Aprendizaje Profundo

Facultad de Ingeniería
Universidad de Buenos Aires

Profesores:

Marcos Maillot
Gerardo Vilcamiza

Introducción al curso

- Materia de 8 clases teórico-prácticas
- Trabajamos con diapositivas y notebooks
- Clases dinámicas, la participación y feedback son bien recibidos
- Clases:
  - 10 minutos resumen de la clase anterior y resolución de dudas de los TPs (si aplica)
  - 3 bloques de 50 minutos de trabajo teórico-práctico
  - 2 bloques de 10 minutos de descanso
  - Ejercicios de práctica (sin nota)

Introducción al curso

- **APROBACIÓN**
  - Trabajos prácticos offline, con entregas por Google Forms.
    - TP1: Envío al término de la clase 2, entrega hasta dos días después de la clase 4 (23 h).
    - TP2: Envío al término de la clase 4, entrega hasta dos días después de la clase 6 (23 h).
    - TP3: Envío al término de la clase 6, entrega hasta dos días después de la clase 8 (23 h).
    - Los 3 trabajos tiene el mismo peso, cada uno vale un tercio de la nota final.
- **MATERIAL DE CLASE**
  - Los contenidos estarán disponibles en el **repositorio**.

Introducción al curso

- **CORREOS DE CONSULTA**
  - Marcos Maillot: marcos_maillot@yahoo.com.ar
  - Gerardo Vilcamiza: gvilcamiza.ext@fi.uba.ar
  - Clase: ap_a22@cursoscapse.com

Contenido

Gerardo Vilcamiza

- **Clase 1**: Introducción al Deep Learning, redes neuronales y forward pass
- **Clase 2**: Backpropagation, funciones de activación, funciones de costo y algoritmos de optimización
- **Clase 3**: Introducción al framework PyTorch
- **Clase 4**: Regularización, hyperparameter tuning y embeddings
- **Clase 5**: Convolutional Neural Networks (CNNs)
- **Clase 6**: Recurrent Neural Networks (RNNs). Attention Layers
- **Clase 7**: Encoder-Decoder. Autoencoder. Transfer learning
- **Clase 8**: Generative Adversarial Networks (GANs)

Marcos Maillot

Referencias

Bibliografía solo a modo de sugerencia y no será obligatorio el uso de dicho material. La materia es completamente autocontenida.

- Goodfellow, I., Bengio, Y., & Courville, A. (2016). Deep Learning. MIT Press. https://www.deeplearningbook.org
- Zhang, A., Lipton, Z. C., Li, M., & Smola, A. J. (2022). Dive into Deep Learning. Cambridge University Press. https://d2l.ai
- Nielsen, M. A. (2015). Neural Networks and Deep Learning. Determination Press. http://neuralnetworksanddeeplearning.com

Herramientas de trabajo

- Lenguaje de programación:
  - Python 3.11
  - Pip / Conda para instalar paquetes y dependencias
- Librerías principales:
  - Numpy, Matplotlib, Pandas, Scikit-Learn, Scipy
  - **Pytorch**
- Consola interactiva:
  - **Google Colab**
  - (Opcional) Jupyter Notebook
- Herramientas:
  - Github para repositorios

Introducción a Deep Learning

“Deep learning is a form of machine learning that enables computers to learn from experience and understand the world in terms of a hierarchy of concepts. Because the computer gathers knowledge from experience, there is no need for a human computer operator to formally specify all the knowledge that the computer needs.”

Ian Goodfellow

“Deep learning is a subset of machine learning that uses multi-layered neural networks, called deep neural networks, to simulate the complex decision-making power of the human brain.”

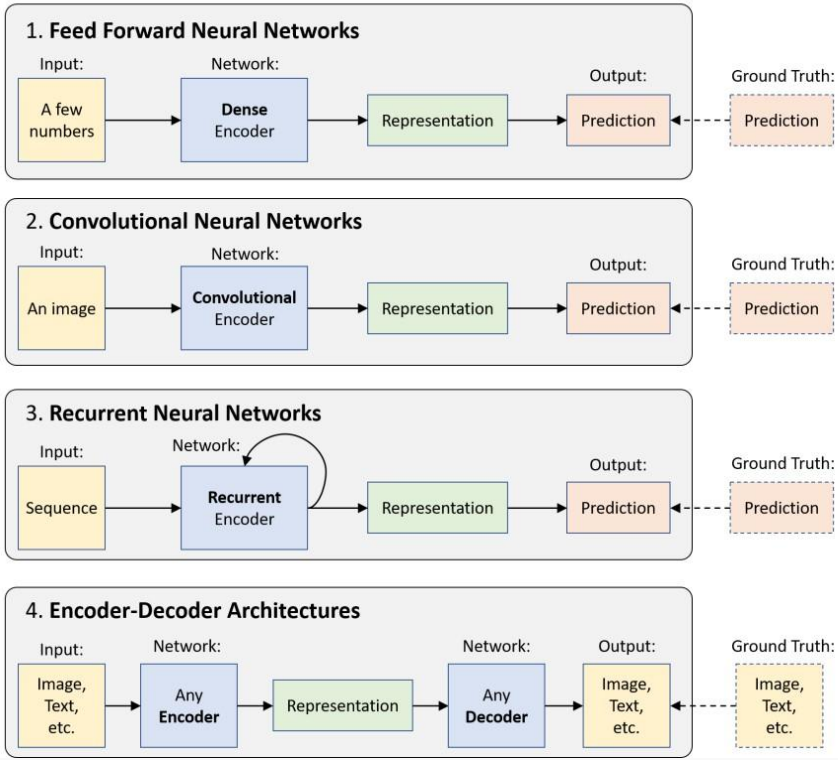
IBM

“*Deep learning has evolved from modeling perception to modeling reasoning. The boundary between pattern recognition and intelligence is starting to blur.***”**

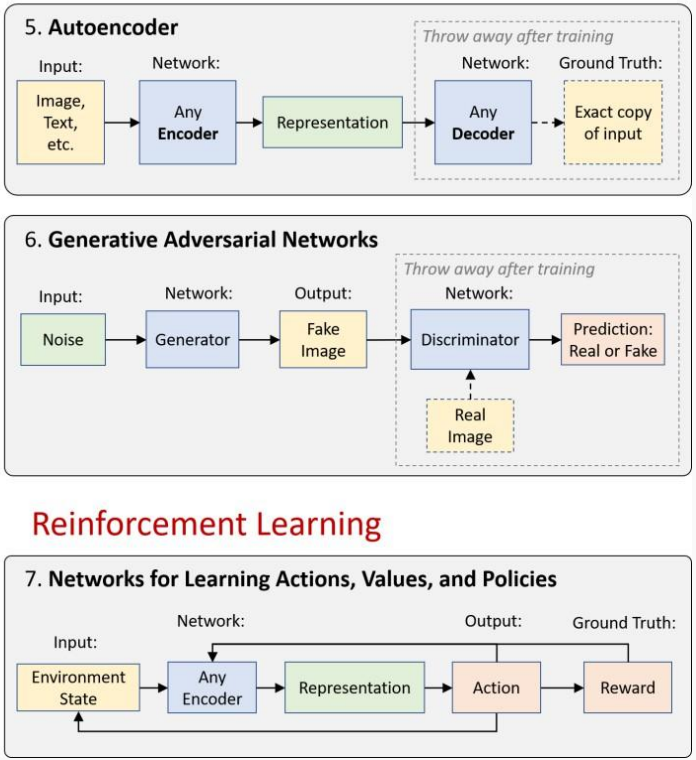
Andrew Ng

Introducción a Deep Learning

Supervised Learning



Unsupervised Learning



Reinforcement Learning

Introducción a Deep Learning

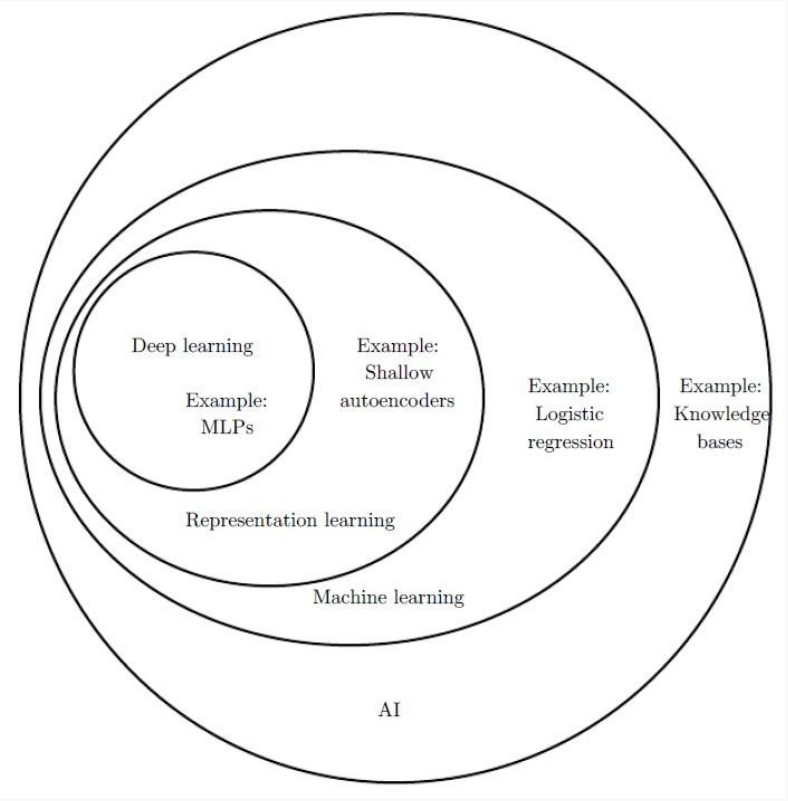
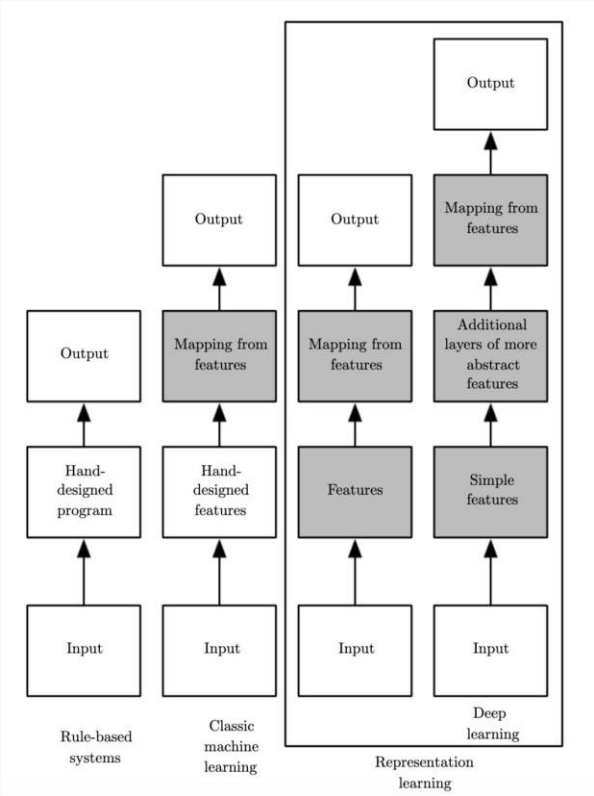


Diagrama de Venn de algoritmos



Enfoques de soluciones

Redes neuronales:

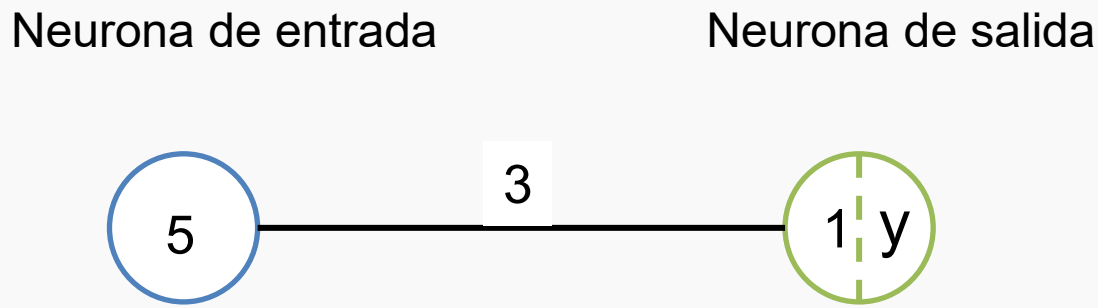
-Aprendizaje end to end.

-Aprenden Composiciones

- NO LINEALES

Feed-Forward neural network

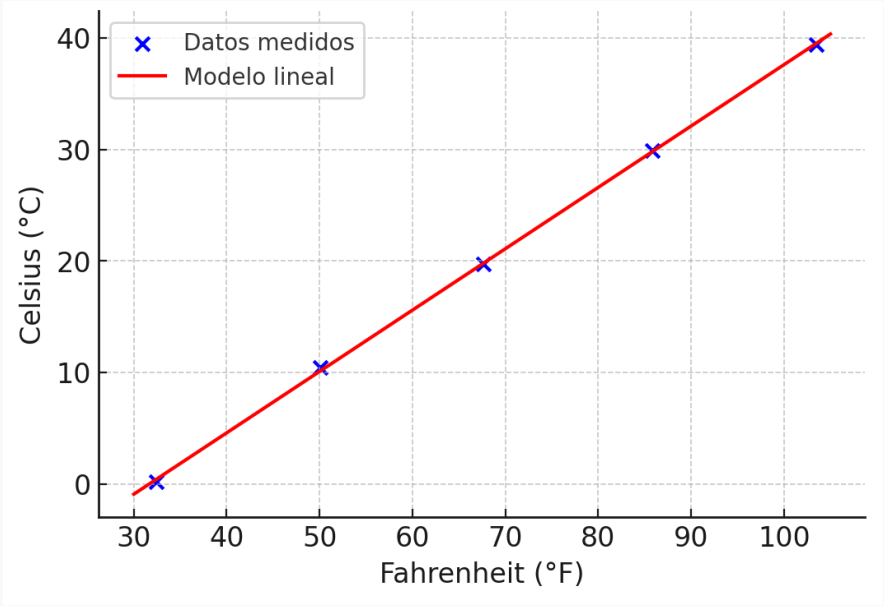
Feed-Forward neural network



$$y = wx + b$$

$$y = 3(5) + 1 = 16$$

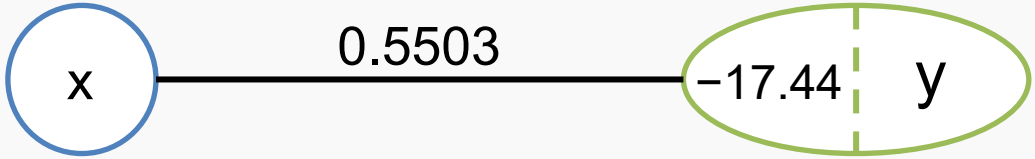
Feed-Forward neural network



Fahrenheit (°F)	Celsius (°C)
32.4	0.2
50.1	10.4
67.6	19.7
85.8	29.9
103.5	39.4

$$\hat{y} = 0.5503x - 17.44$$

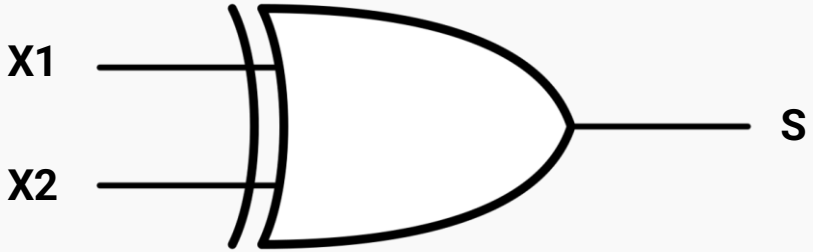
$$y_r = 0.5556x - 17.78$$



Feed-Forward neural network

¿Por qué necesitamos modelos no lineales?

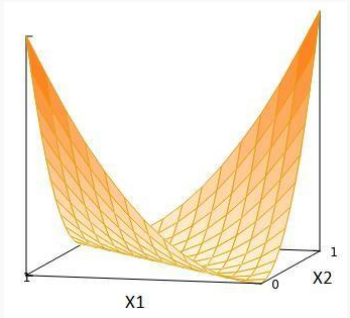
- Caso simple: Compuerta XOR



	X1	X2	S	
X_i	0	0	0	y
	0	1	1	y_B
X_B	1	0	1	
	1	1	0	
$X_{i,j}$		X		

$Nomenclatura:$

- $\vec{X} \rightarrow dataset\ de\ entrada \in R^{n \times m}$
- $\vec{y} \rightarrow salida \in R^{n \times 1}$
- $m \rightarrow cantidad\ de\ columnas,\ n \rightarrow cantidad\ de\ filas$
- $X_{i,j} \rightarrow parámetro\ j\ de\ la\ muestra\ i \in R$
- $\vec{X}_i \rightarrow vector\ de\ la\ fila\ i \in R^{1 \times m}$
- $\vec{X}_b \rightarrow matriz\ de\ batch \in R^{b \times m}$



Feed-Forward neural network

- Arquitectura: Modelo Lineal

$$\hat{f} \ : \ R^2 \rightarrow R / \hat{y}_i = \hat{f}\left(X_{i,1}, X_{i,2}\right) = W_1 \cdot X_{i,1} + W_2 \cdot X_{i,2} + b$$

- Loss function: Error cuadrático medio

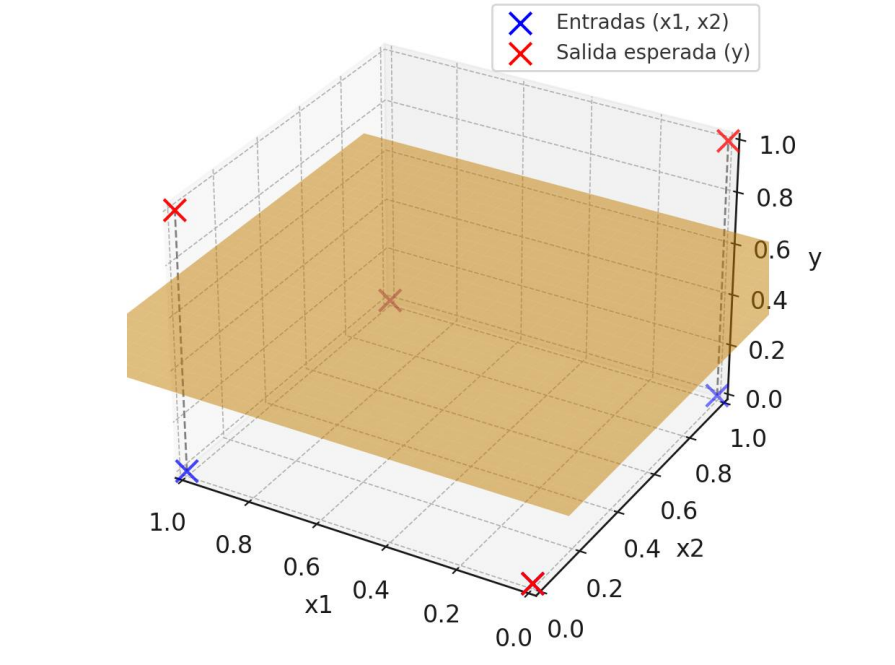
$$L\left(W_1, W_2, b, \vec{X}, \vec{y}\right) = L(W_1, W_2, b) = \frac{1}{4} \cdot \sum_{i=1}^{4} \left(y_i - \hat{y_i}\right)^2$$

- Optimizador: Solución cerrada

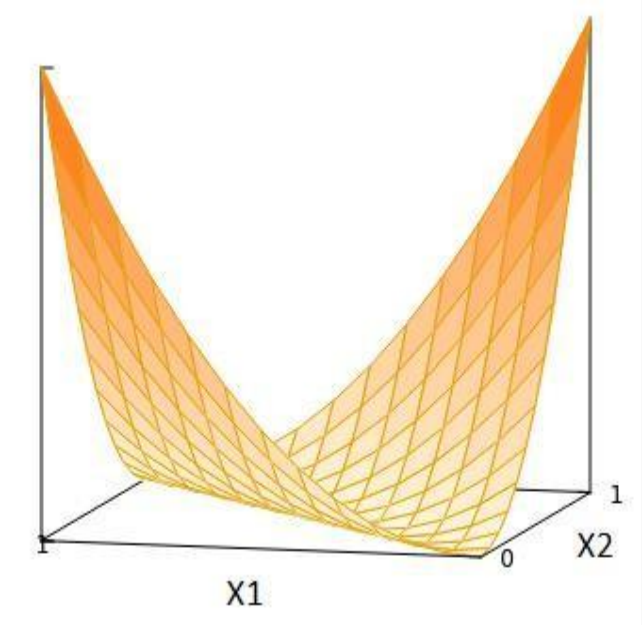
$$\vec{\nabla}_{\vec{w}} L = \vec{0} \rightarrow \vec{\nabla}_{\vec{w}} L = \left\{ \begin{matrix} \frac{\partial L}{\partial W_1} \\ \frac{\partial L}{\partial W_2} \\ \frac{\partial L}{\partial b} \end{matrix} \right\} = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}$$

$$\vec{W} = \begin{bmatrix} W_1 \\ W_2 \\ b \end{bmatrix} = \left(\vec{X}^T \cdot \vec{X}\right)^{-1} \cdot \vec{X}^T \cdot \vec{y} \rightarrow \vec{W} = \begin{bmatrix} 0 \\ 0 \\ 0.5 \end{bmatrix}$$

Feed-Forward neural network

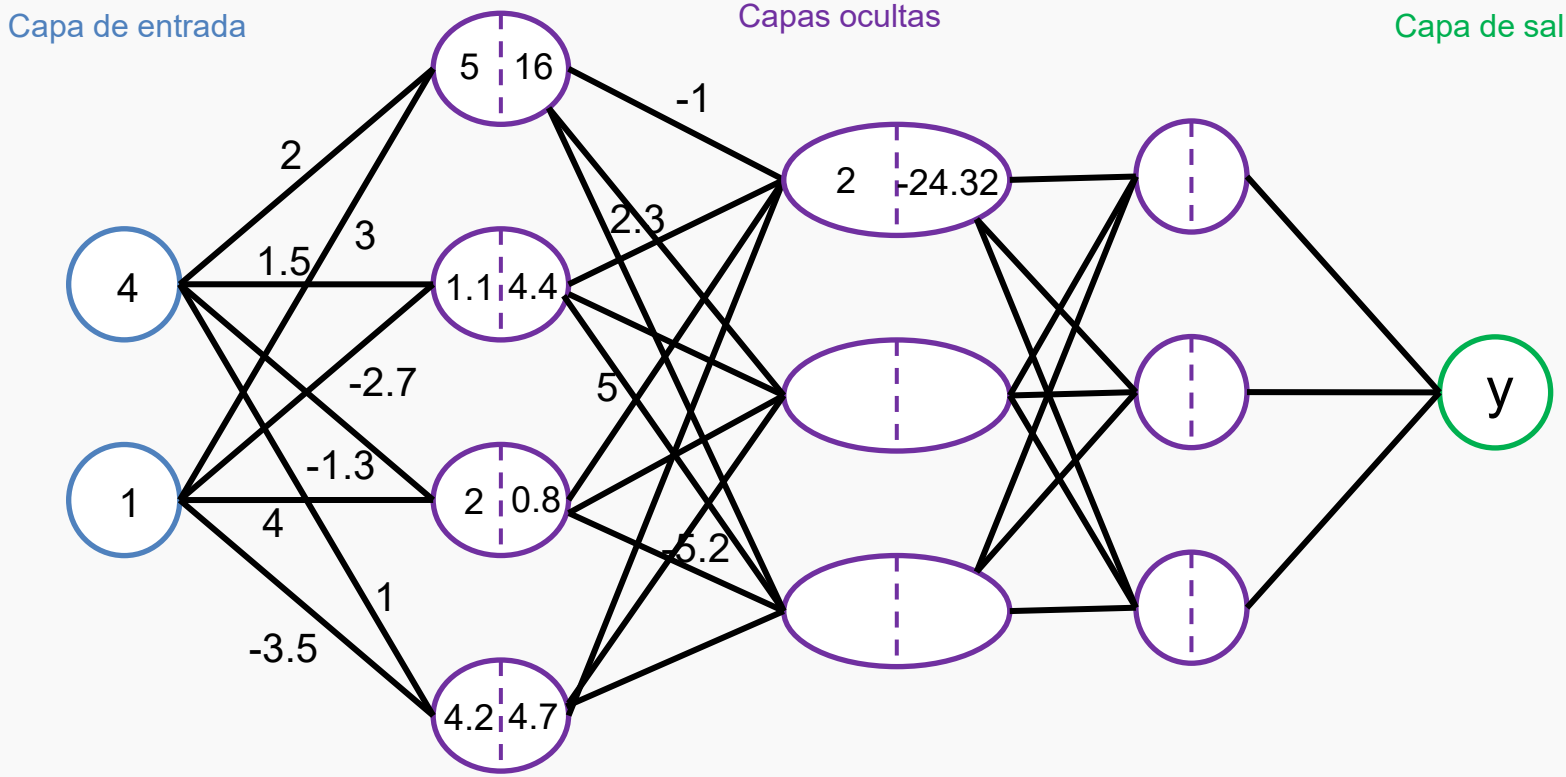


Lineal o Constante

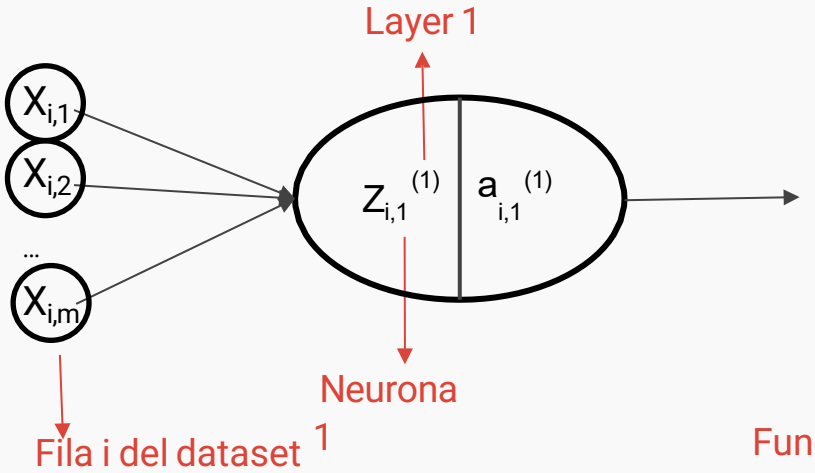


No lineal

Feed-Forward neural network



Neurona



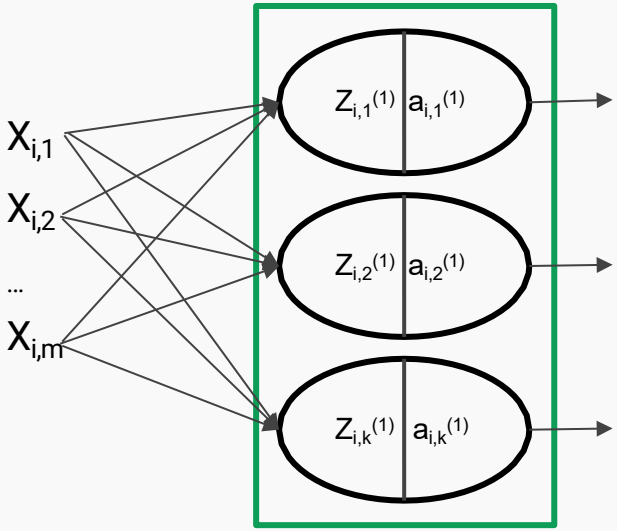
$$Z_{i,1}^{(1)} = W_{1,1}^{(1)} \cdot X_{i,1} + W_{1,2}^{(1)} \cdot X_{i,2} + \ldots + W_{1,m}^{(1)} \cdot X_{i,m} + b_1^{(1)}$$

$$a_{i,1}^{(1)} = \sigma\left(Z_{i,1}^{(1)}\right)$$

Función de activación:

- Sigmoid
- ReLU
- Tanh
- Softmax

Layer Lineal con función de activación



Layer 1

$$a_{i,1}^{(1)} = \sigma\left(Z_{i,1}^{(1)}\right) = \sigma\left(W_{1,1}^{(1)} \cdot X_{i,1} + W_{1,2}^{(1)} \cdot X_{i,2} + \ldots + W_{1,m}^{(1)} \cdot X_{i,m} + b_1^{(1)}\right)$$

$$a_{i,2}^{(1)} = \sigma\left(Z_{i,2}^{(1)}\right) = \sigma\left(W_{2,1}^{(1)} \cdot X_{i,1} + W_{2,2}^{(1)} \cdot X_{i,2} + \ldots + W_{2,m}^{(1)} \cdot X_{i,m} + b_2^{(1)}\right)$$

$$a_{i,k}^{(1)} = \sigma\left(Z_{i,k}^{(1)}\right) = \sigma\left(W_{k,1}^{(1)} \cdot X_{i,1} + W_{k,2}^{(1)} \cdot X_{i,2} + \ldots + W_{k,m}^{(1)} \cdot X_{i,m} + b_k^{(1)}\right)$$

En formato matricial:

$$\vec{A}_i^{(1)} = \sigma\left(\vec{Z}_i^{(1)}\right) = \sigma\left(\vec{W}^{(1)} \cdot \vec{X}_i + \vec{b}^{(1)}\right)$$

$$\#\, de\, parámetros:\ k \times (m+1)$$

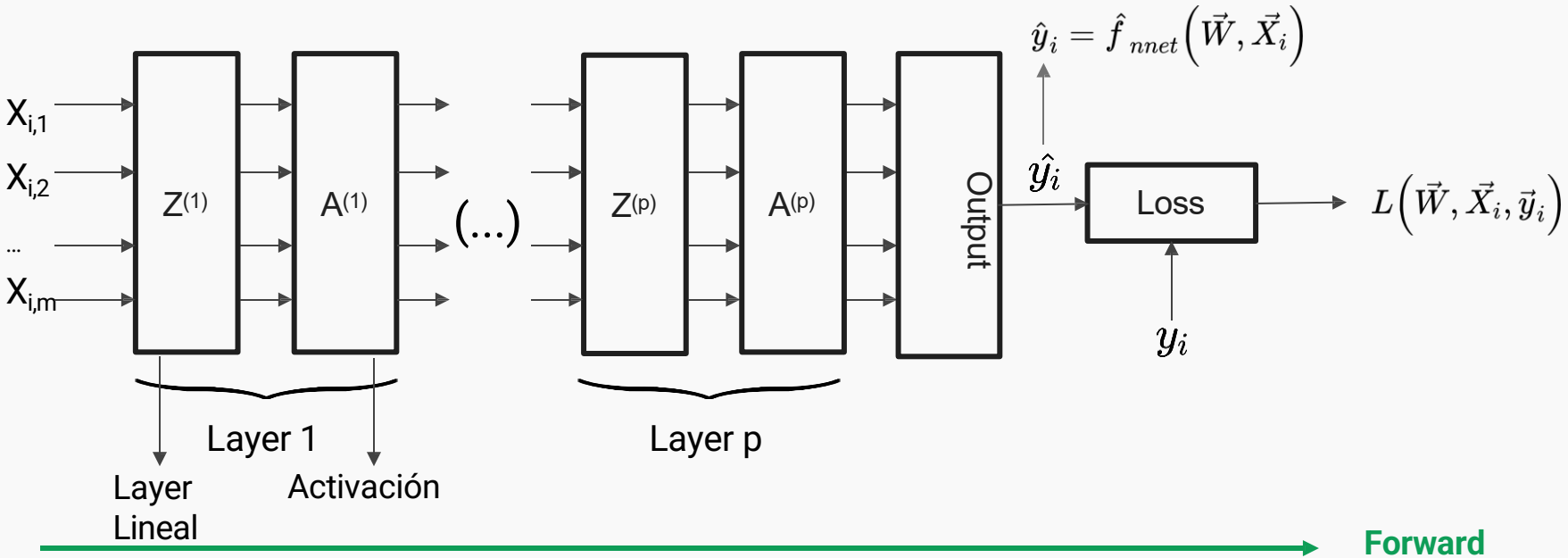
$$\vec{A}_i^{(1)}, \vec{Z}_i^{(1)} \in R^{k \times 1}$$

$$\vec{W}^{(1)} \in R^{k \times m}$$

$$\vec{X}_i \in R^{m \times 1}$$

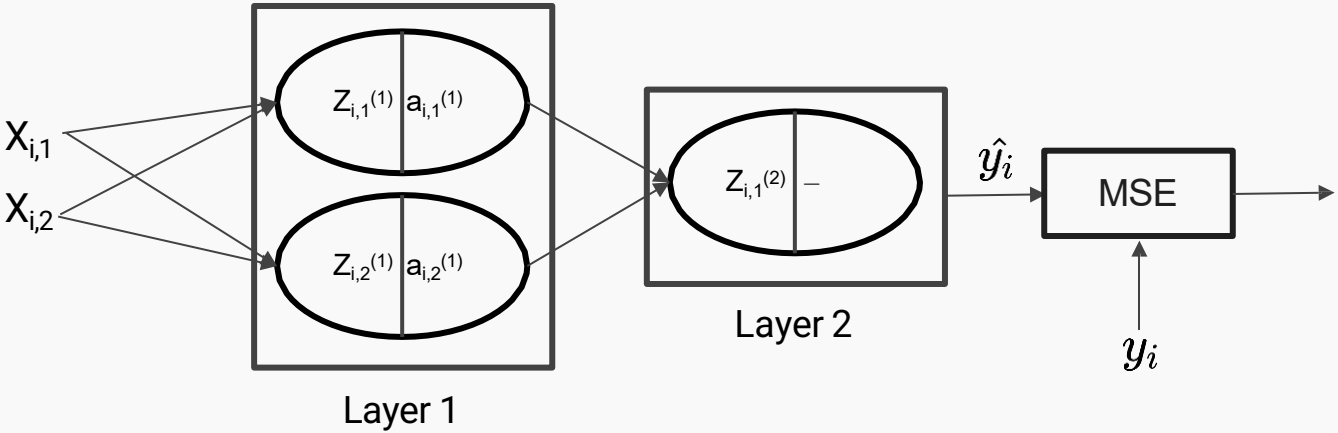
$$\vec{b}^{(1)} \in R^{k \times 1}$$

Red neuronal feedforward con p layers



Resolvemos backpropagation en forma numérica: $\nabla_{\vec{W}} L \rightarrow \vec{W} = \vec{W} - \alpha \times \nabla_{\vec{W}} L$

Red neuronal feedforward



- Arquitectura de 2 layers: 1 layer hidden, 1 layer de salida
- 2 neuronas en layer 1, función de activación sigmoid
- 1 neurona layer 2, sin activación
- ¿Cuántos parámetros entreno?

$$\left.\begin{aligned} \vec{W}^{(1)} &\in R^{2\times 2} \rightarrow 4 \\ \vec{b}^{(1)} &\in R^{2\times 1} \rightarrow 2 \\ \vec{W}^{(2)} &\in R^{1\times 2} \rightarrow 2 \\ \vec{b}^{(2)} &\in R^{1} \rightarrow 1 \end{aligned}\right\} \text{9 parámetros}$$

Red neuronal feedforward

- **Paso Forward:**

$$Z_{i,1}^{(1)} = W_{1,1}^{(1)} \cdot X_{i,1} + W_{1,2}^{(1)} \cdot X_{i,2} + b_1^{(1)}$$

$$Z_{i,2}^{(1)} = W_{2,1}^{(1)} \cdot X_{i,1} + W_{2,2}^{(1)} \cdot X_{i,2} + b_2^{(1)}$$

$$a_{i,1}^{(1)} = \sigma\left(Z_{i,1}^{(1)}\right)$$

$$a_{i,2}^{(1)} = \sigma\left(Z_{i,2}^{(1)}\right)$$

$$Z_{i,1}^{(2)} = W_{1,1}^{(2)} \cdot a_{i,1}^{(1)} + W_{1,2}^{(2)} \cdot a_{i,2}^{(1)} + b_1^{(2)}$$

$$\hat{y}_i = a_{i,1}^{(2)} = Z_{i,1}^{(2)}$$

$$L_{\vec{W}} = (y_i - \hat{y}_i)^2$$