

# Modelos Generativos

## Variational Autoencoders

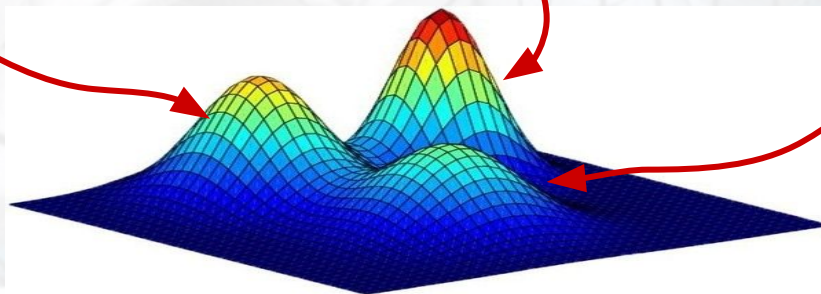
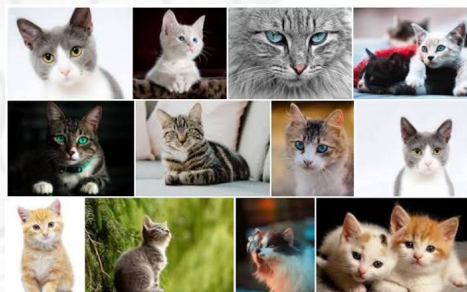
### VAE

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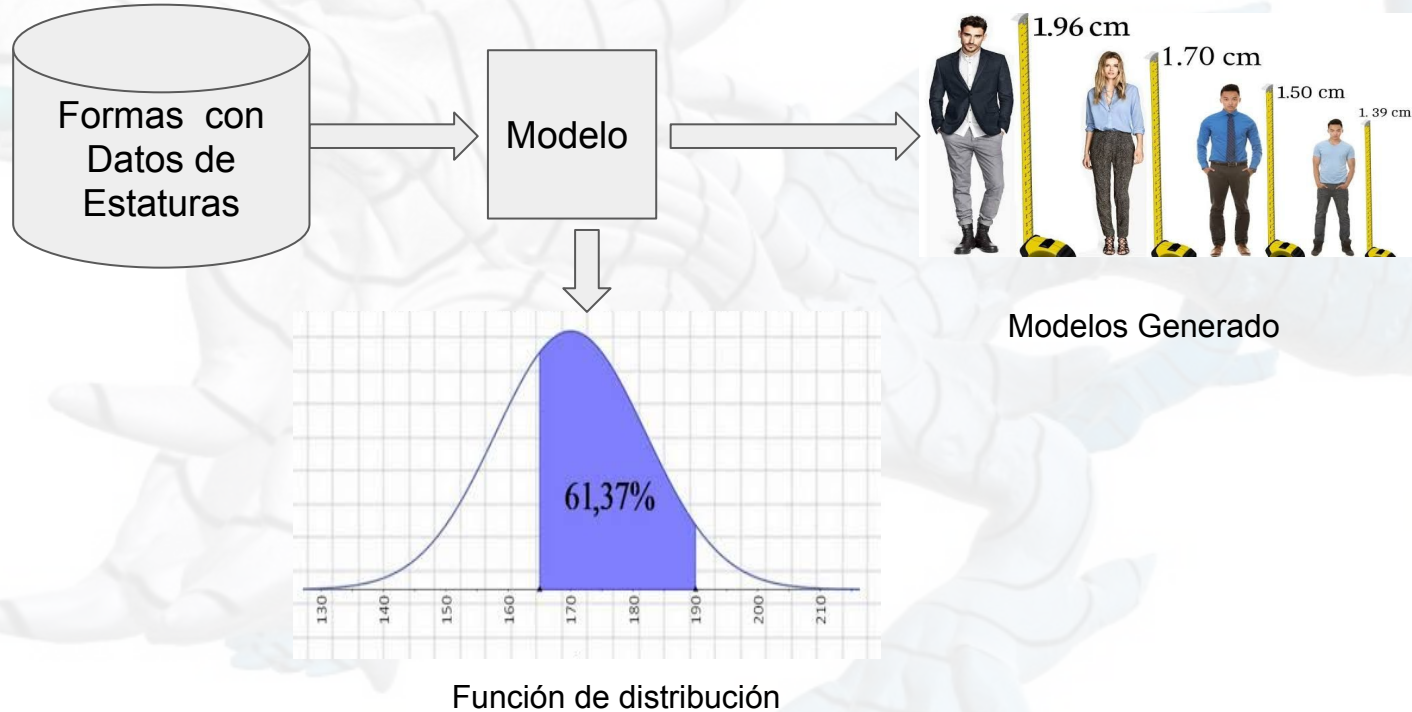
Junio 21, 2022

## Generative Modelos



Función de distribución

## Generative Modelos





MODELO  
DL/ML  
Parámetros  $\Theta$



$\hat{Y}_i$

Salida del modelo

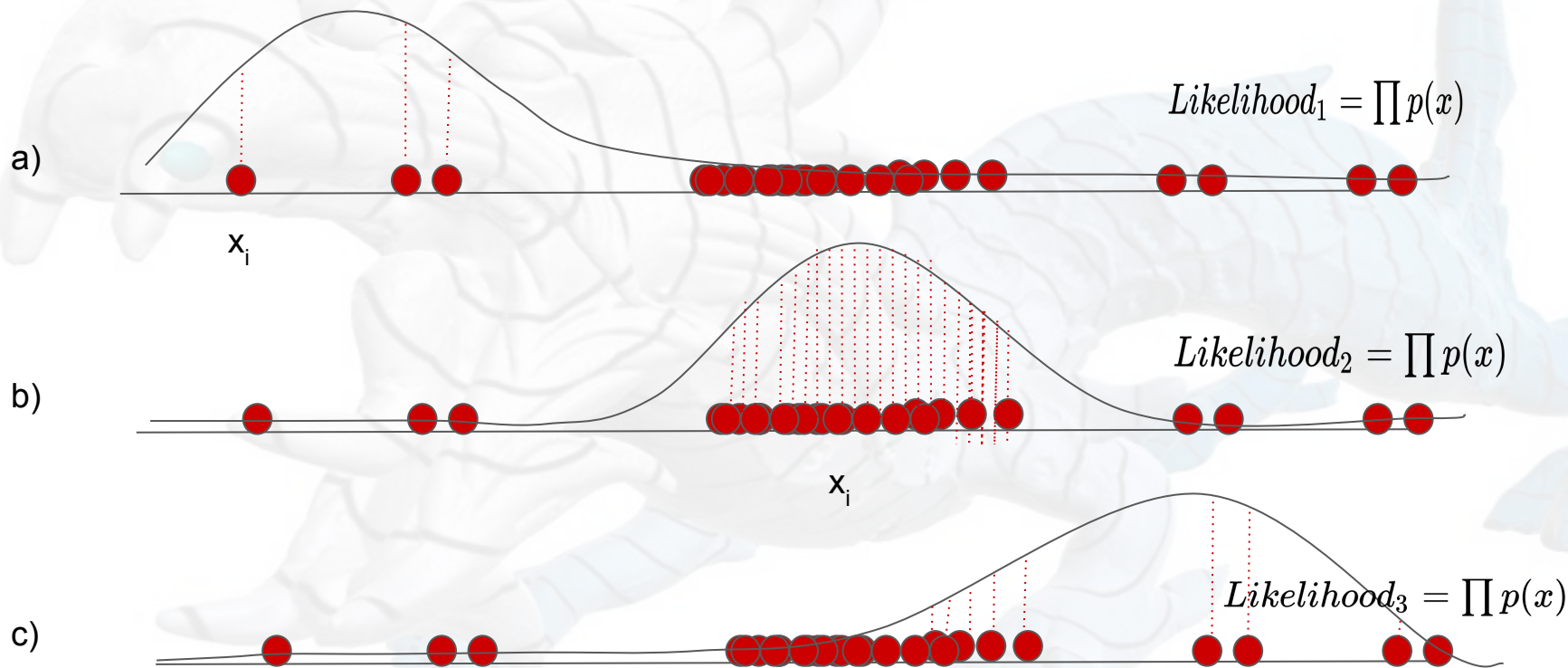
$Y_i$

Salida Esperada

$$\hat{\mathcal{L}}(\Theta) = \underset{\Theta}{\operatorname{argmin}} ( \| \tilde{y} - y \|_2 )$$

$$\hat{\mathcal{L}}(\Theta) = (\frac{1}{2}) * \sum ( \tilde{y}_i - y_i )^2$$

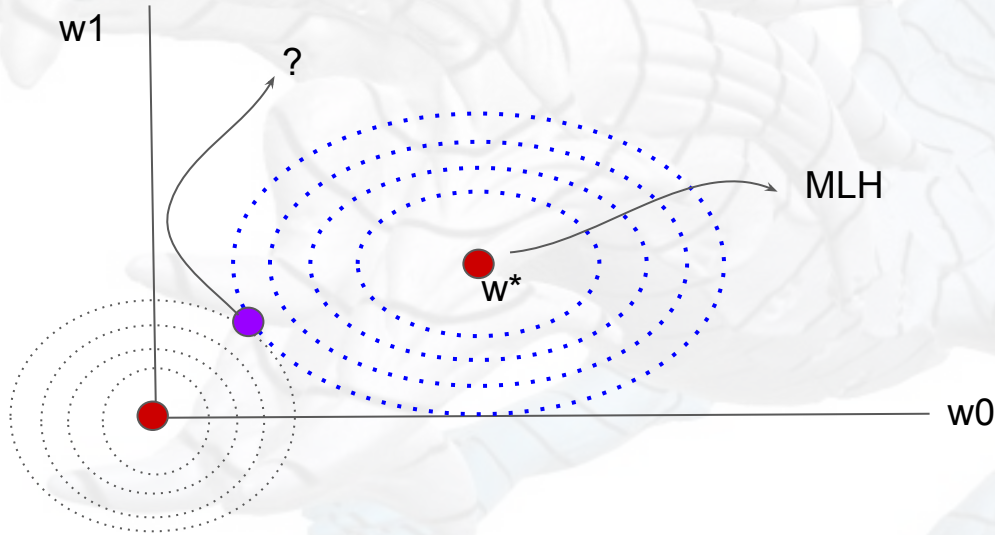
# Concepto: Máxima Verosimilitud : $\max \prod p(x)$





maximum log Likelihood

$$\max -\log -\text{likelihood} \Rightarrow \arg\theta \min \frac{1}{2} \|y_i - f(x, \theta)\|_2$$



# maximum a posteriori

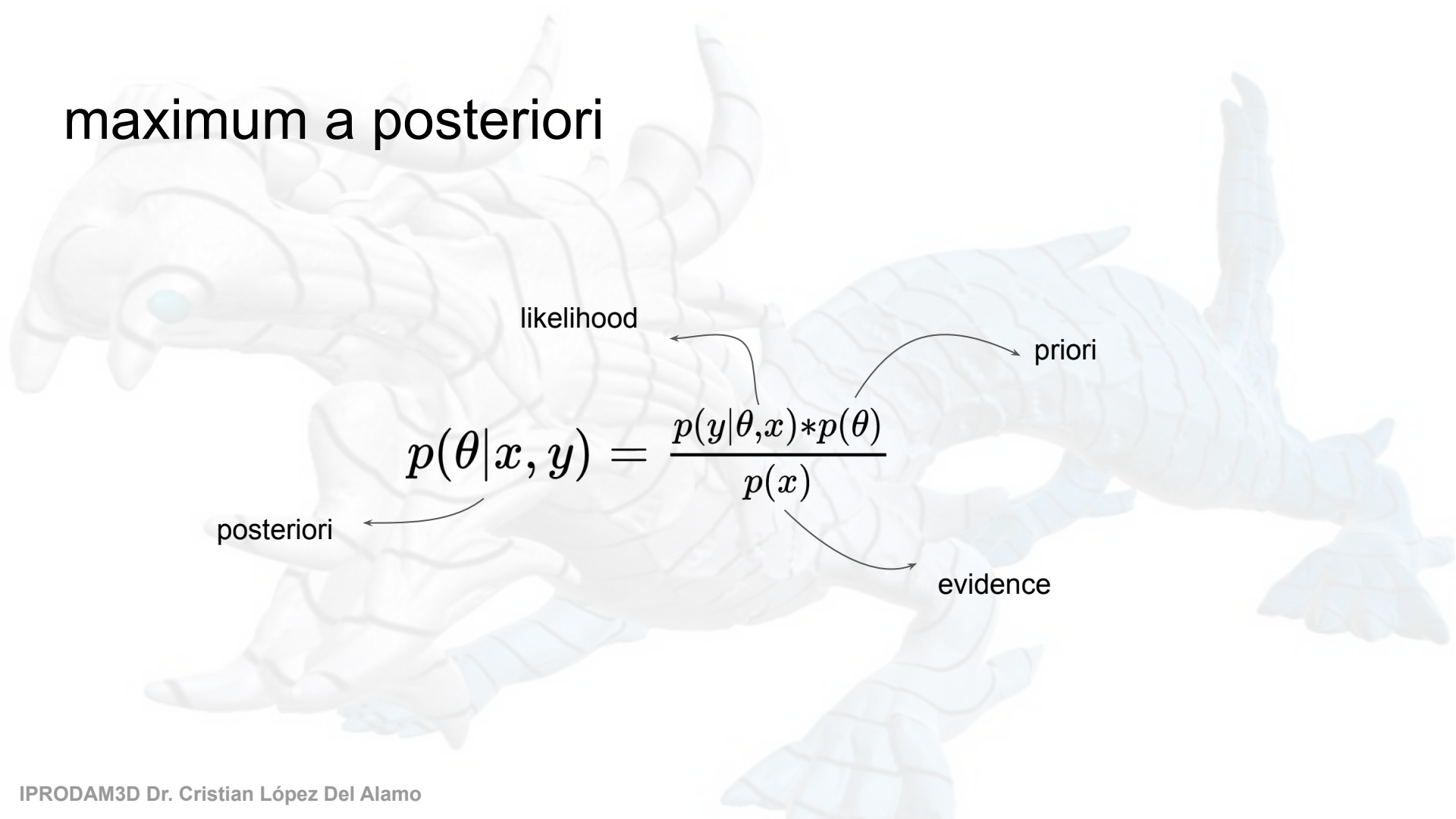


Diagram illustrating the Maximum A Posteriori (MAP) formula:

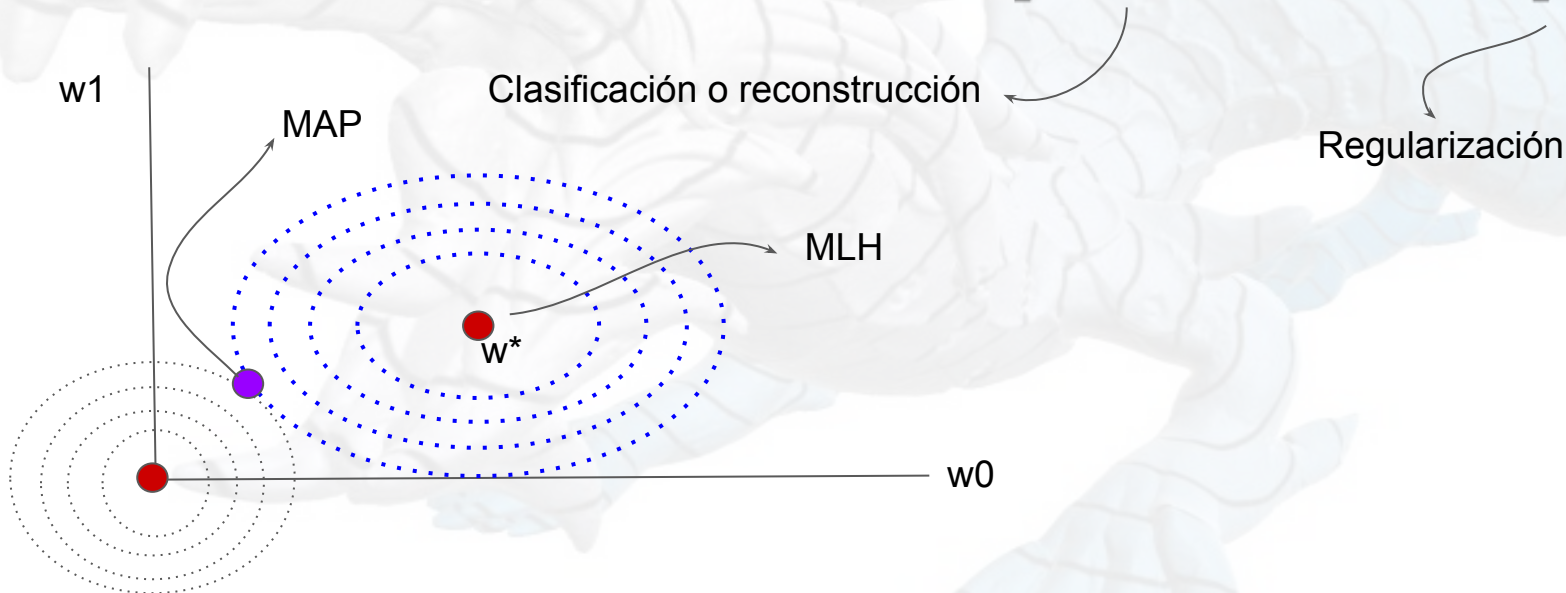
$$p(\theta|x, y) = \frac{p(y|\theta, x) * p(\theta)}{p(x)}$$

The components are labeled with arrows:

- posteriori** points to  $p(\theta|x, y)$
- likelihood** points to  $p(y|\theta, x)$
- priori** points to  $p(\theta)$
- evidence** points to  $p(x)$

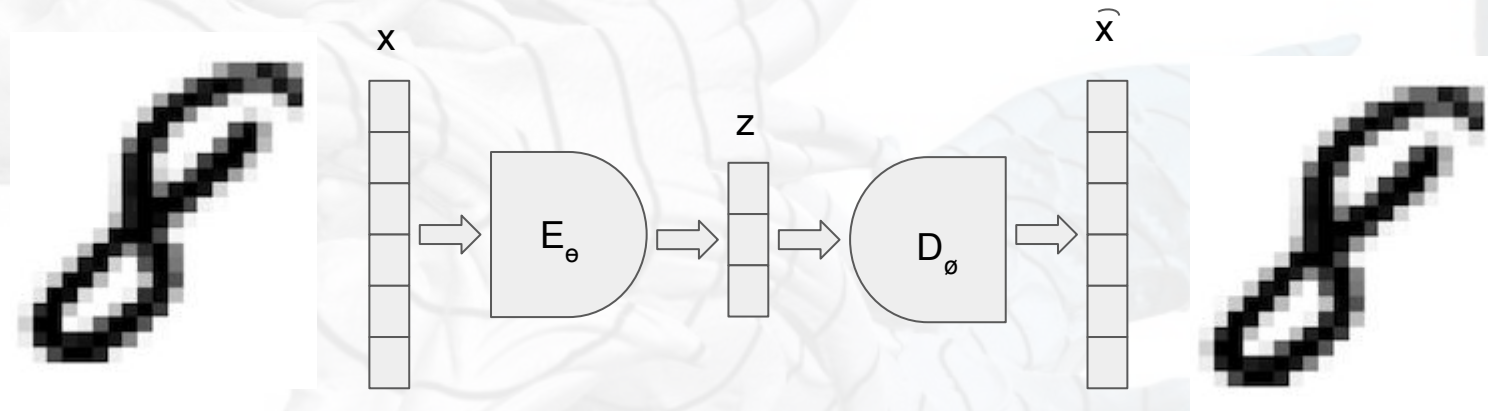
# maximum a posteriori

$$\text{max - posteriori} \Rightarrow \text{arg} \theta \text{mix} \quad \frac{1}{2} ||y_i - f(x, \theta)||_2 + \frac{\lambda}{2} ||\theta||_2$$





# Autoencoders



Sea  $x \in \mathcal{R}^n, E(.) : \mathcal{R}^n \rightarrow \mathcal{R}^d$  y  $D(.) : \mathcal{R}^d \rightarrow \mathcal{R}^n$

$\hat{x} = D(E(x))$  tal que,  $\operatorname{argmin}_\theta ||x - \hat{x}||^2$

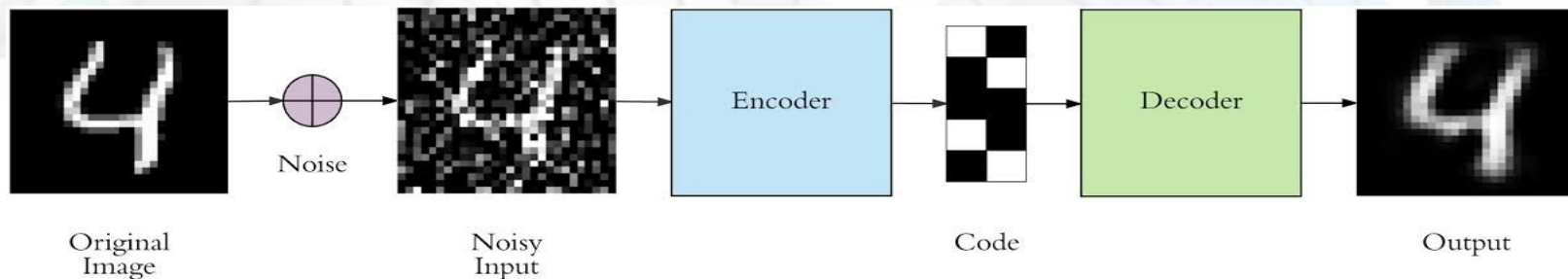
Recuerde

$\max - \log - \text{likelihood} \Rightarrow \operatorname{argmin}_\theta \frac{1}{2} ||y_i - f(x, \theta)||_2$

# Autoencoders

Denoising autoencoder

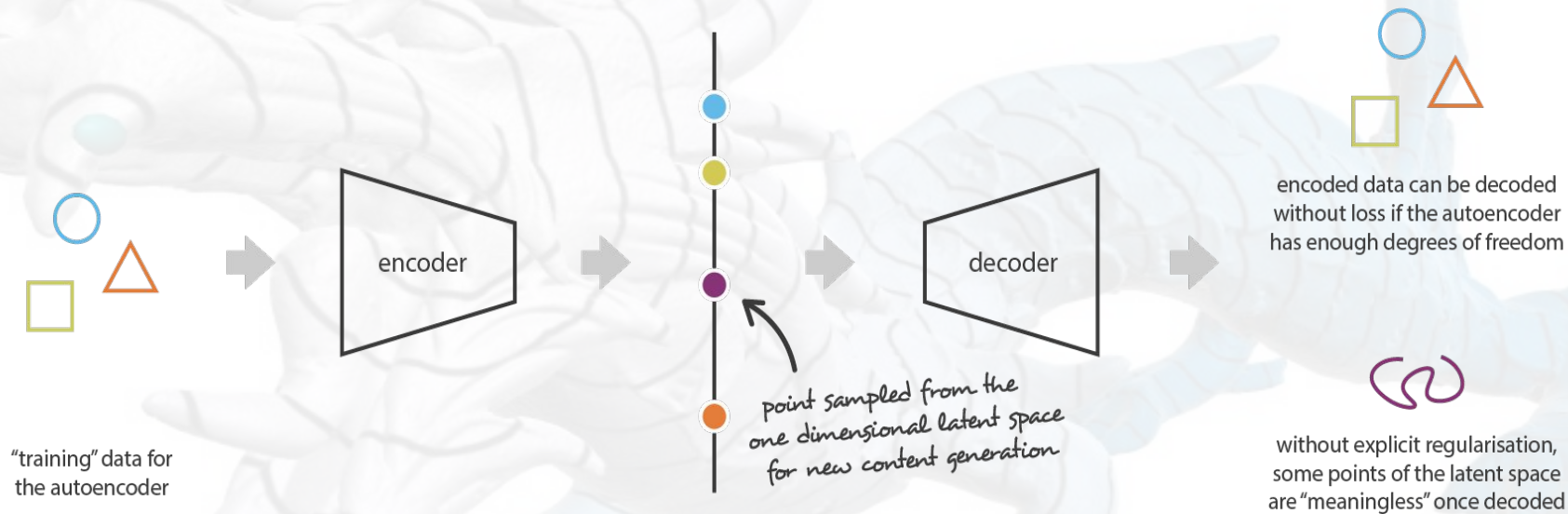
$$\argmin_{\theta} \|(x - \hat{x})\|^2, \quad \hat{x} = D(z), z = E(x + \mathcal{N}(0, 1))$$



Sparse autoencoder

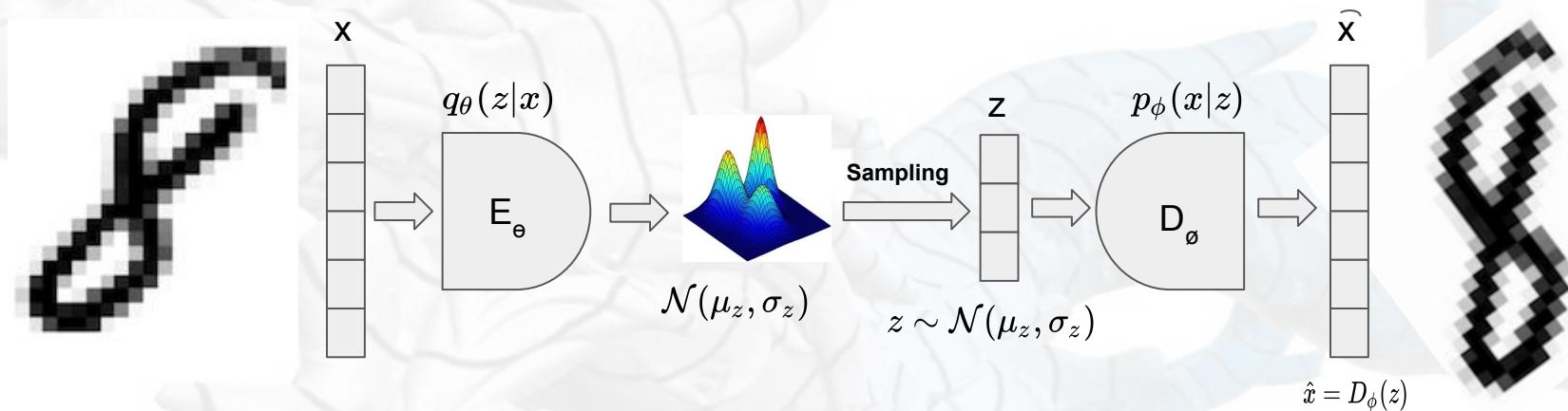
$$\argmin_{\theta} \|(x - \hat{x})\|^2 + \frac{\lambda}{2} \sum |z_i|, \quad \hat{x} = D(z), z = E(x)$$

# Autoencoder



Fuente: <https://towardsdatascience.com/understanding-variational-autoencoders-vaes-f70510919f73>

# Variational autoencoders



$$\mathcal{L}(\theta, \phi) = \|x - \hat{x}\| + KL(\mathcal{N}(\mu_x, \sigma_x), \mathcal{N}(0, 1))$$

Calidad de reconstrucción

Asegura continuidad, completitud

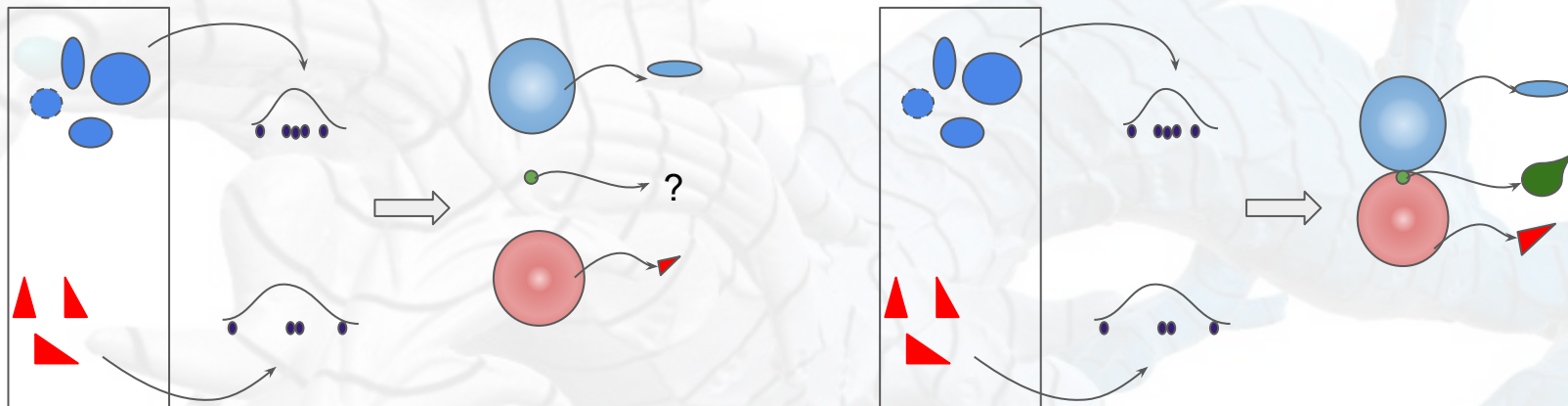
# Variational autoencoders



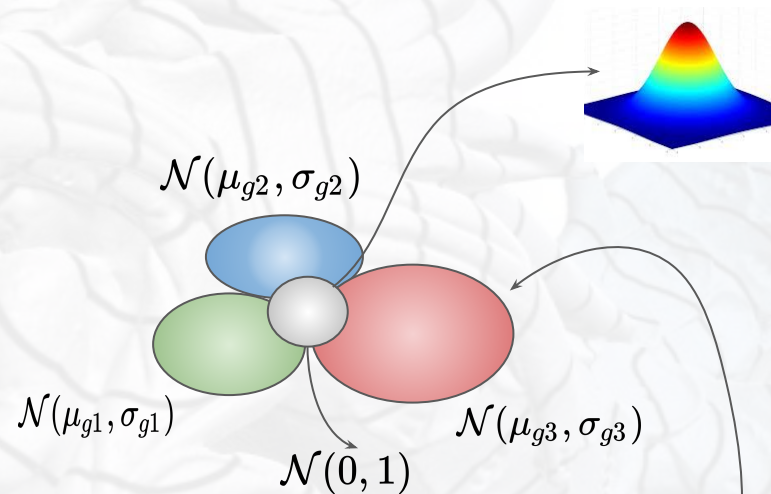
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# Variational autoencoders

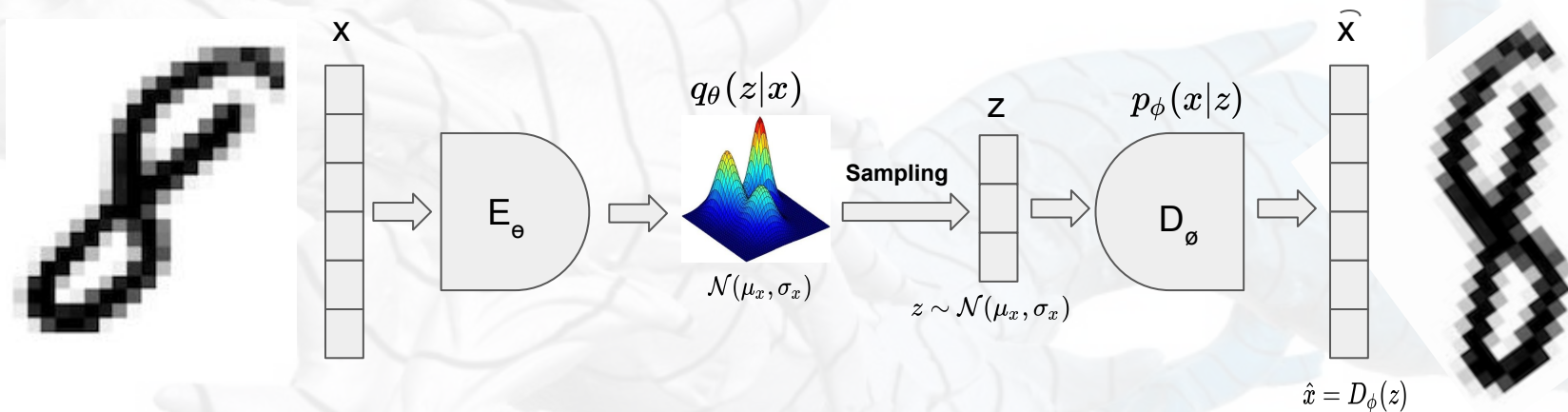


# Variational autoencoders



$$\mathcal{L}(\theta, \phi) = ||x - \hat{x}|| + KL(\mathcal{N}(\mu_x, \sigma_x), \mathcal{N}(0, 1))$$

# Autoencoder



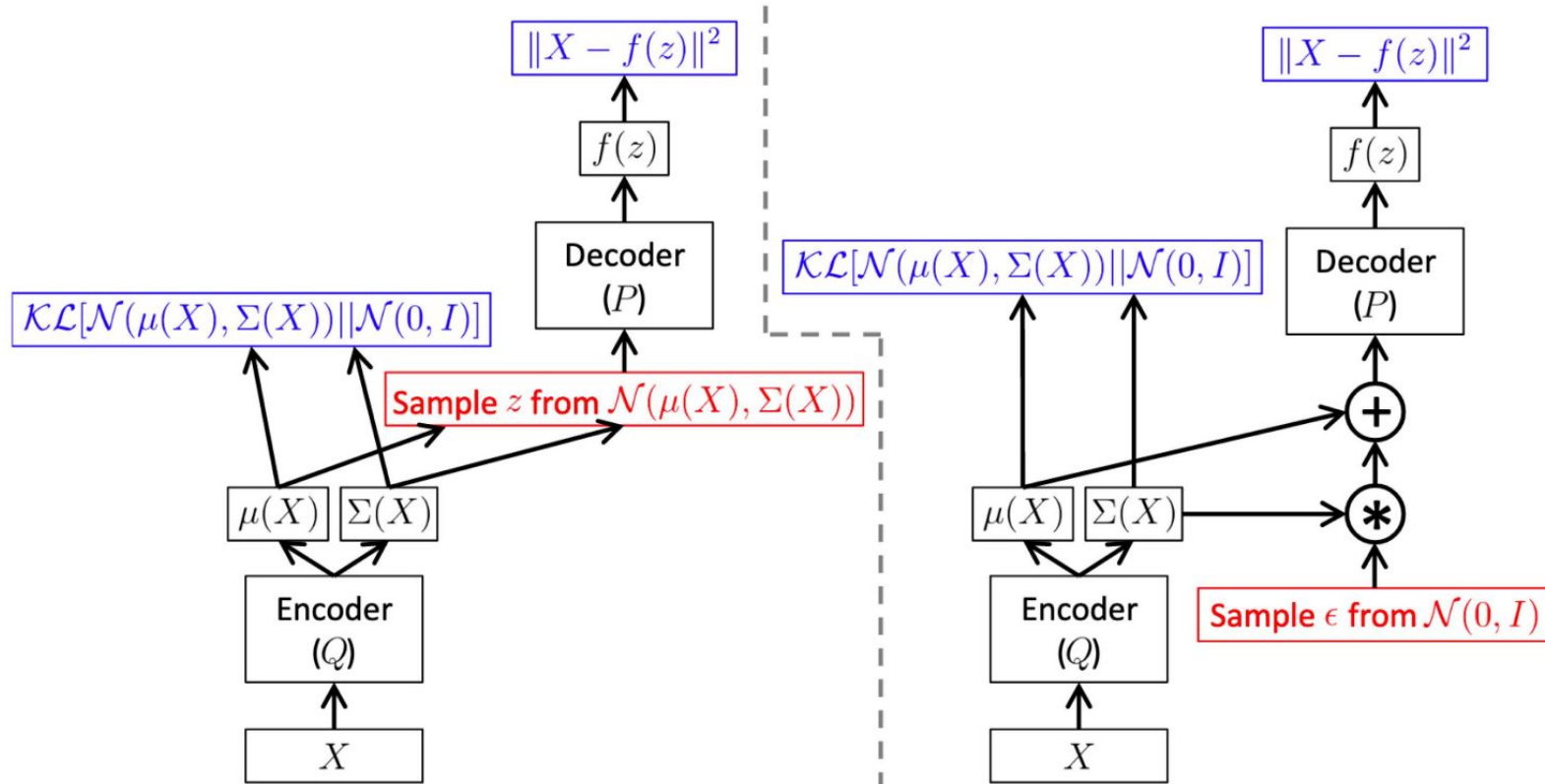
$$z = \mu + \sigma$$

No es continuo, no es posible aplicar la gradiente descendiente

$$z = \mu_x + \sigma_x * \mathcal{N}(0,1)$$

Continuo, es posible aplicar la gradiente descendiente

$$\mathcal{L}(\theta, \phi) = ||x - \hat{x}|| + KL(\mathcal{N}(\mu_x, \sigma_x), \mathcal{N}(0, 1))$$



Trained by minimizing negative ELBO:

$$l_i(\theta, \phi) = -E_{z \sim q_\phi(z|x_i)} [\log p_\theta(x_i | z)] + KL(q_\phi(z | x_i) \parallel p(z))$$

Fuente: Sargur N. Srihari

# Aplicaciones



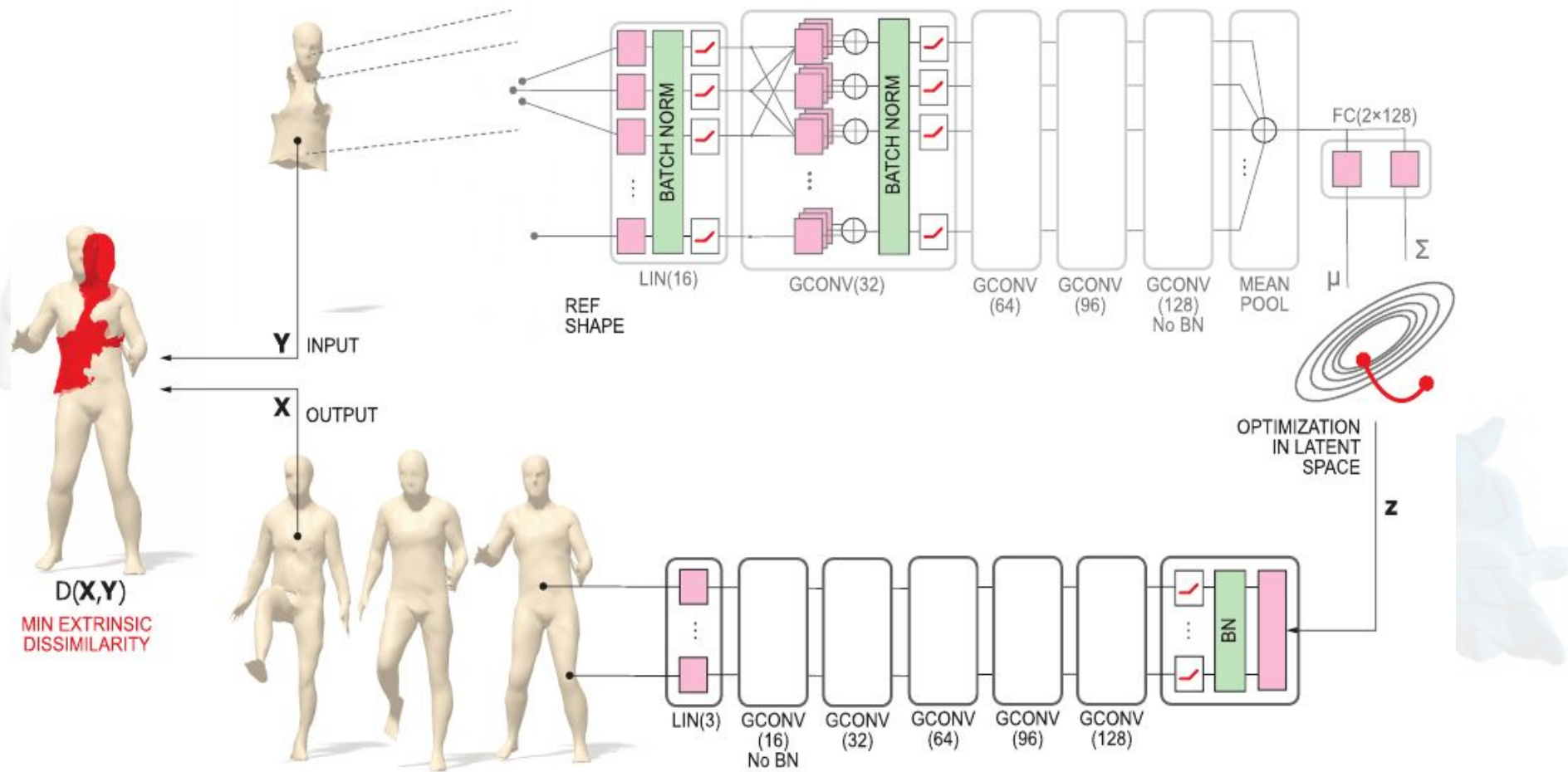
Fuente: <https://medium.com/analytics-vidhya/an-introduction-to-generative-deep-learning-792e93d1c6d4>



# Aplicaciones



Fuente: <https://medium.com/analytics-vidhya/an-introduction-to-generative-deep-learning-792e93d1c6d4>



# ¿Preguntas?



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