAN es una traducción de imagen a imagen de un dominio a otro.

Por ejemplo, dada una cara feliz, queremos transformarla en una cara de miedo.

Aplicaciones

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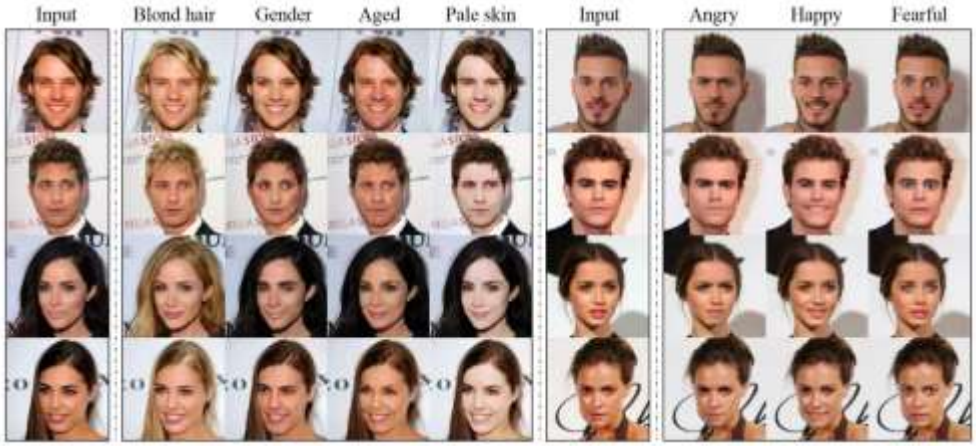
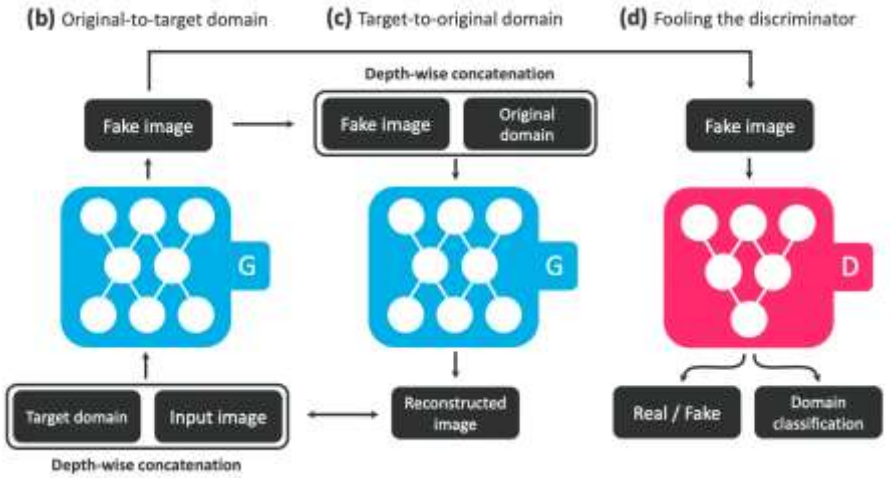


Aplicaciones

StarGAN

https://arxiv.org/pdf/1711.09020.pdf

En (b), el generador genera una imagen falsa basada en una imagen de entrada y una etiqueta de dominio de destino (por ejemplo, enojado).

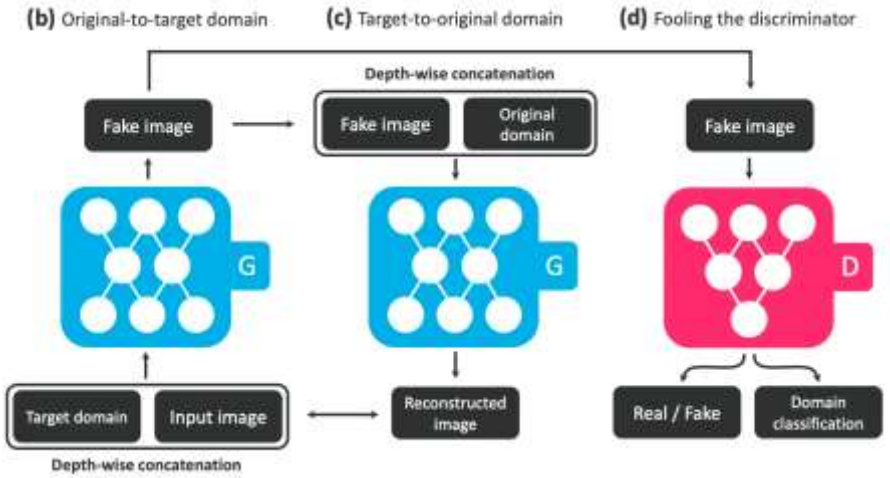


Aplicaciones

StarGAN

https://arxiv.org/pdf/1711.09020.pdf

En (d), alimentamos imágenes reales y falsas al discriminador para etiquetarlo como real o no, así como su clasificación de dominio.

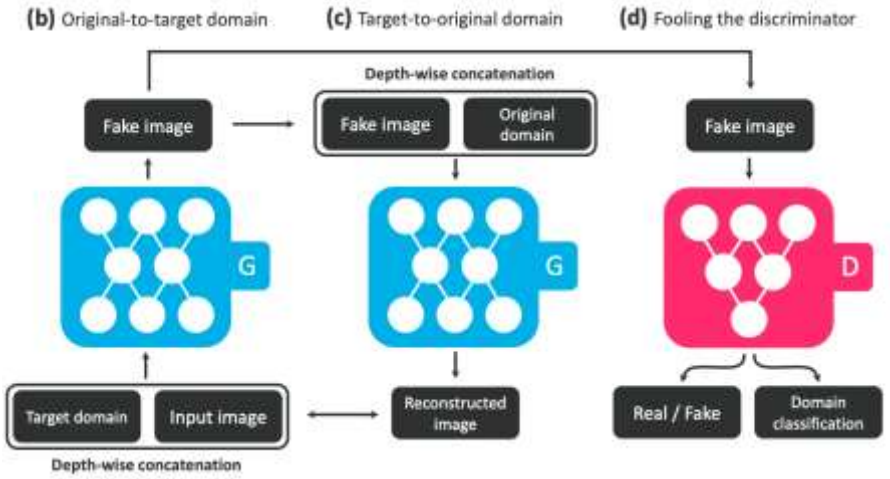


Aplicaciones

StarGAN

https://arxiv.org/pdf/1711.09020.pdf

La función de costo involucrará errores de reconstrucción así como el costo del discriminador en la identificación de las imágenes y sus etiquetas.



Aplicaciones

PixelDTGAN

https://github.com/fxia22/PixelDTGAN

Aplicaciones

PixelDTGAN

https://github.com/fxia22/PixelDTGAN

A source image. Possible target images.

Aplicaciones

PixelDTGAN

https://github.com/fxia22/PixelDTGAN

Aplicaciones

PixelDTGAN

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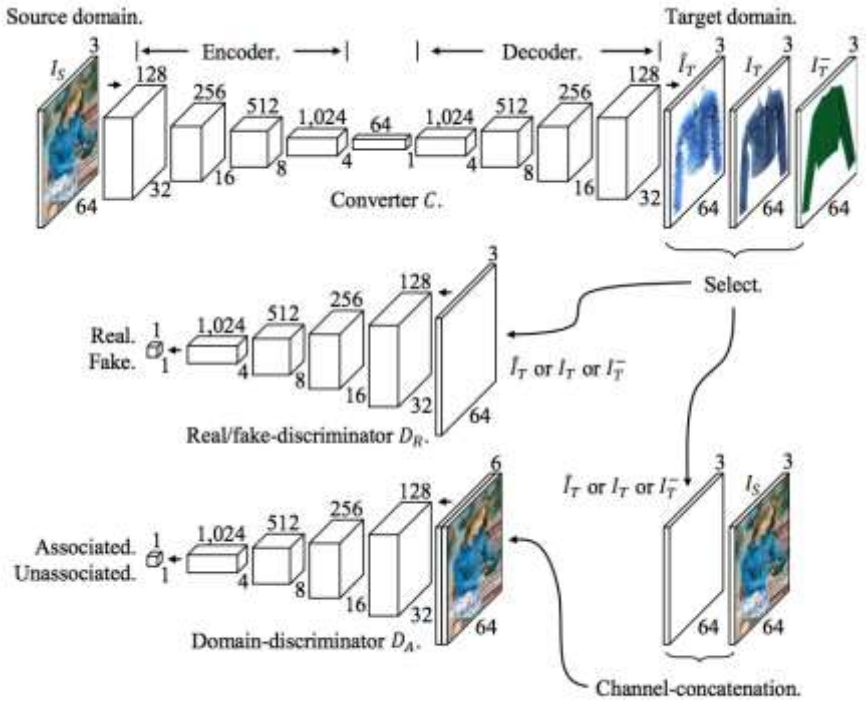


Fig. 2. Whole architecture for pixel-level domain transfer.

Aplicaciones

SuperResolution GAN

https://arxiv.org/pdf/1609.04802.pdf

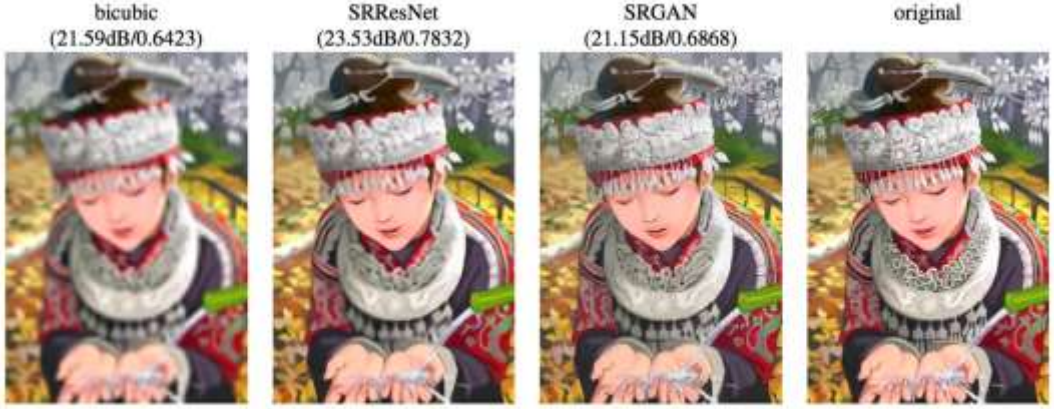


Figure 2: From left to right: bicubic interpolation, deep residual network optimized for MSE, deep residual generative adversarial network optimized for a loss more sensitive to human perception, original HR image. Corresponding PSNR and SSIM are shown in brackets. [4× upscaling]

Aplicaciones

StyleGAN 2

https://arxiv.org/pdf/1912.04958.pdf

Aplicaciones

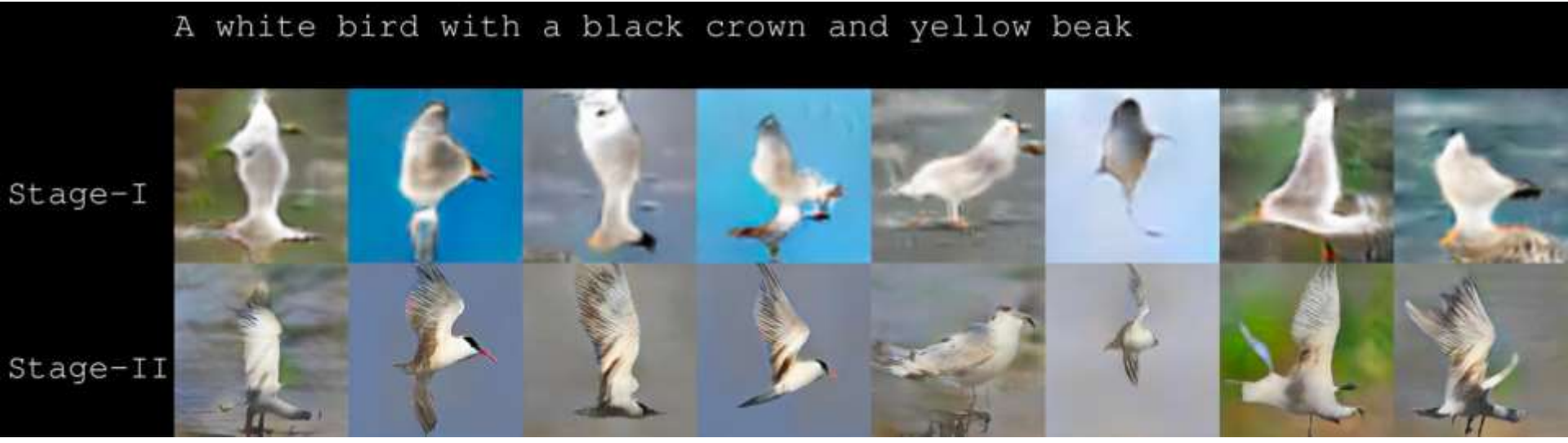
Text 2 Imagen GAN (StackGAN)

https://github.com/hanzhanggit/StackGAN

Aplicaciones

Text 2 Imagen GAN (StackGAN)

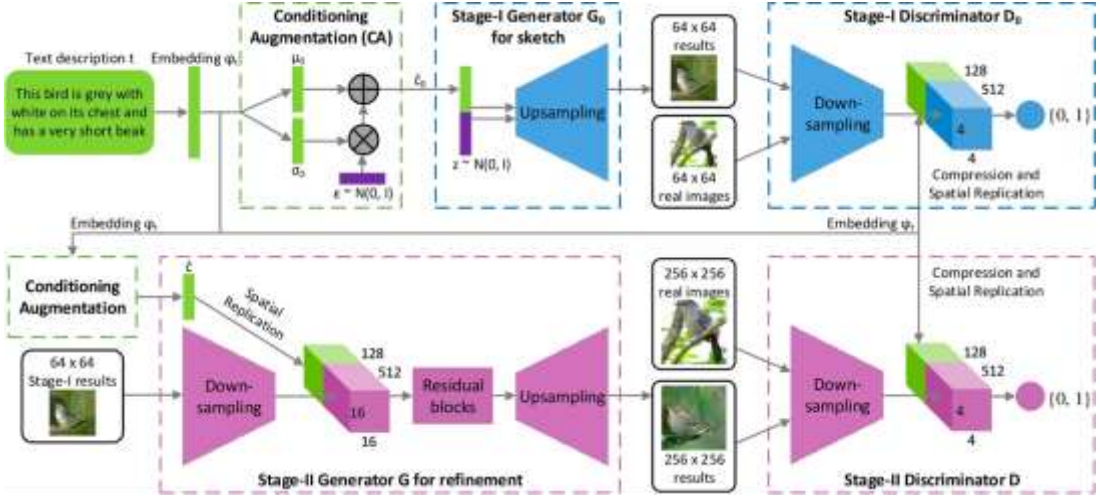
https://github.com/hanzhanggit/StackGAN



Aplicaciones

Text 2 Imagen GAN (StackGAN)

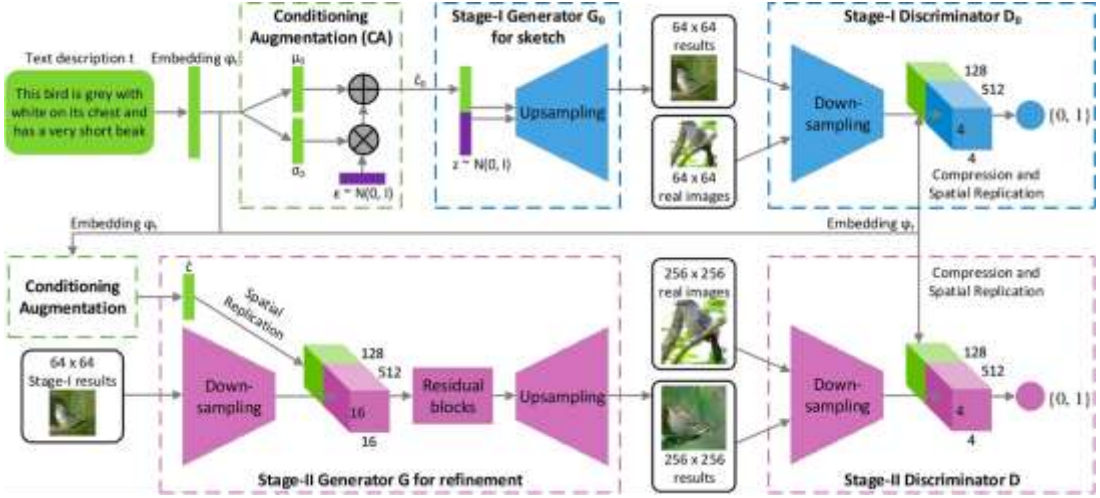
https://github.com/hanzhanggit/StackGAN



Aplicaciones

Text 2 Imagen GAN (StackGAN)

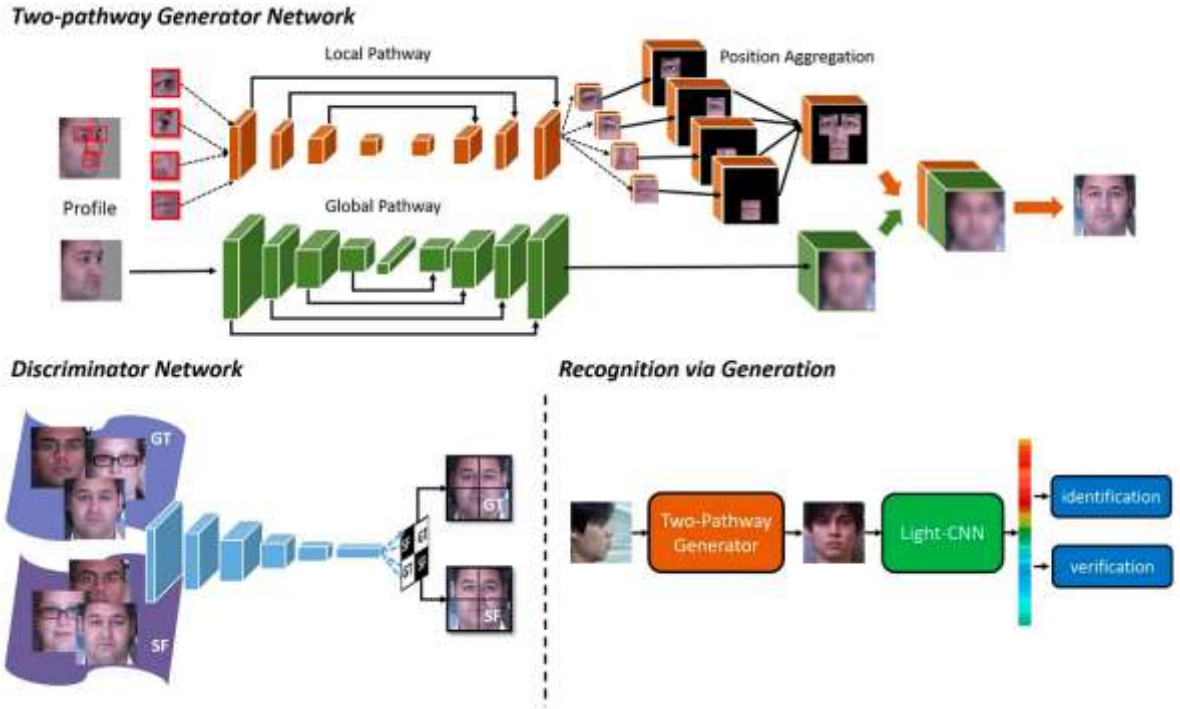
https://github.com/hanzhanggit/StackGAN - Demo: https://www.craiyon.com/



Aplicaciones

TPGAN

https://arxiv.org/pdf/1704.04086.pdf

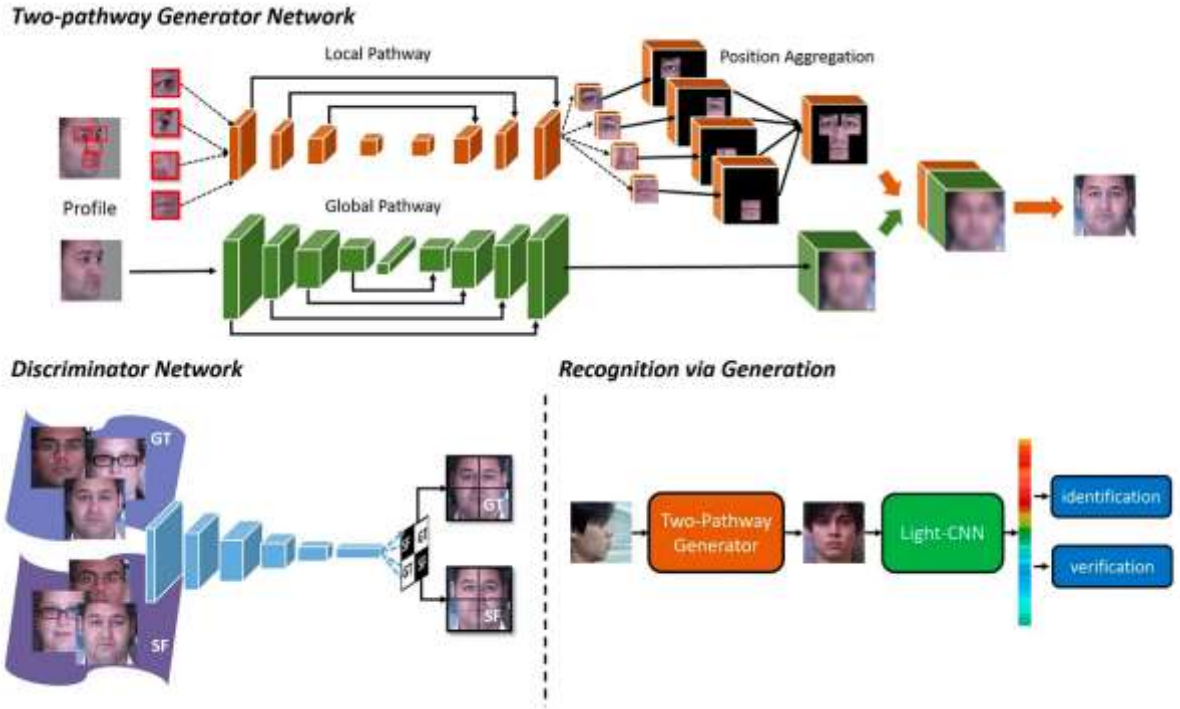


Aplicaciones

TPGAN

https://arxiv.org/pdf/1704.04086.pdf

Caras de síntesis en diferentes poses: Con una única imagen de entrada, crea caras en diferentes ángulos de visión.

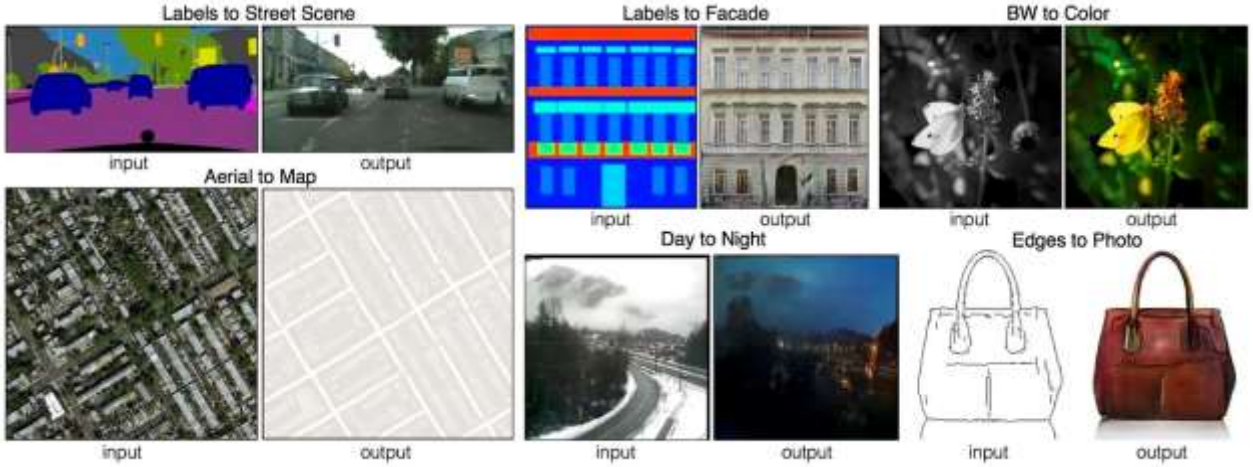


Aplicaciones

Pix2Pix

https://github.com/phillipi/pix2pix

Traducción de imágenes en diferentes tareas.



Aplicaciones

DeBlur

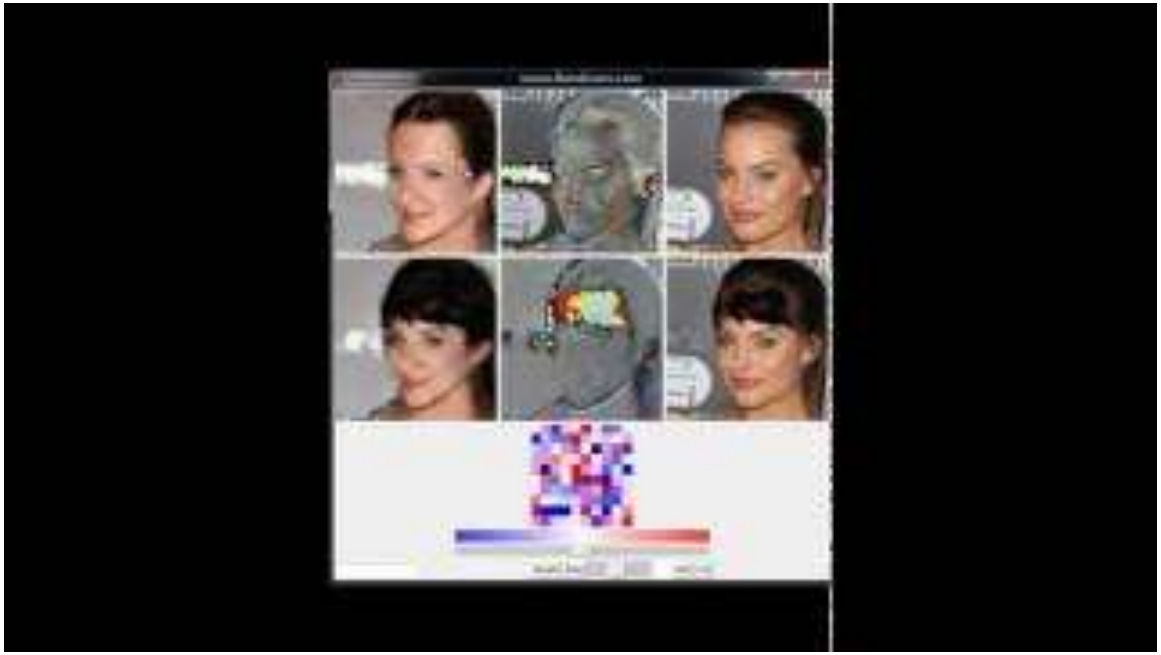
https://arxiv.org/pdf/1711.07064.pdf

Figure 2: GoPro images [25] processed by DeblurGAN. Blurred – left, DeblurGAN – center, ground truth sharp – right.

Aplicaciones

Neural Photo Editor

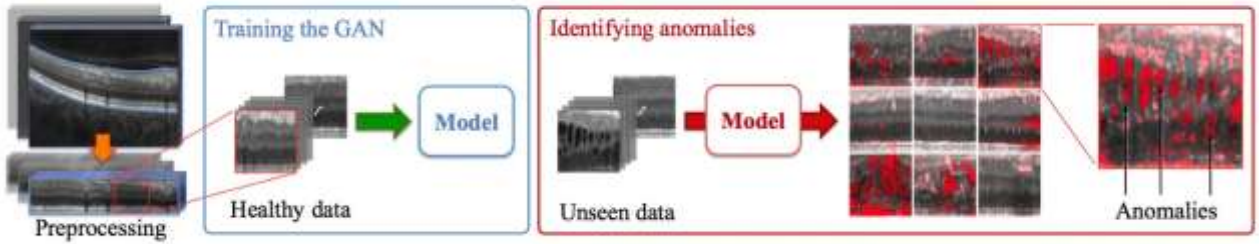
https://github.com/ajbrock/Neural-Photo-Editor



Aplicaciones

MediGAN

https://arxiv.org/pdf/1703.05921.pdf



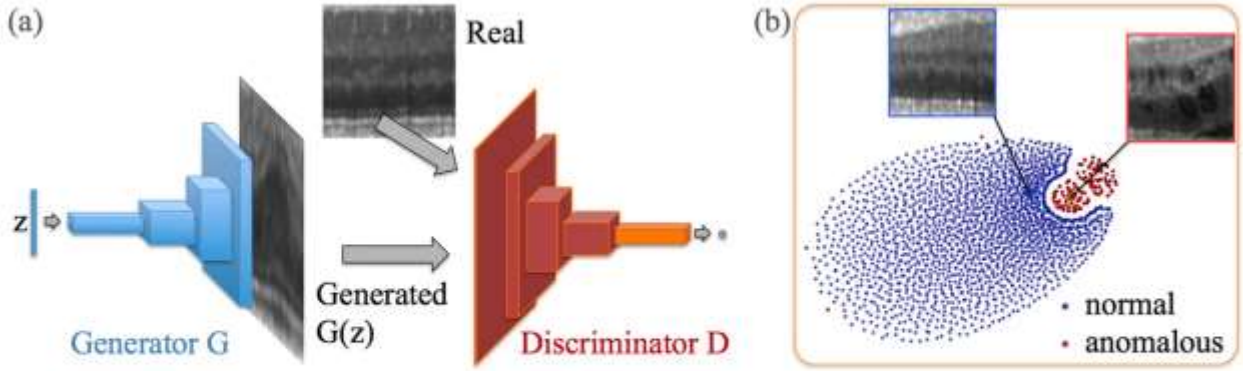


Fig. 2. (a) Deep convolutional generative adversarial network. (b) t-SNE embedding of normal (blue) and anomalous (red) images on the feature representation of the last convolution layer (orange in (a)) of the discriminator.

Aplicaciones

3D GAN

https://proceedings.neurips.cc/paper_files/paper/2016/file/44f683a84163b3523afe57c2e008bc8c-Paper.pdf

Aplicaciones

3D GAN

https://proceedings.neurips.cc/paper_files/paper/2016/file/44f683a84163b3523afe57c2e008bc8c-Paper.pdf

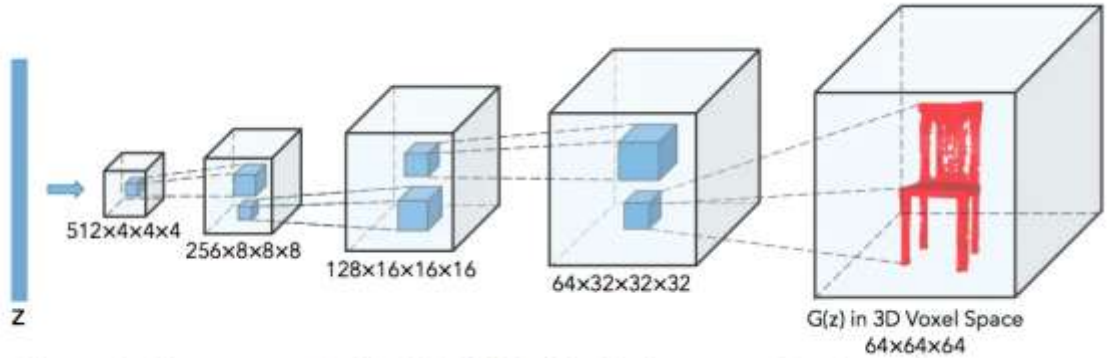


Figure 1: The generator in 3D-GAN. The discriminator mostly mirrors the generator.

Fuentes:

GAN (2014) Ian J. Goodfellow, Jean Pouget-Abadie, Mehdi Mirza, Bing Xu, David Warde-Farley, Sherjil Ozair, Aaron Courville, Yoshua Bengio
https://arxiv.org/abs/1406.2661

https://github.com/soumith/ganhacks

https://jonathan-hui.medium.com/gan-some-cool-applications-of-gans-4c9ecca35900