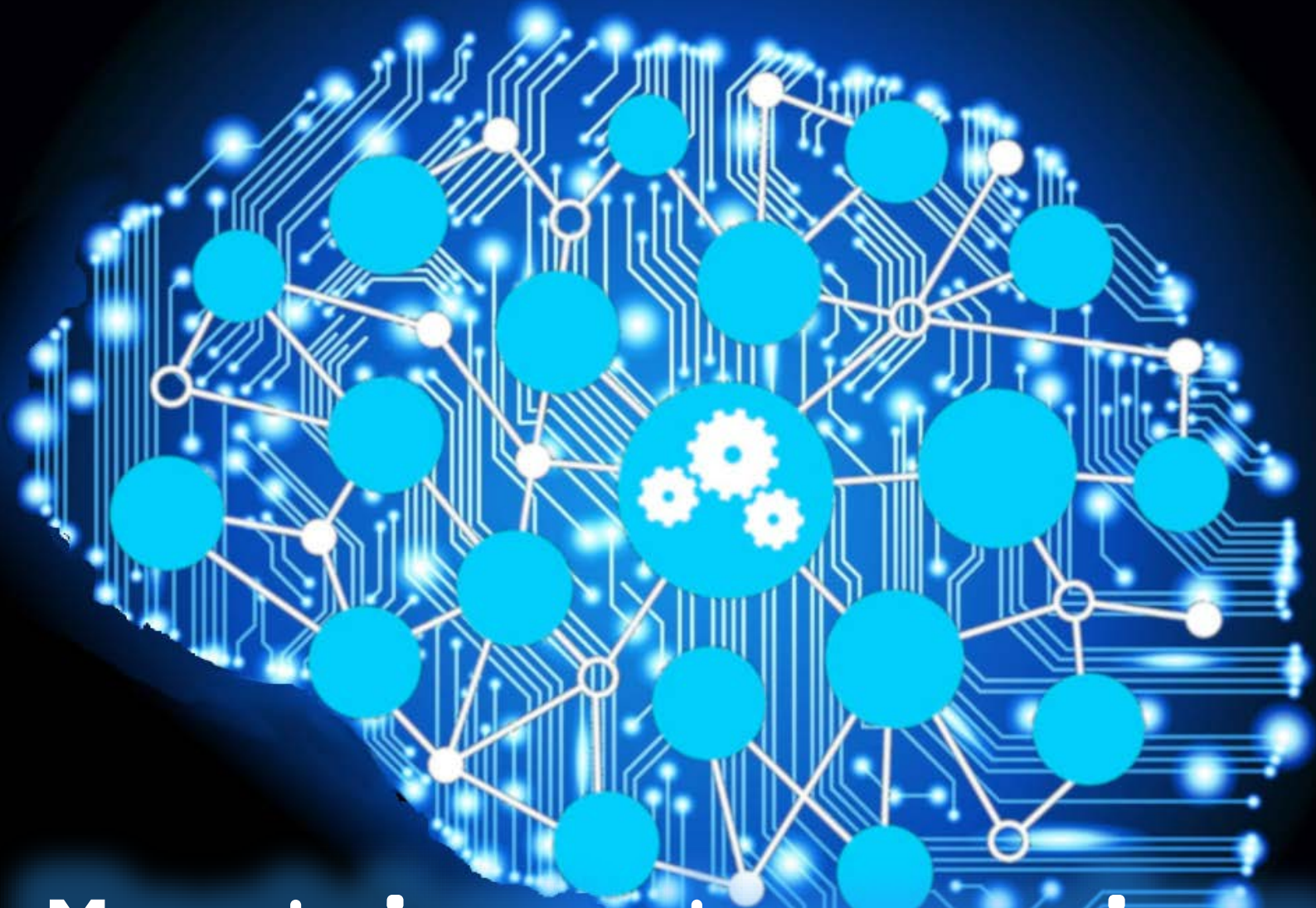
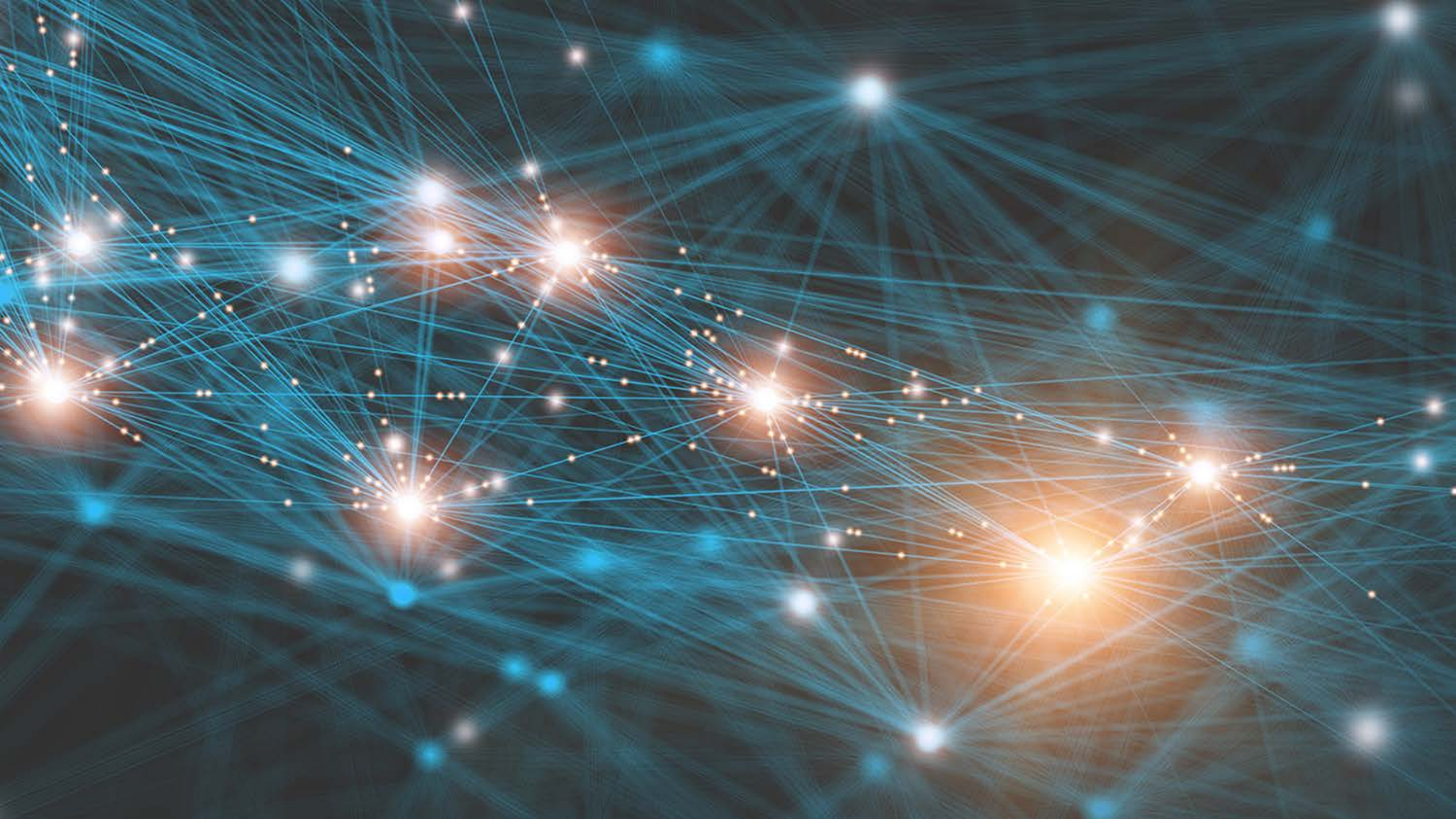
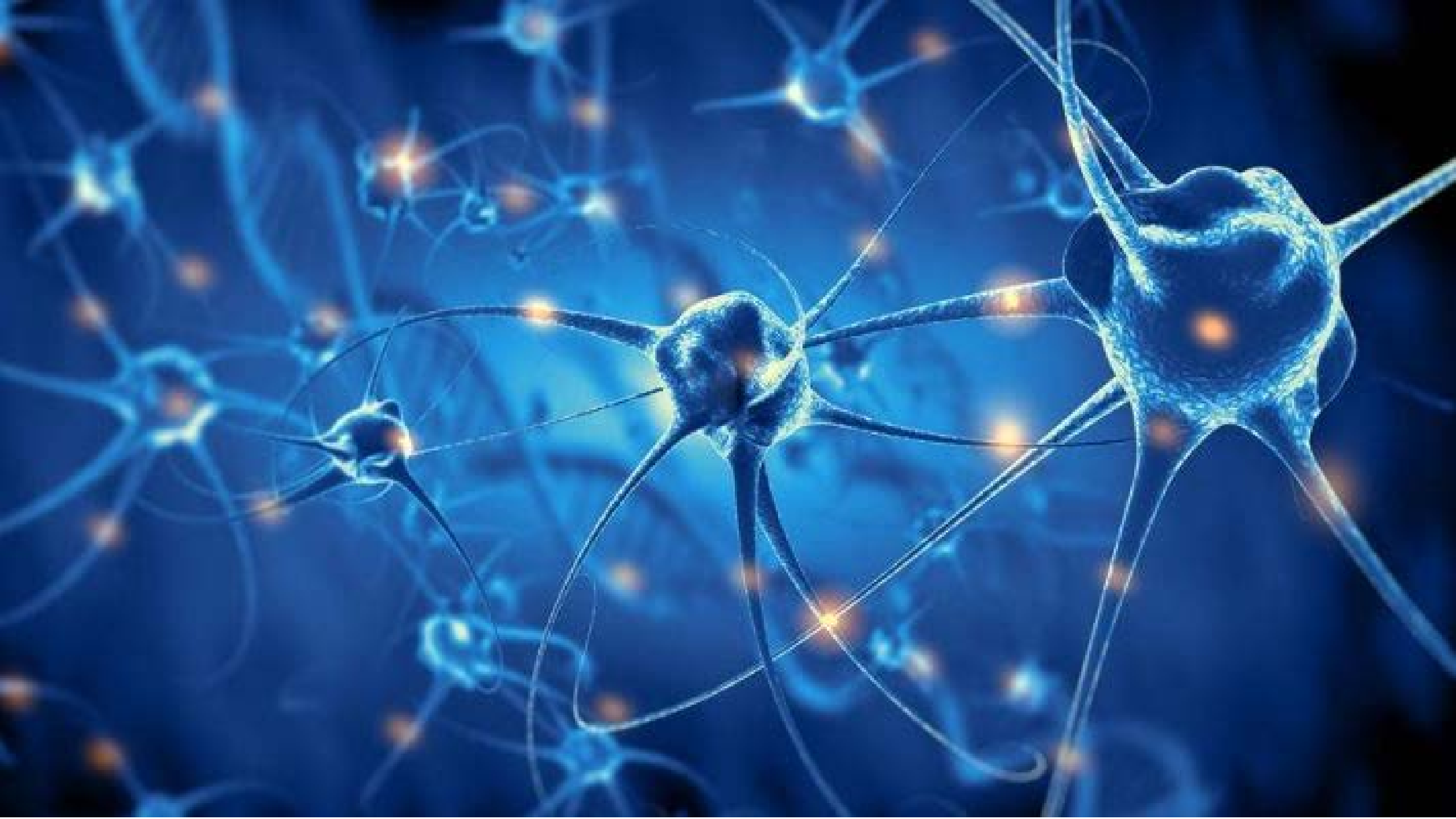




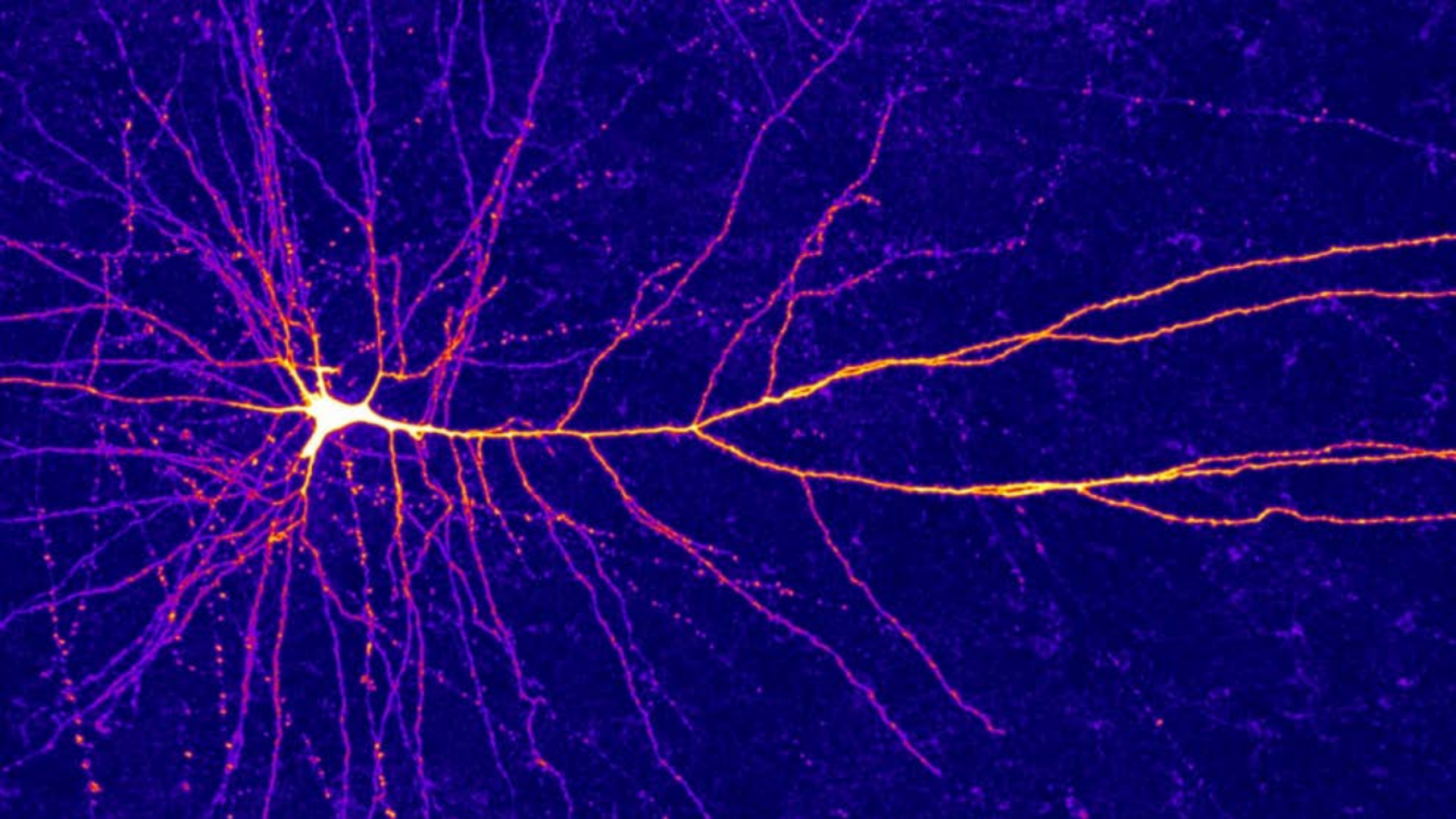
Machine Learning

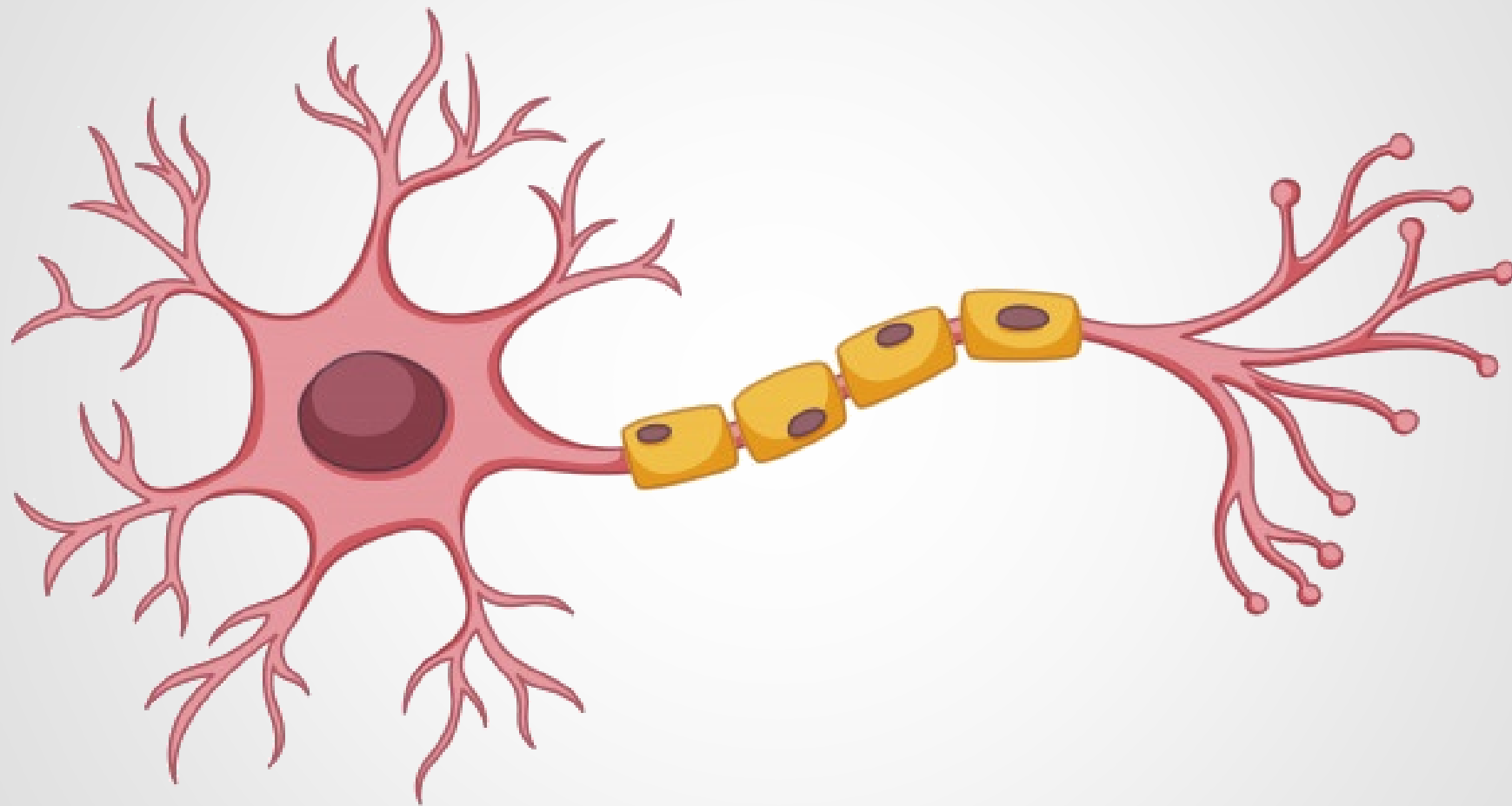
IV. Redes Neuronales



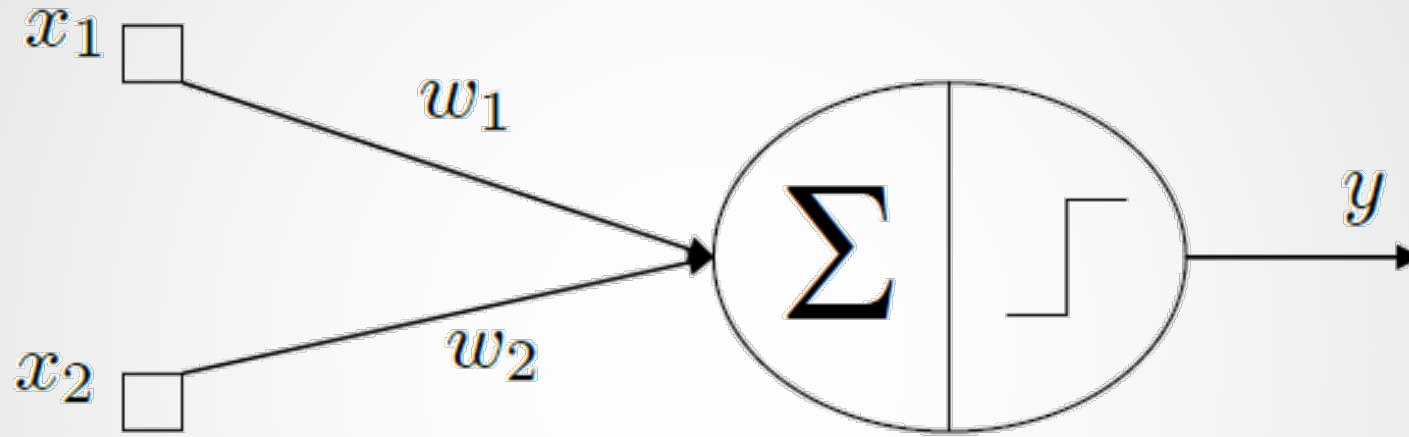








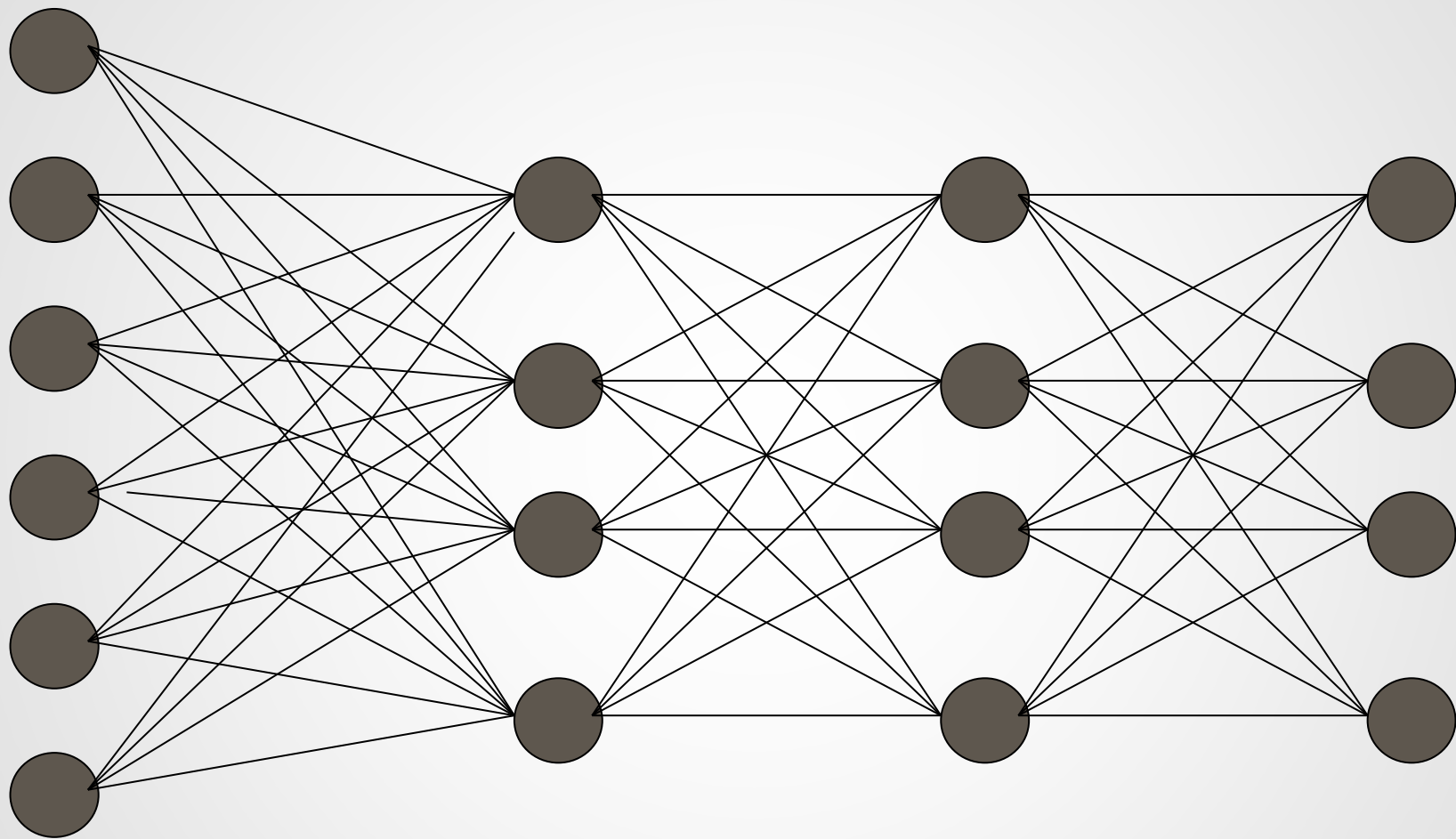
Modelo neuronal de McCulloch-Pitts (1943)

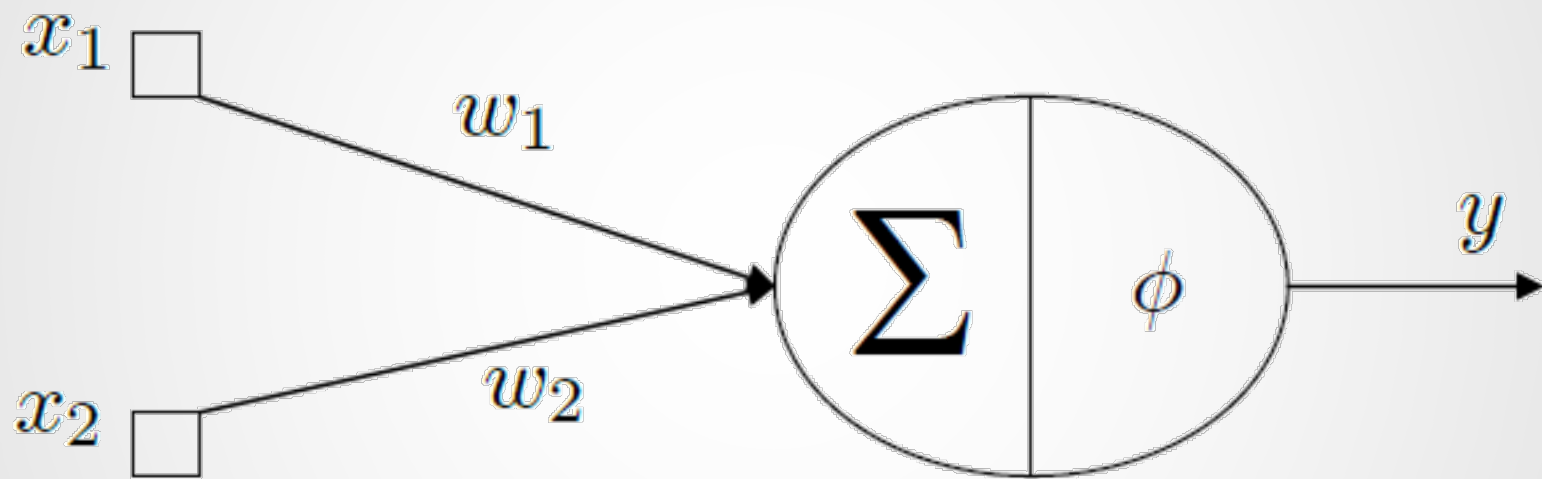


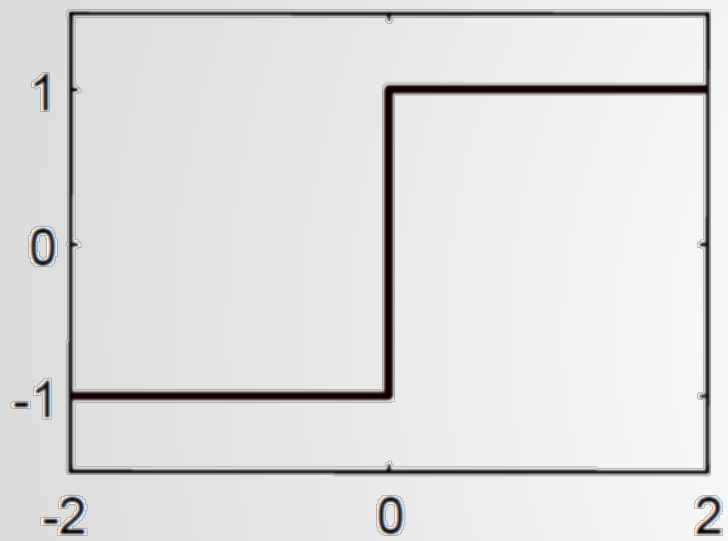
$$y = \phi \left(\sum_{i=1}^D w_i x_i + b \right)$$

$$\phi(x) = +1, \quad z \geq 0$$

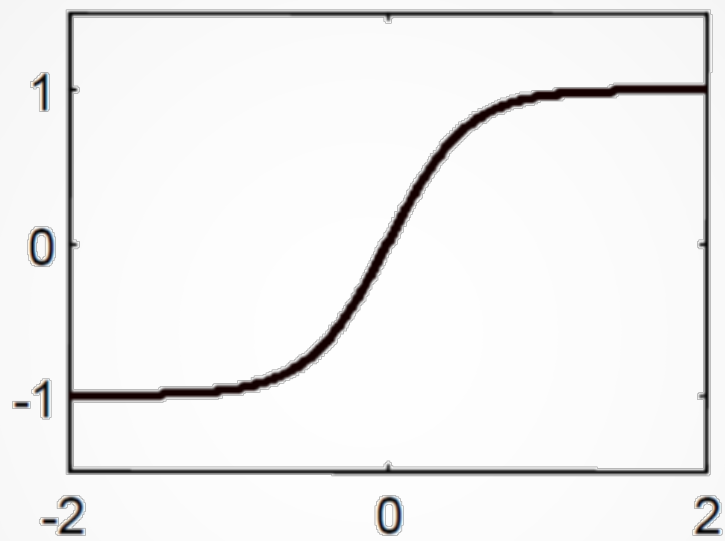
$$\phi(x) = -1, \quad z < 0$$



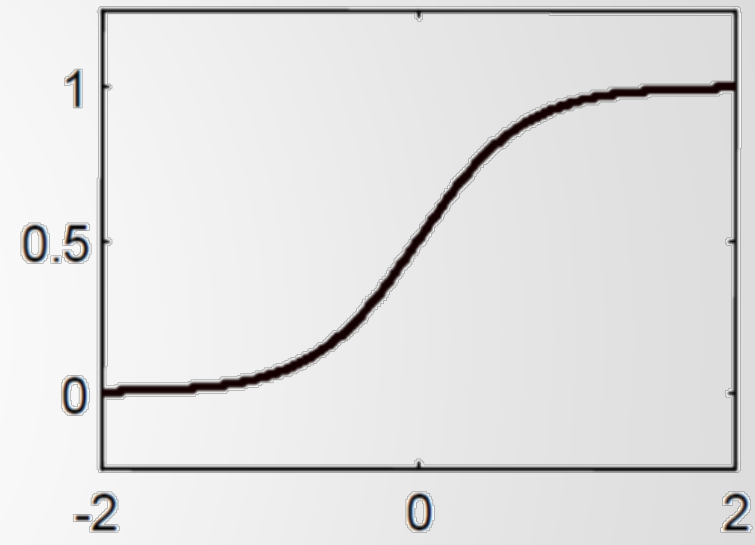




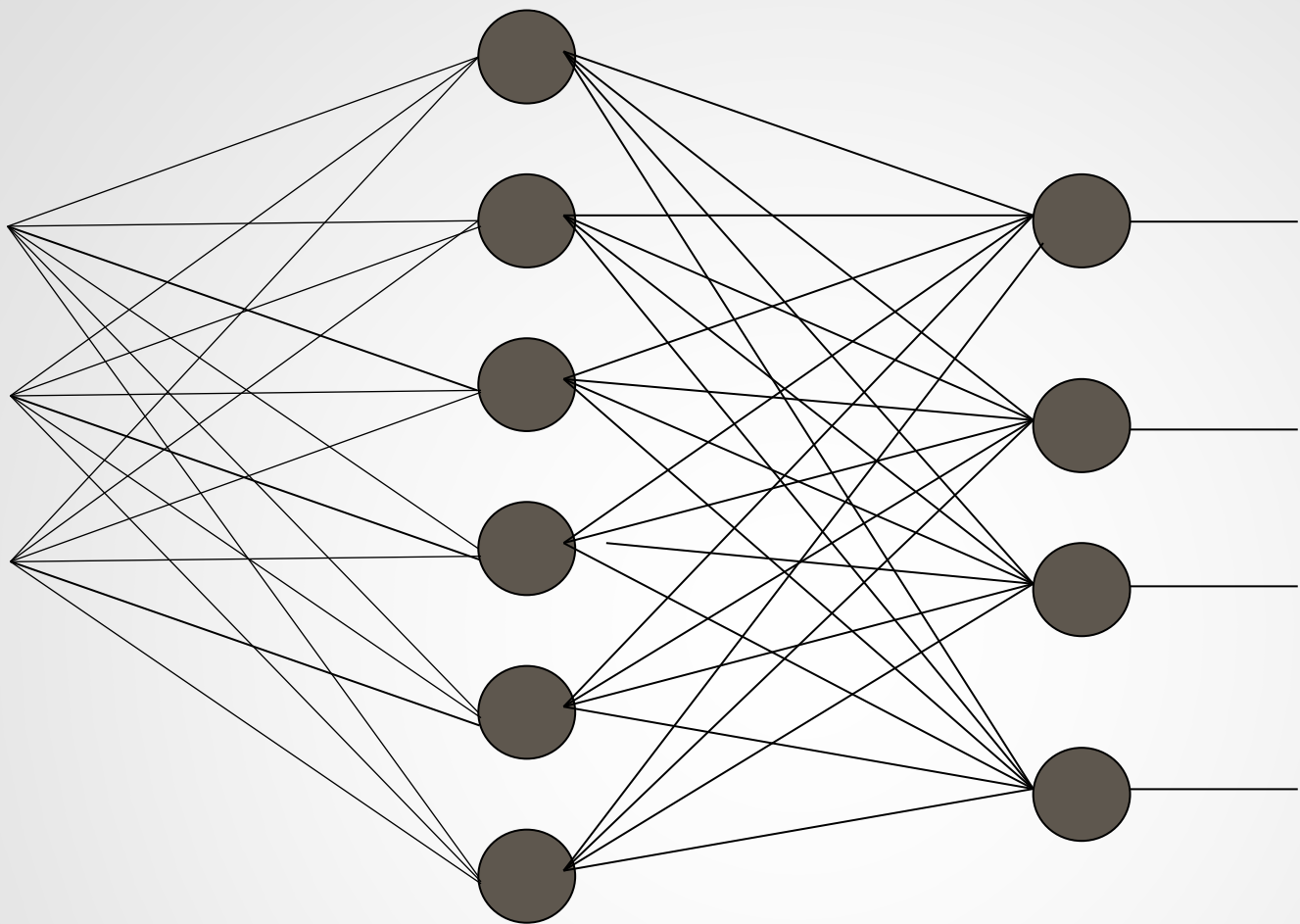
$$\varphi(u) = \text{sgn}(u)$$



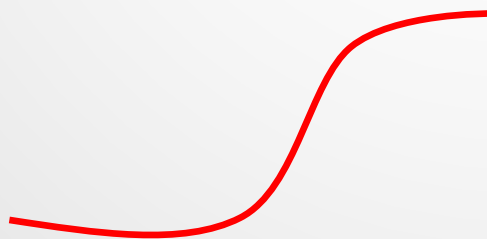
$$\varphi(u) = \tanh(au)$$

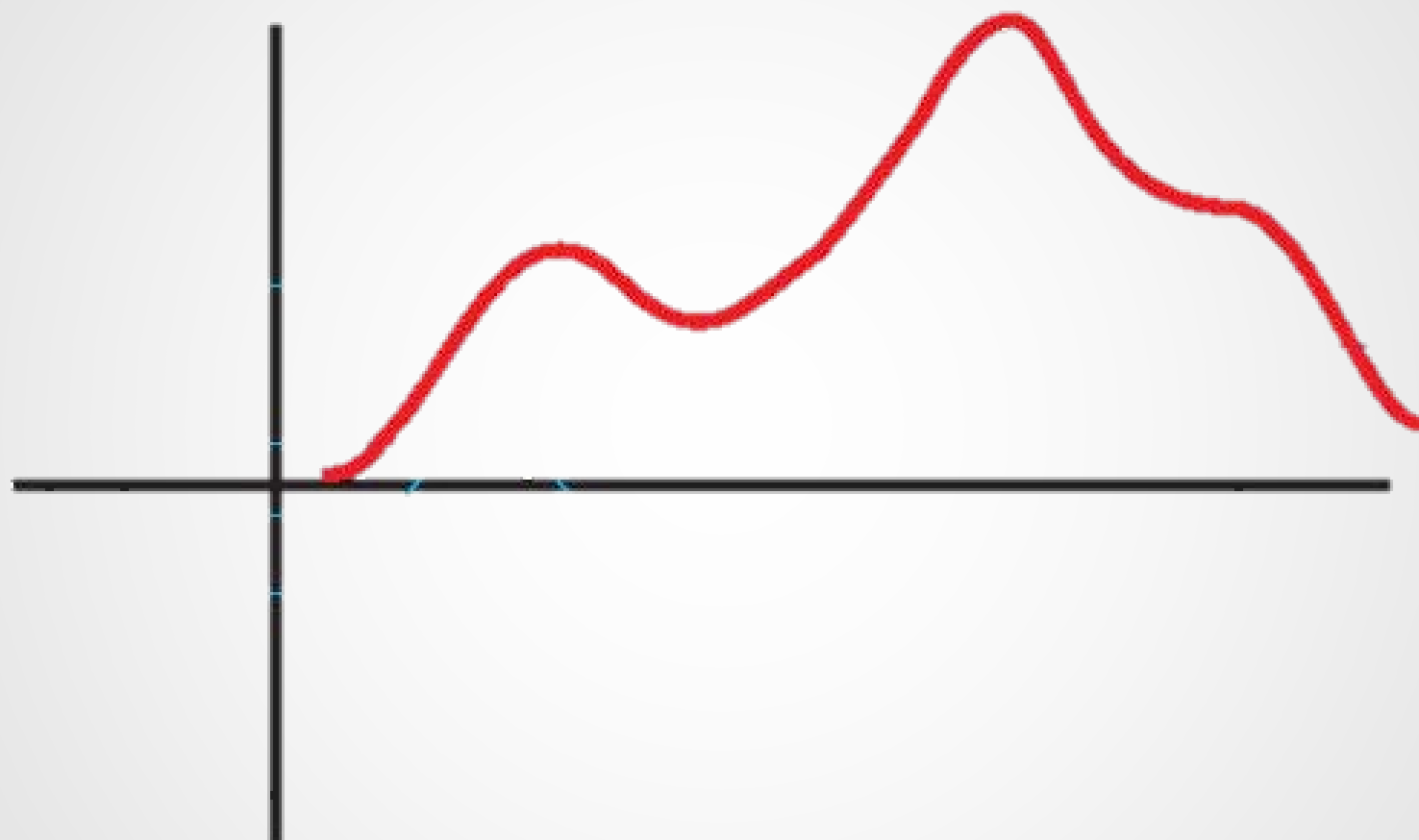


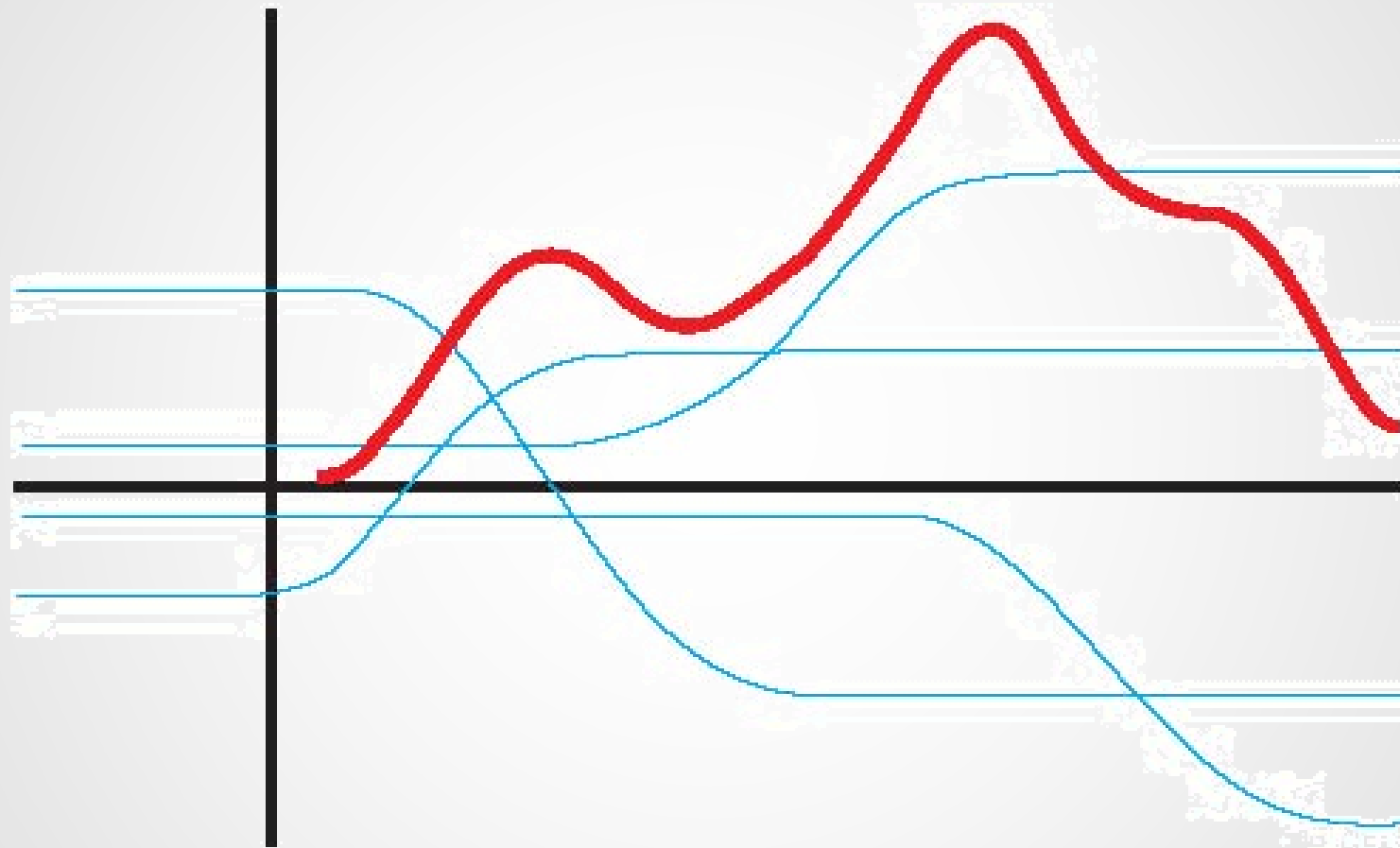
$$\varphi(u) = \frac{1}{1 + \exp(-au)}$$



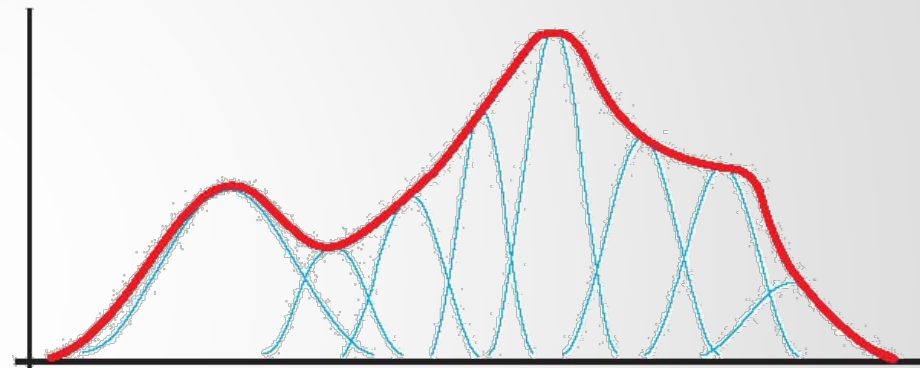
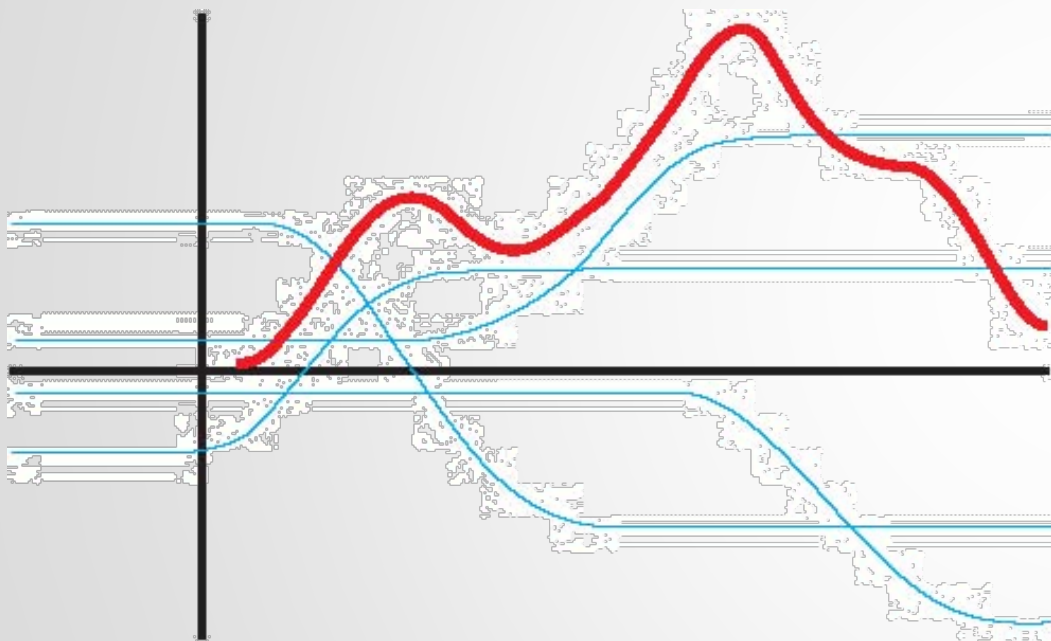
$$\Sigma(\text{red sigmoid curve})$$

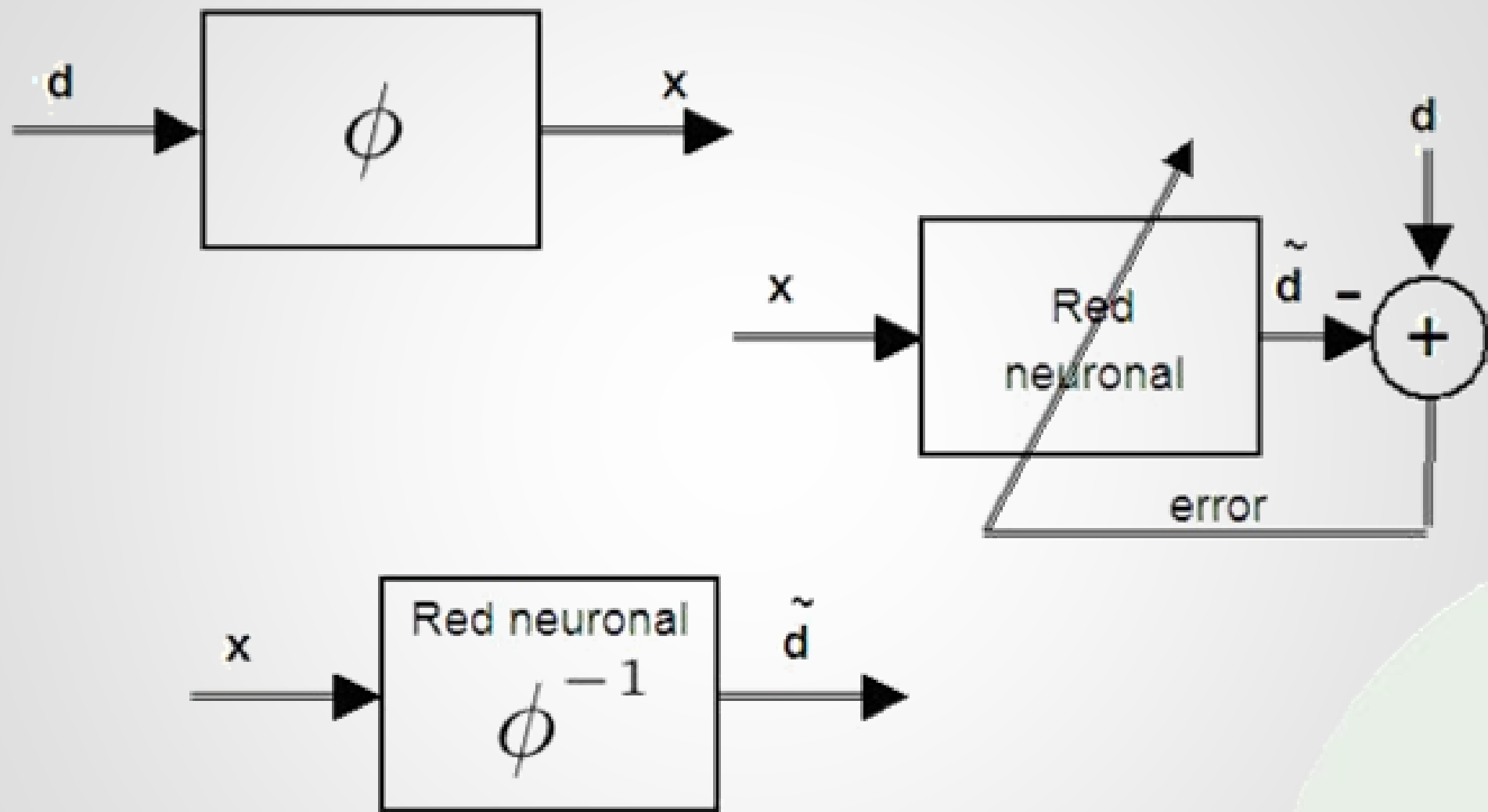




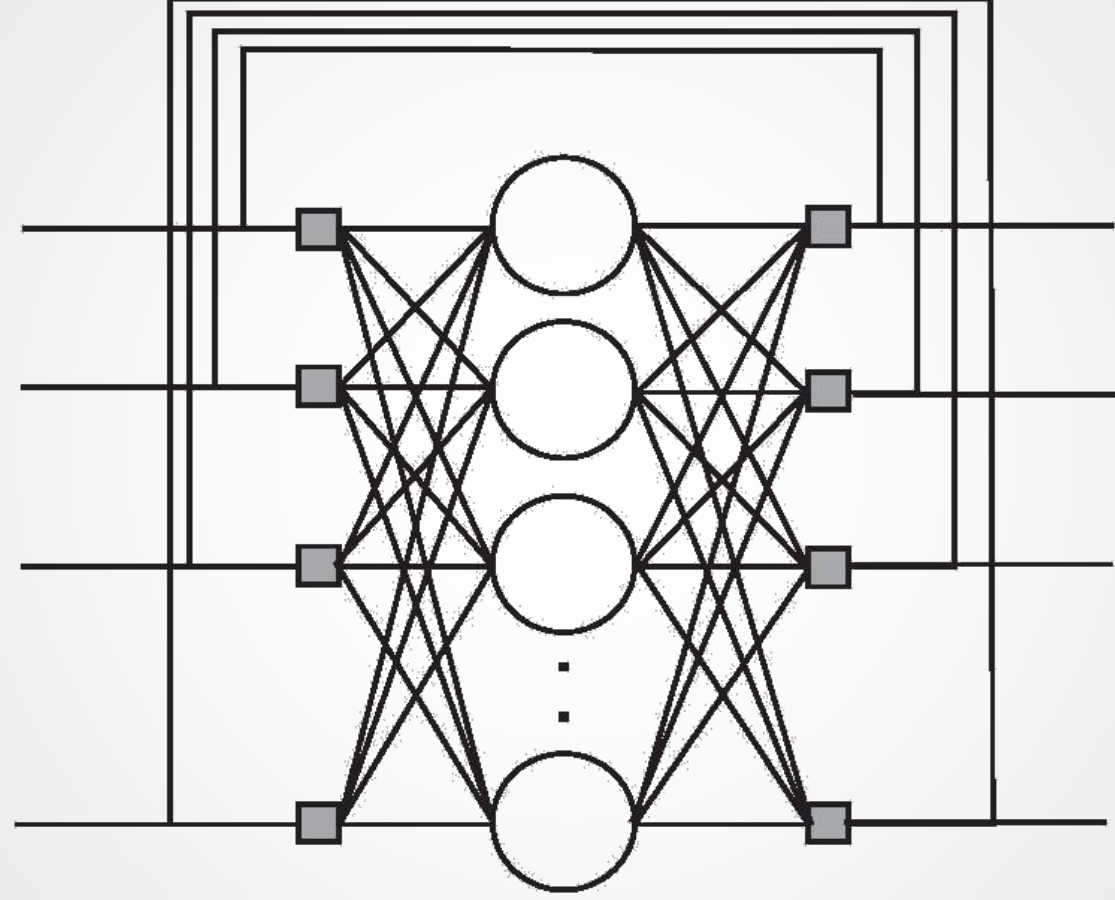


Principio de Aproximación Universal



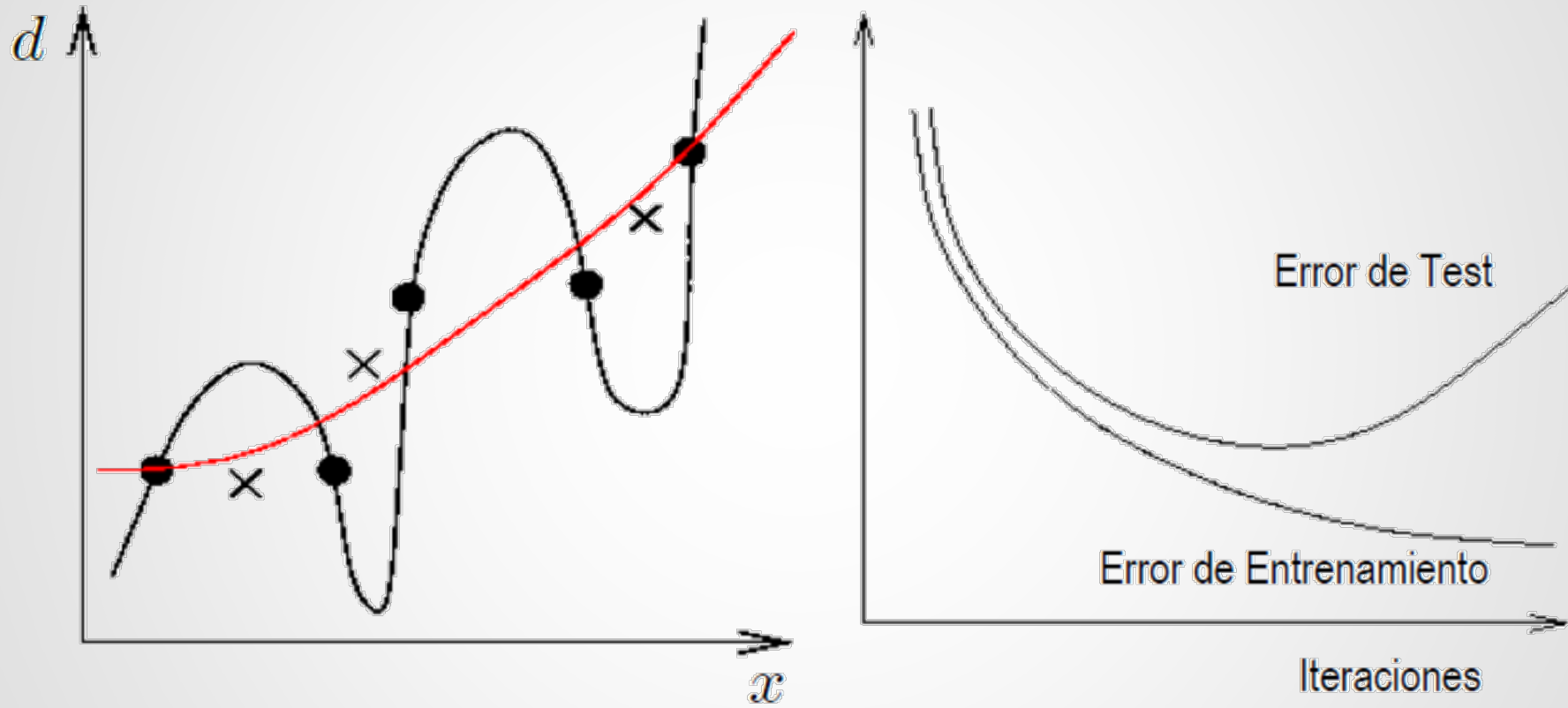


Entradas



Salidas

Overfitting



La “Maldición de la Dimensionalidad” (Curse of Dimensionality)

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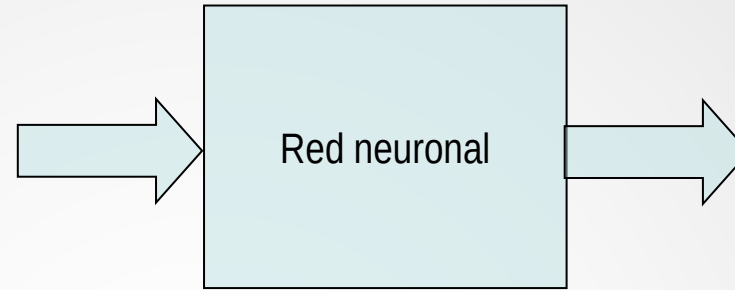
La complejidad de la red neuronal crece exponencialmente con la dimensión (complejidad del problema)

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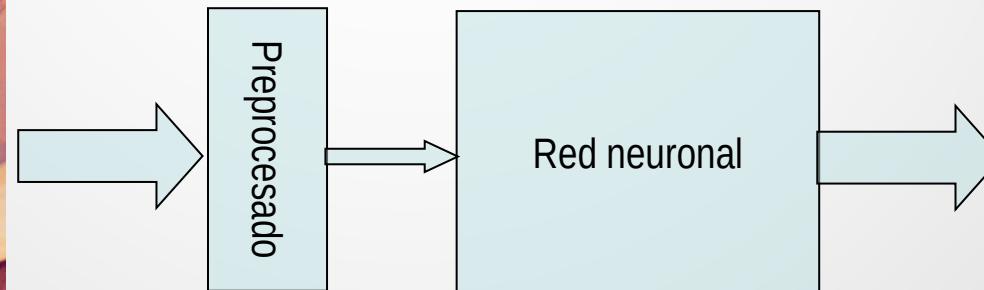
La complejidad de la red neuronal crece exponencialmente con la dimensión (complejidad del problema)

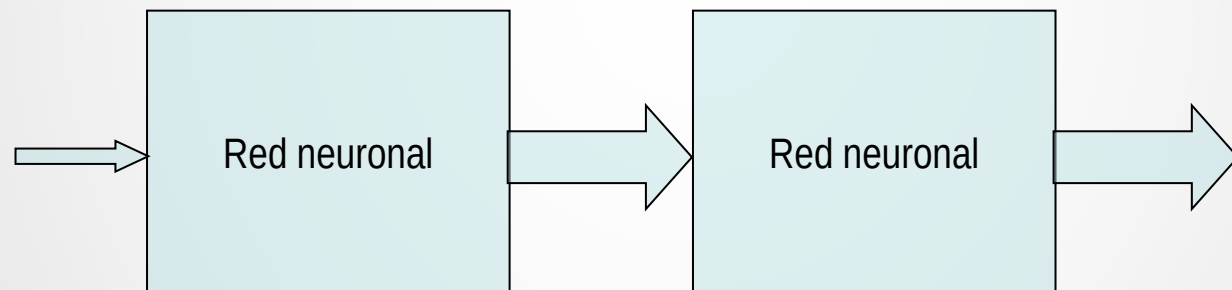
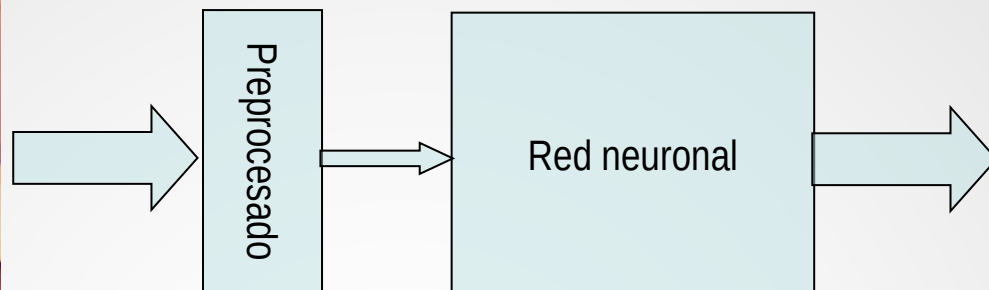
- Neuronas necesarias
 - Datos de entrenamiento necesarios
 - Tiempo de entrenamiento
 - Etc.
- Siempre que sea posible reducir un problema, es MUY conveniente hacerlo: preprocesado de los datos
- Extracción de las características relevantes del problema
 - Eliminación de información redundante

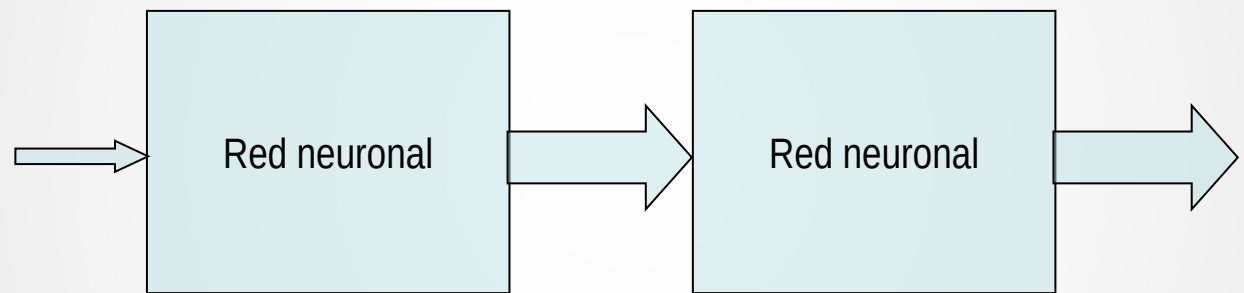
- Si se pretende procesar...



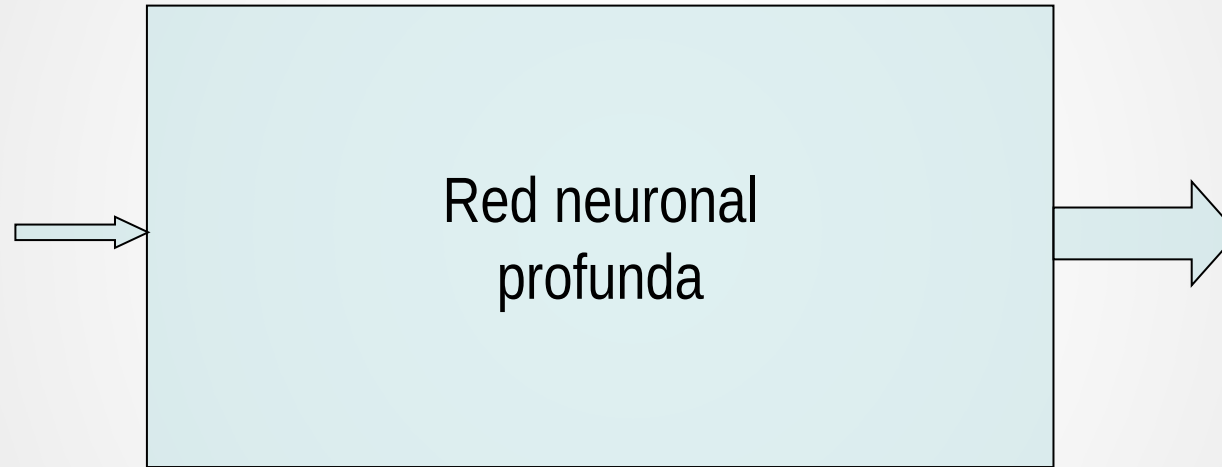
- Si la imagen es de $256 \times 256 = 65536$ píxeles (parámetros de entrada) se necesita una red neuronal muy grande
- Se puede reducir el número de datos eliminando redundancia de la imagen, extrayendo bordes, etc.







Deep Learning





Happy : 49.24 %

Surprise : 0.11 %

Angry : 0.01 %

Disgust : 0.00 %

Fear : 0.50 %

Sad : 1.62 %

Status:

* Source: Picture

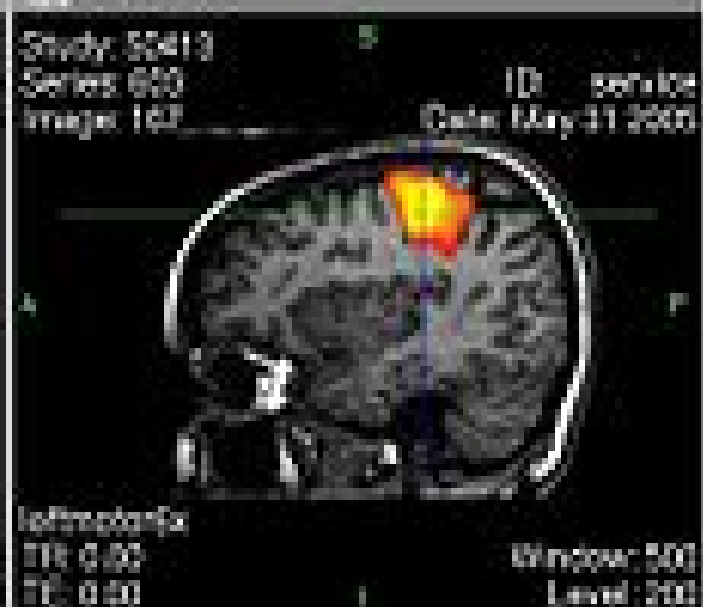
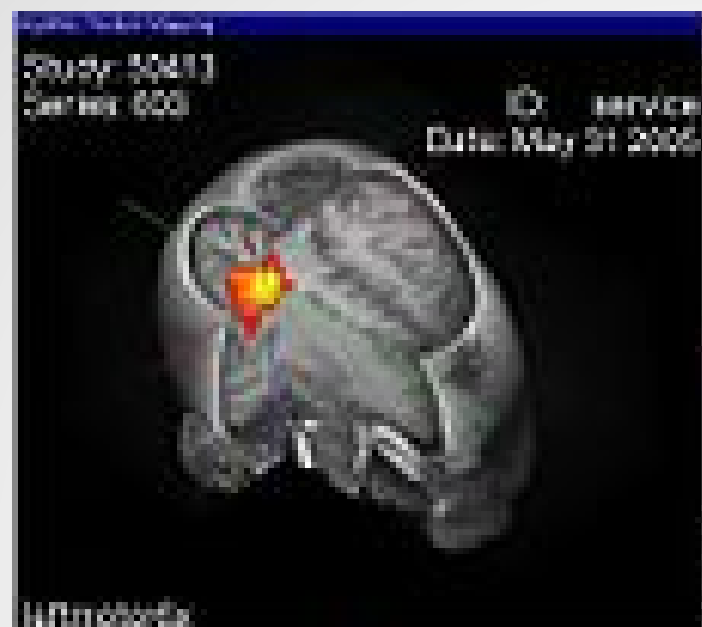
* Player: Playing

* Face: Tracking

* Markers: Loaded Existing

Hint:

Keep your face frontal

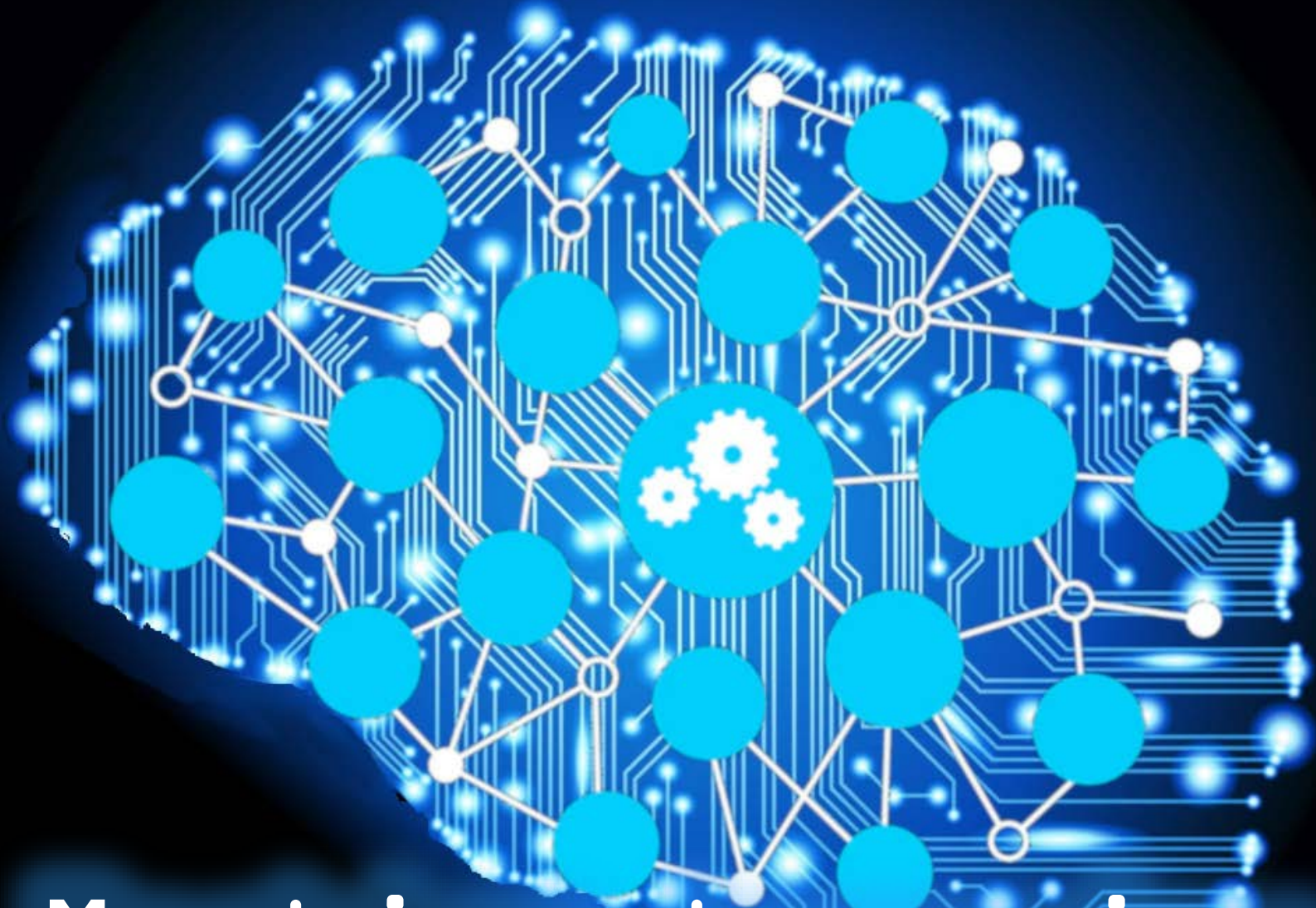


Google





$$\ln(2) \mathfrak{E}(s_P(t)) = \sum_{k=-\infty}^{+\infty} \ln(2) S[k] \cos\left(2\pi \frac{k}{P} t\right)$$
$$\Pr\left(\xi \leq \frac{p(x)}{bq(x)}\right) = \int_0^{\frac{p(x)}{bq(x)}} dx' = \frac{p(x)}{bq(x)}$$



Machine Learning