



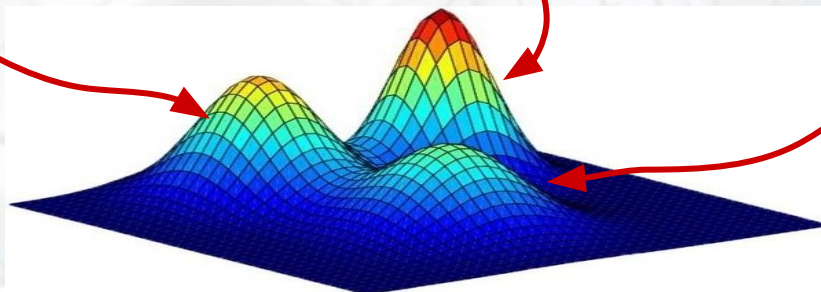
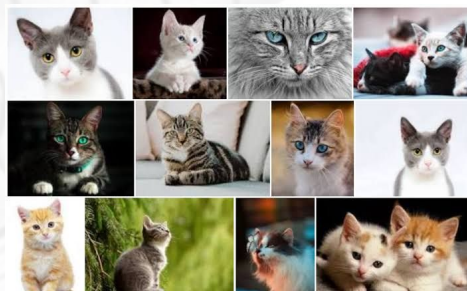
Modelos Generativos Autoencoders

RESEARCHGROUP
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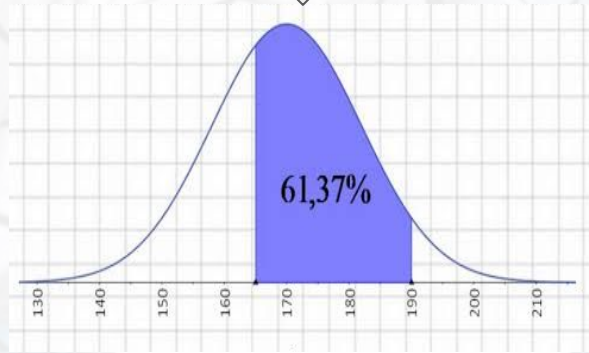
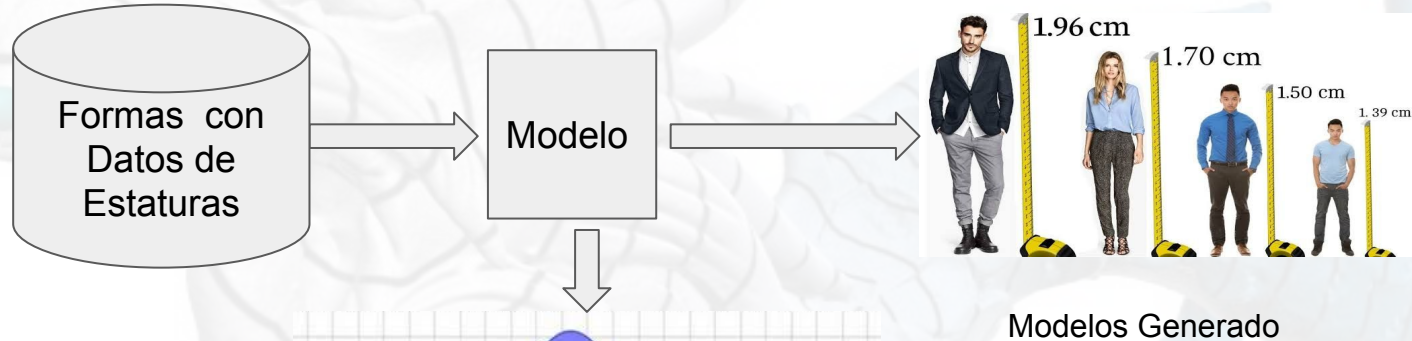
Enero 8, 2020

Generative Modelos



Función de distribución

Generative Modelos



Función de distribución



MODELO
DL/ML
Parámetros Θ



\hat{Y}_i

Salida del modelo

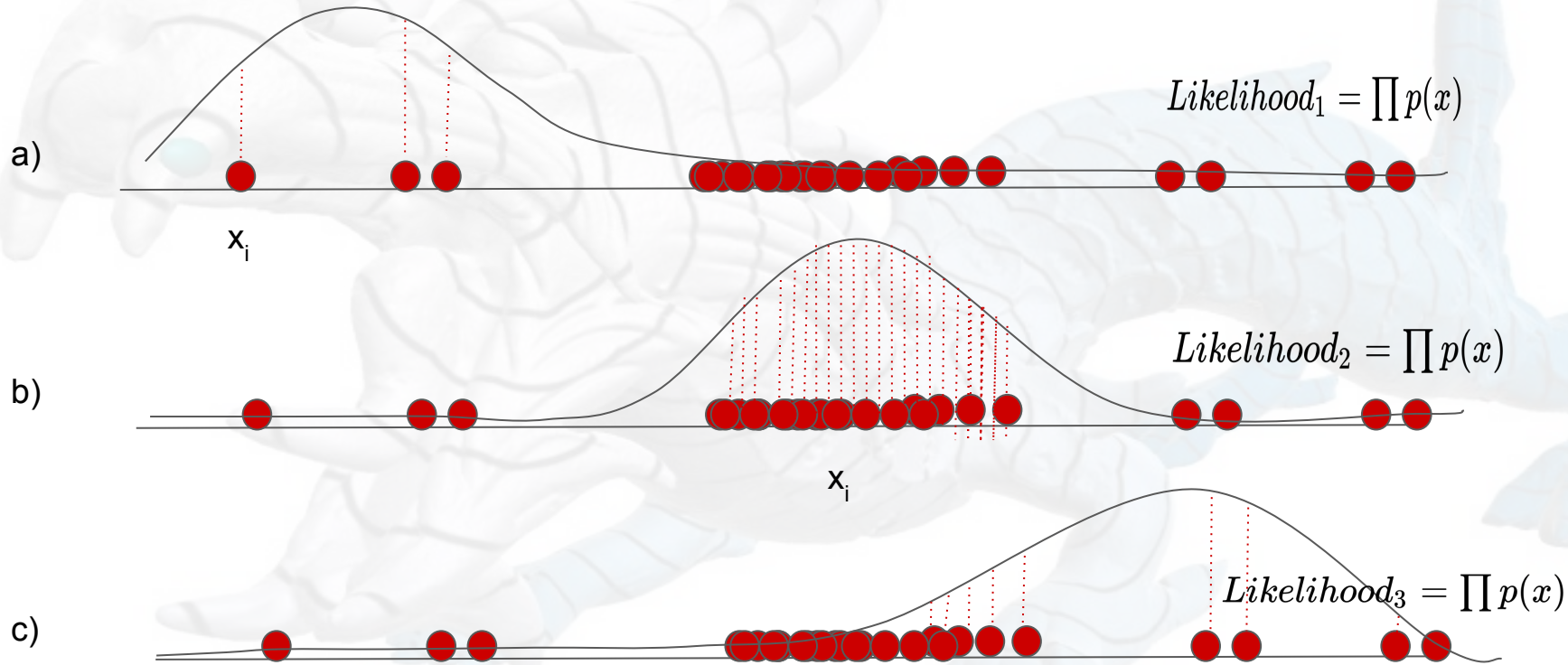
Y_i

Salida Esperada

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

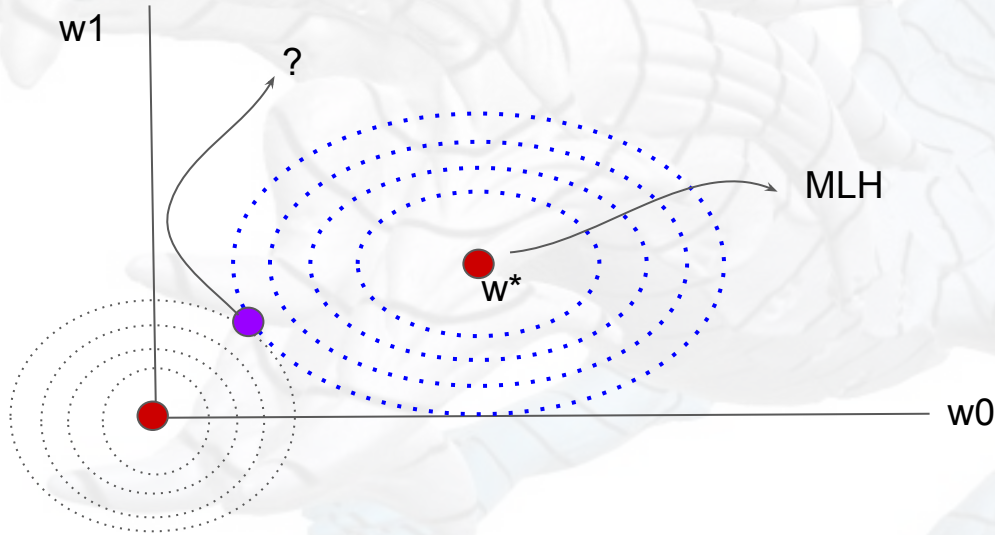
$$\hat{\mathcal{L}}(\Theta) = (1/2) * \sum (\tilde{y}_i - y_i)^2$$

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

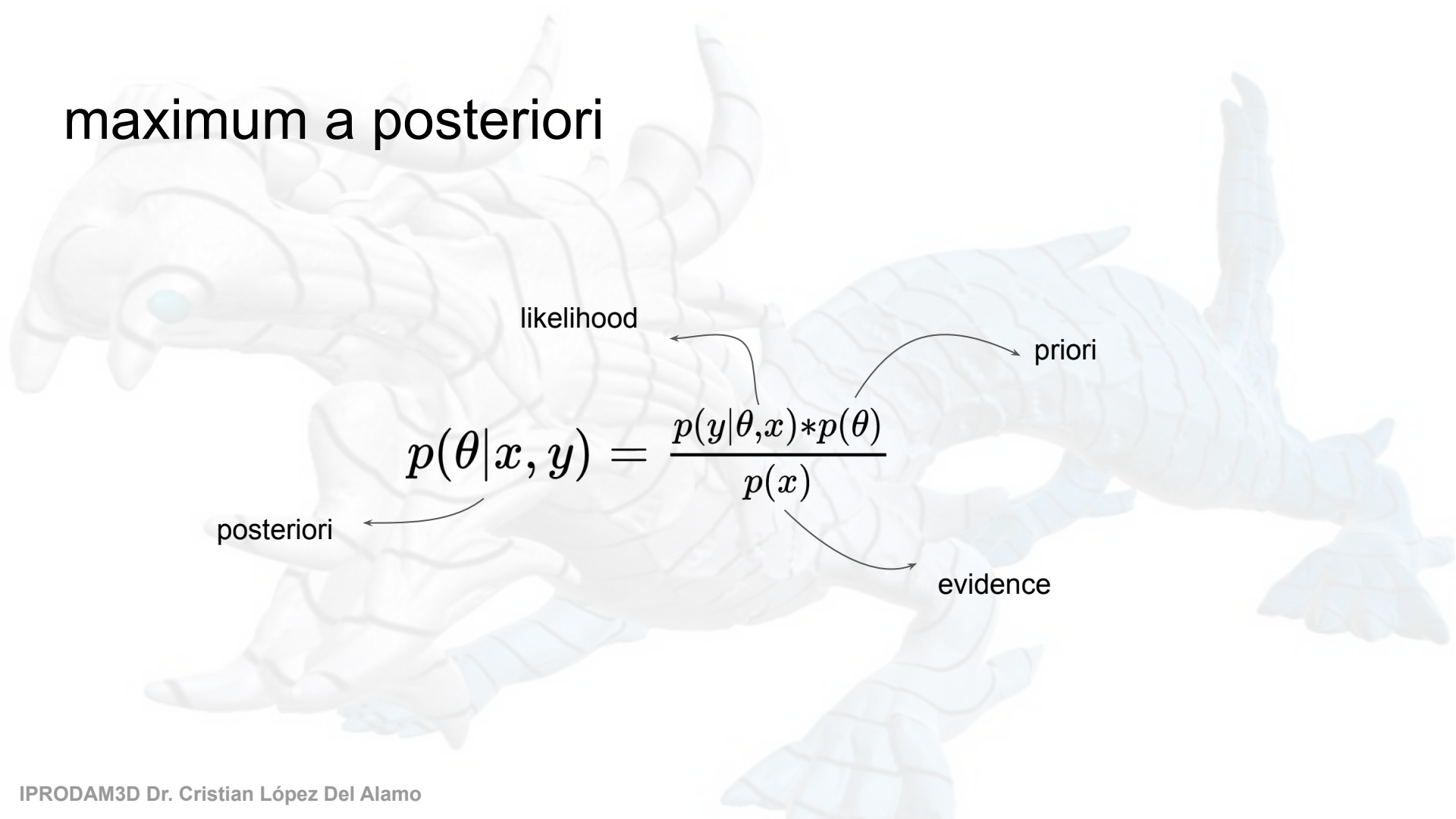


Diagram illustrating the Maximum A Posteriori (MAP) formula:

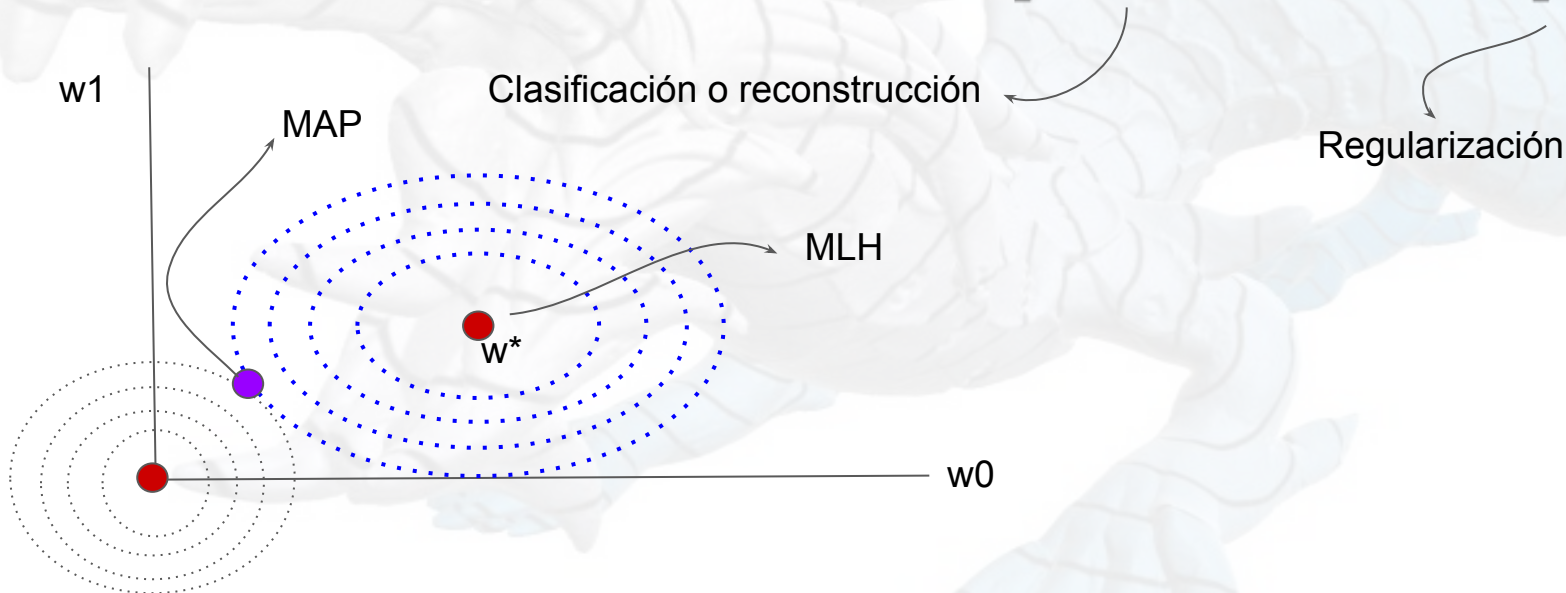
$$p(\theta|x, y) = \frac{p(y|\theta, x) * p(\theta)}{p(x)}$$

The components are labeled with arrows:

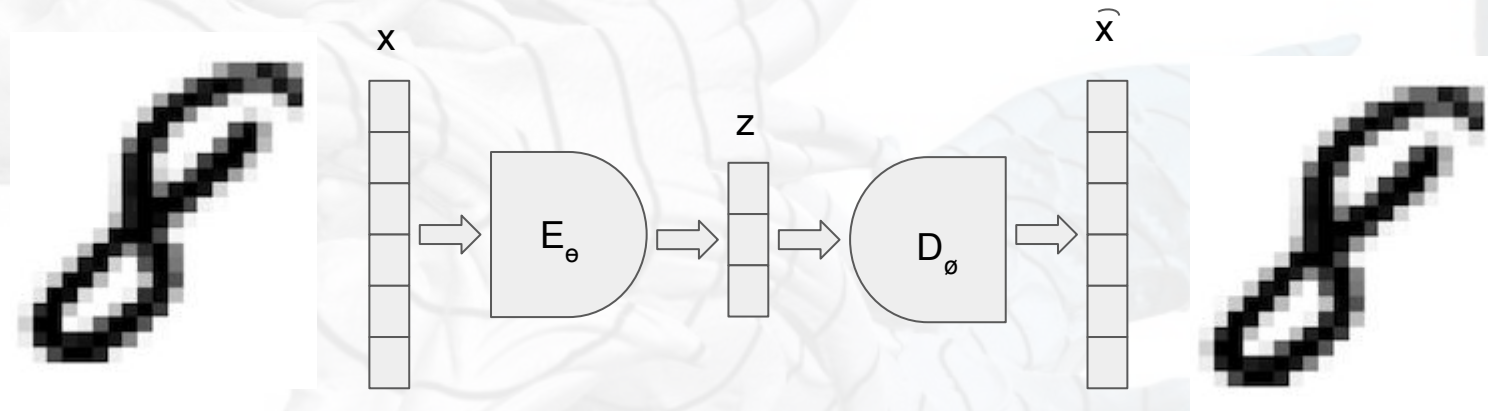
- posteriori** points to $p(\theta|x, y)$
- evidence** points to $p(x)$
- likelihood** points to $p(y|\theta, x)$
- priori** points to $p(\theta)$

maximum a posteriori

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



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, $\operatorname{argmin}_\theta ||x - \hat{x}||^2$

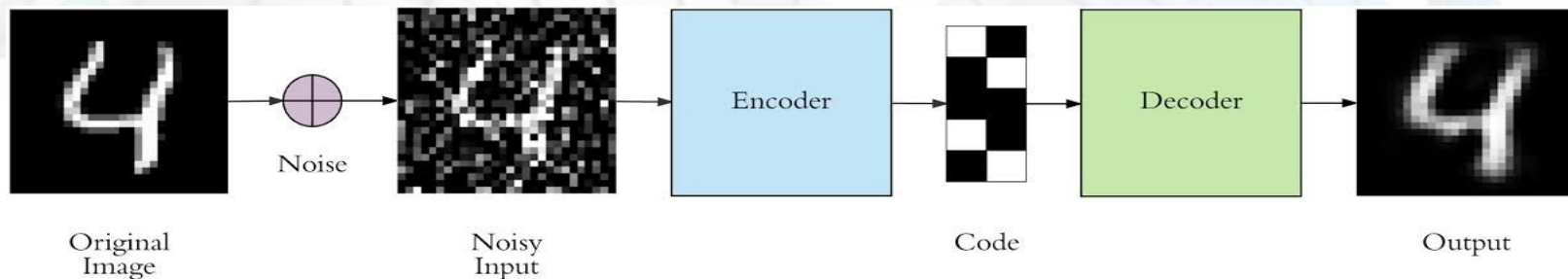
Recuerde

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

Autoencoders

Denoising autoencoder

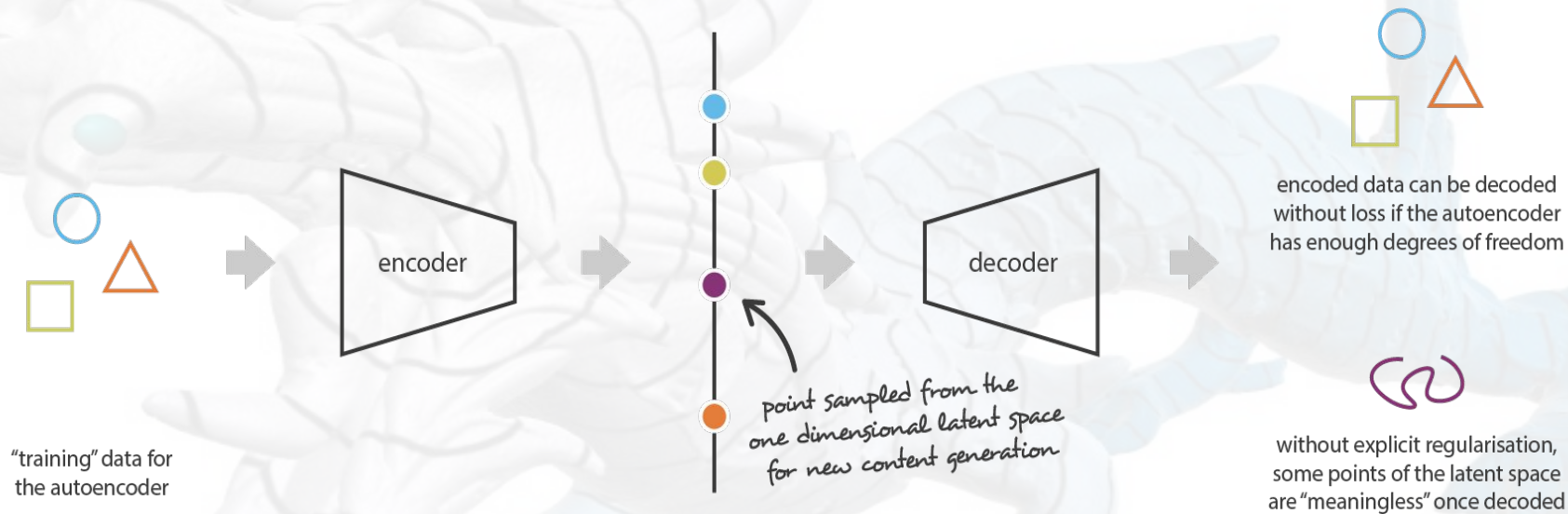
$$\argmin_{\theta} \|(x - \hat{x})\|^2, \quad \hat{x} = D(z), z = E(x + \mathcal{N}(0, 1))$$



Sparse autoencoder

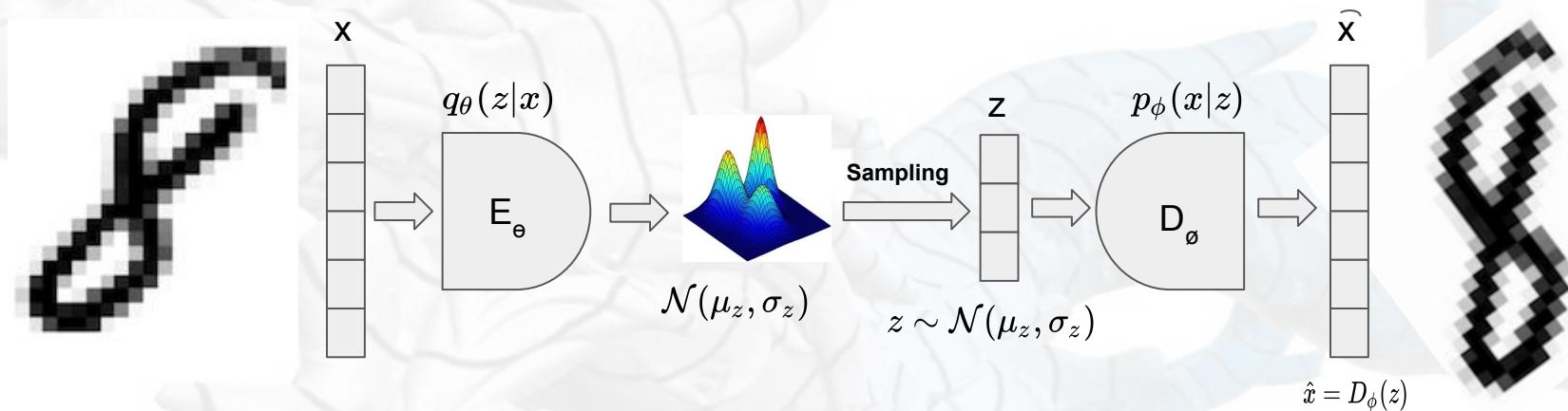
$$\argmin_{\theta} \|(x - \hat{x})\|^2 + \frac{\lambda}{2} \sum |z_i|, \quad \hat{x} = D(z), z = E(x)$$

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

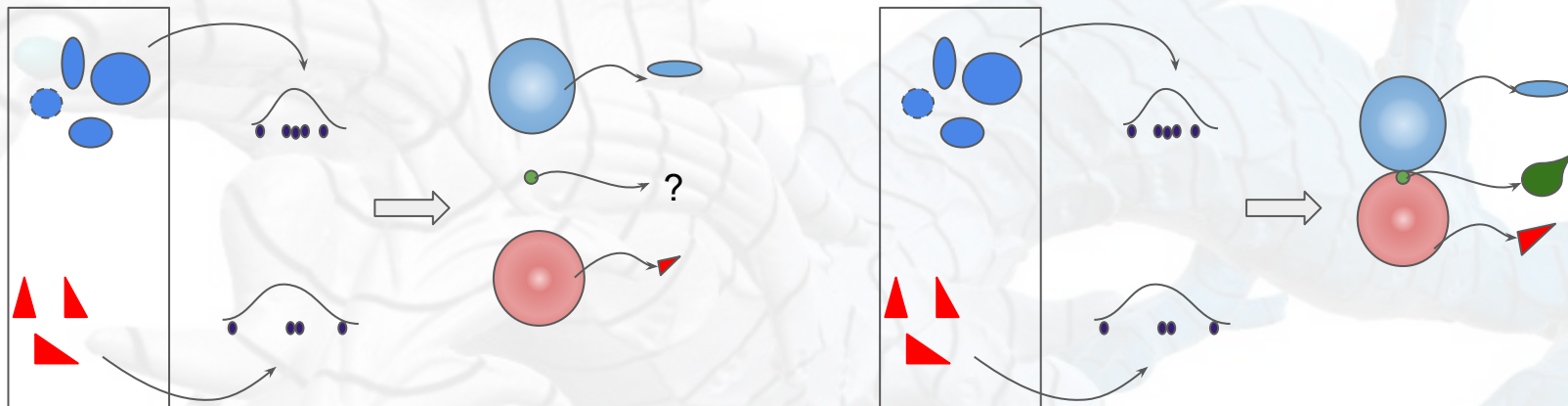
Asegura continuidad, completitud

Variational autoencoders

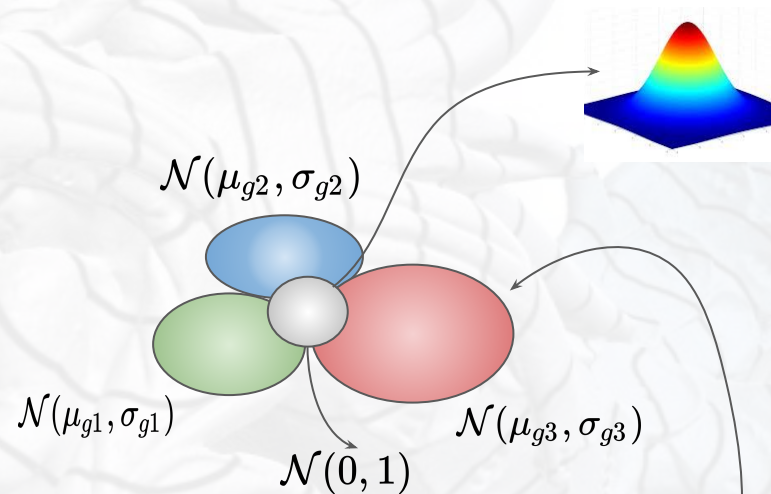


Fuente: <https://towardsdatascience.com/understanding-variational-autoencoders-vaes-f70510919f73>

Variational autoencoders

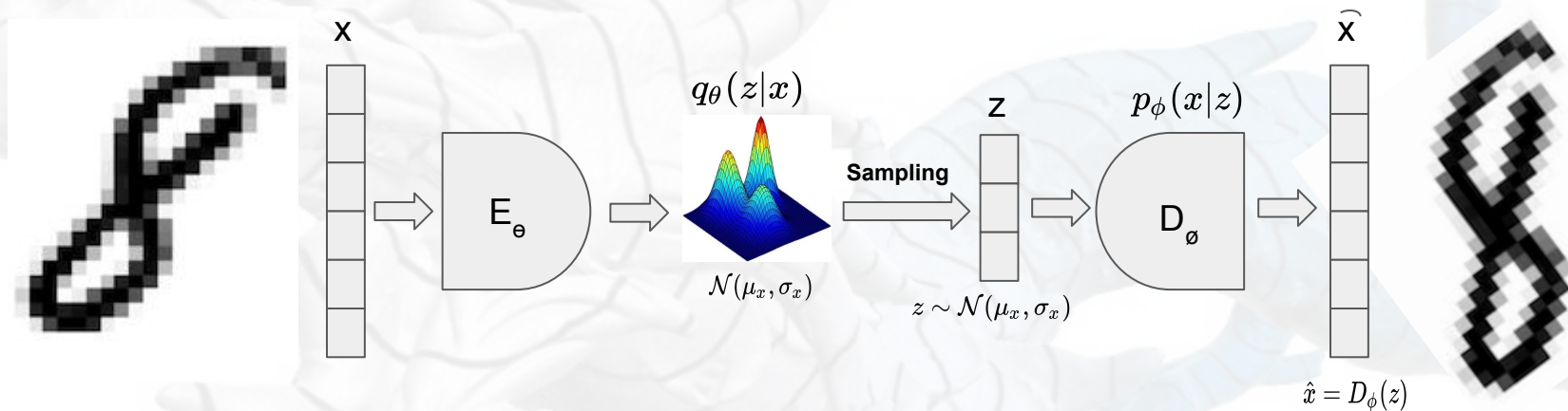


Variational autoencoders



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

Autoencoder



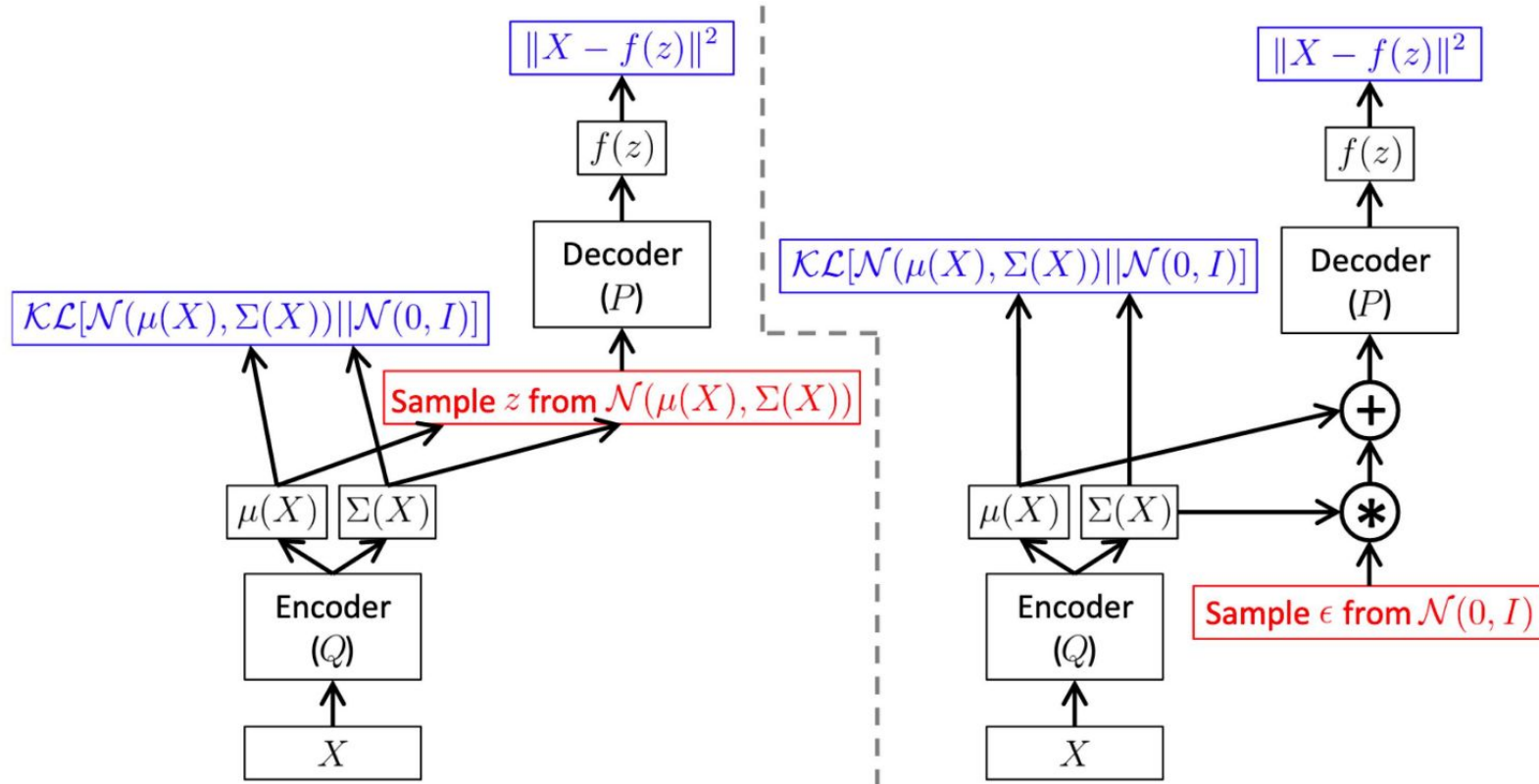
$$z = \mu + \sigma$$

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

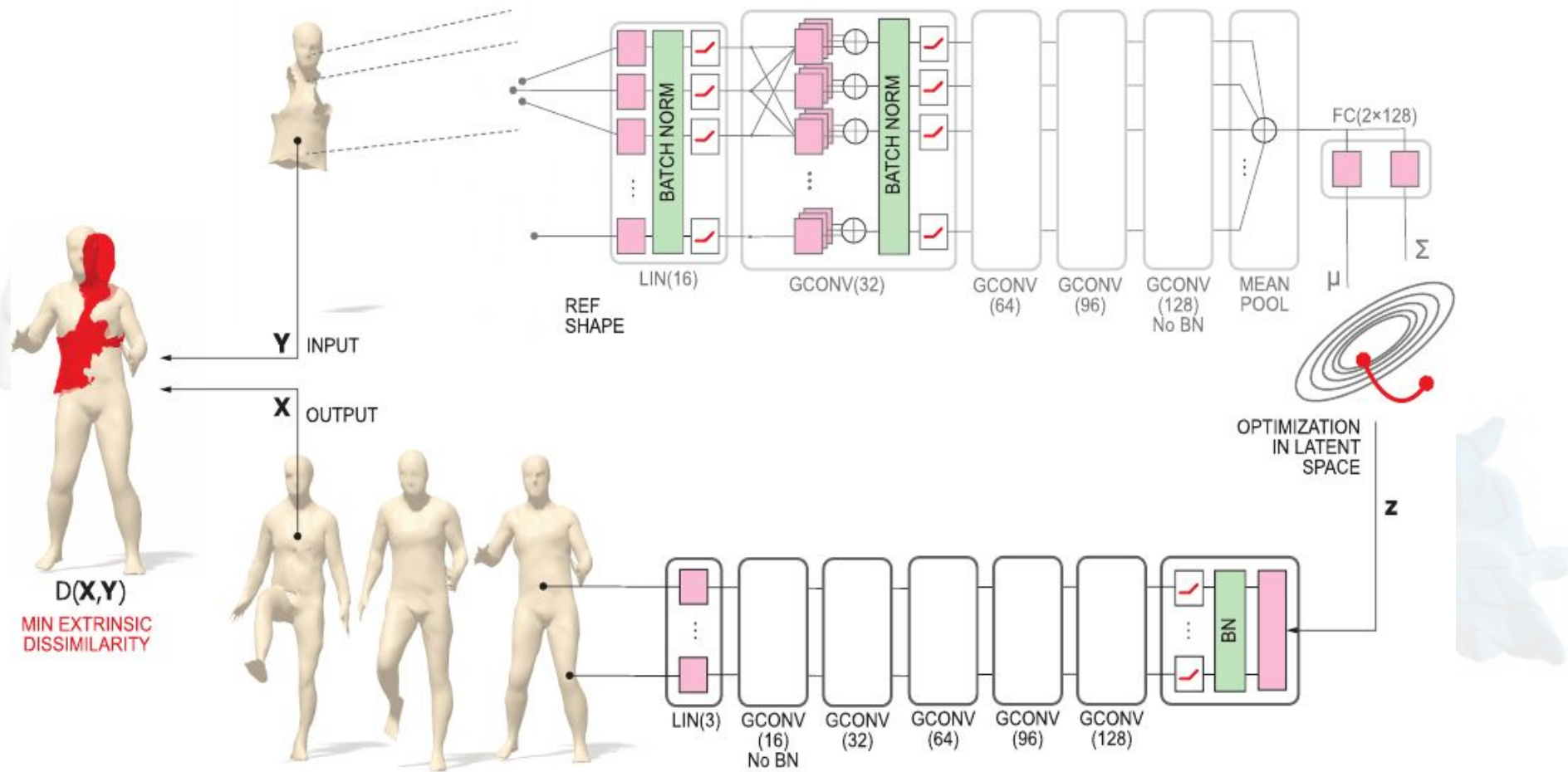


Fuente: <https://medium.com/analytics-vidhya/an-introduction-to-generative-deep-learning-792e93d1c6d4>

Aplicaciones



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



¿Preguntas?





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