

Last time :

- Backprop example
- Neural networks

Today: neural networks continued

## Neural Network

# of layers = "depth" of nn

- A type of function which is defined as a composition of "layers" (sub-functions) e.g.  $f(x) = H_2(x, H_0(x), H_1(H_0(x)))$
- Each layer has a linear piece and a nonlinear "activation function".
- Several foundational types of layers we will cover
  - fully connected ①
  - convolutional ②
  - batch normalization ④
  - dropout ⑤
  - pooling ③
  - residual ⑥
  - attention ⑦
- the composition of many simple nonlinear layers builds a very expressive function

## Fully - connected (Dense) Layer

→ linear piece :

$$\overset{[n \times d_k]}{Z_k(X)} = \overset{[n \times p]}{X} \overset{[p \times d_k]}{W_k} + \overset{[n \times d_k]}{B_k} \rightarrow \begin{bmatrix} \text{---} b_k \text{---} \\ \vdots \\ \text{---} b_k \text{---} \end{bmatrix}$$

only  $d_k$  free parameters

→ this layer is said to have  $d_k$  "neurons" (# columns of  $W_k$ )

→ intuition: each neuron represents a template or definition of a concept that is then searched for in the input  $X$  (via dot product)

→ number of parameters:  $p \times d_k + d_k = (p+1)d_k$

## Activation Functions

→ each layer is (usually) associated with an activation function ( $\sigma_k$ ) which is applied after the linear piece ( $Z_k(X)$ ).

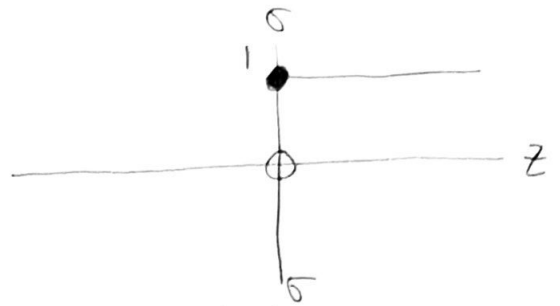
$$\overset{[n \times d_k]}{H_k(X)} = \sigma_k(\overset{[n \times d_k]}{Z_k(X)})$$

→  $\sigma_k$  is <sup>(usually)</sup> applied to either each element of  $Z_k$  independently, or row-wise (e.g. softmax)

→ indicator / heaviside:

$$\sigma(z) = \mathbb{1}\{z \geq 0\}$$

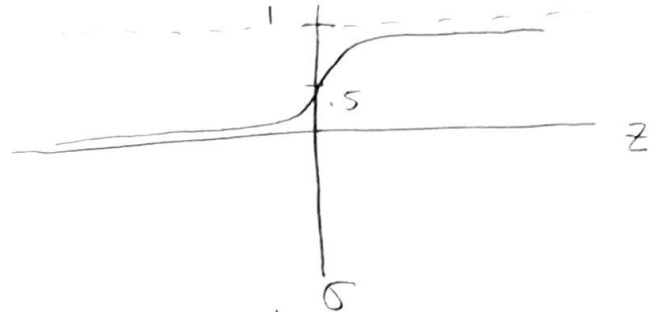
$$\sigma'(z) = 0$$



→ Sigmoid:

$$\sigma(z) = \frac{1}{1 + \exp(-z)}$$

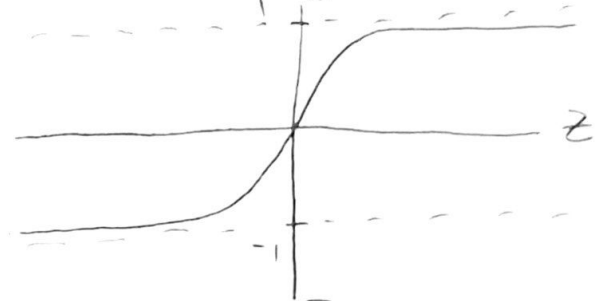
$$\sigma'(z) = (1 - \sigma(z))\sigma(z)$$



→ tanh:

$$\sigma(z) = \frac{\exp(2z) - 1}{\exp(2z) + 1}$$

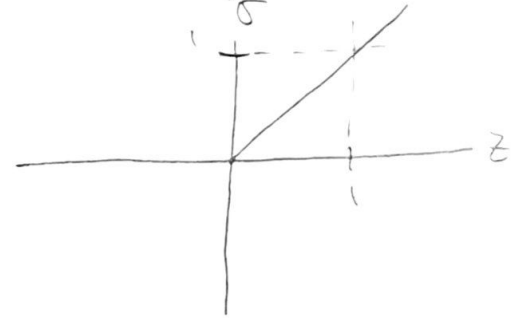
$$\sigma'(z) = 1 - [\sigma(z)]^2$$



→ rectified linear unit (relu):

$$\sigma(z) = \max(0, z)$$

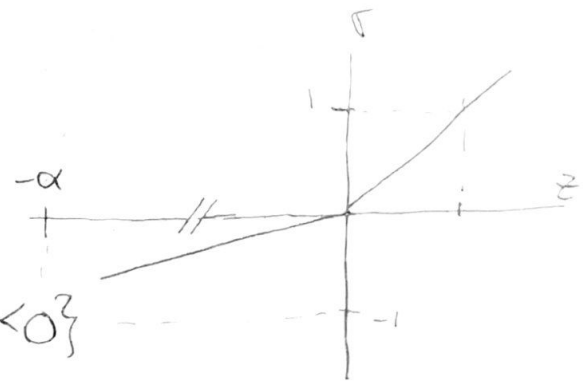
$$\sigma'(z) = \mathbb{1}\{z \geq 0\}$$



→ leaky relu:

$$\sigma(z) = \max(z, \frac{z}{\alpha})$$

$$\sigma'(z) = \mathbb{1}\{z \geq 0\} + \frac{1}{\alpha} \mathbb{1}\{z < 0\}$$



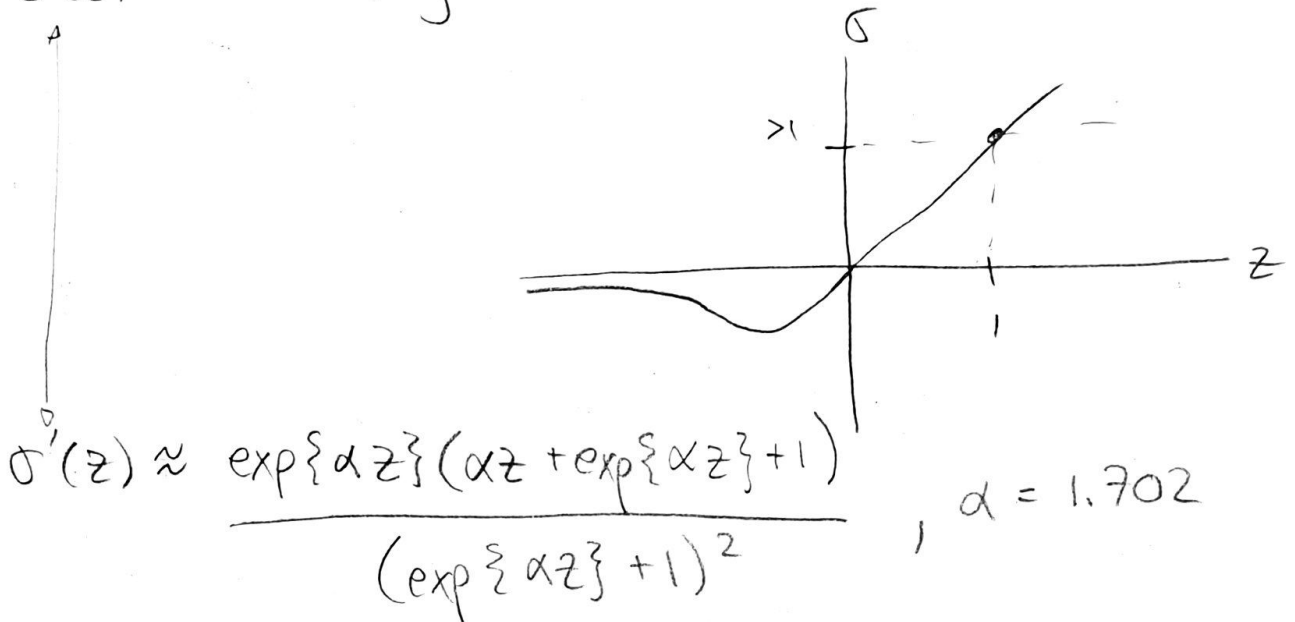
→ gaussian error linear unit (gelu)

$$\sigma(z) = z \Phi(z)$$

$\uparrow$  standard normal cdf

$$\sigma(z) \approx \frac{1}{2} z \left( 1 + \tanh \left[ \sqrt{\frac{2}{\pi}} (z + 0.044715 z^3) \right] \right)$$

$$\sigma(z) \approx z \cdot \text{sigmoid}(1.702 \cdot z)$$



$$\sigma'(z) \approx \frac{\exp\{\alpha z\}(\alpha z + \exp\{\alpha z\} + 1)}{(\exp\{\alpha z\} + 1)^2}, \quad \alpha = 1.702$$

→ softmax (applied row-wise to  $z$ )

$$\sigma(z) : \mathbb{R}^d \rightarrow S^d, \quad S = \left\{ s \in \mathbb{R}_+^d : \sum_{j=1}^d s_j = 1, s_j \geq 0 \forall j \right\}$$

$$\sigma_j(z_i) = \frac{\exp\{z_{ji}\}}{\sum_{j=1}^d \exp\{z_{ji}\}}$$

e.g.  $z = [1, 2, 3, -1]$        $\sigma(z) = [0.089, 0.242, 0.657, 0.012]$

→ can use to transform any vector into a probability distn.

Example: "feedforward" (fully connected) n.n.

$$X = [n \times p]$$

$$f(X) = \overset{[n \times d_3]}{\left[ \max(0, \underbrace{\max(0, X W_1 + B_1)}_{H_1} W_2 + B_2 \right)} W_3 + B_3$$

$\begin{matrix} [p \times d_1] & [n \times d_1] & [d_1 \times d_2] & [d_2 \times d_3] \\ W_1 & B_1 & W_2 & B_2 \\ [n \times d_2] & [n \times d_2] & & [n \times d_3] \end{matrix}$

- batch size?  $n$
- activation function? relu
- number of layers? 3 (2 hidden layers)
- output shape?  $[n \times d_3]$
- number of parameters?  $p=9, d_1=16, d_2=8, d_3=1$   
$$= [(p \times d_1) + d_1] + [(d_1 \times d_2) + d_2] + [(d_2 \times d_3) + d_3]$$
$$= [(9 \times 16) + 16] + (16 \times 8) + 8 + (8 \times 1) + 1$$
$$= [144 + 16] + [128 + 8] + [8 + 1]$$
$$= 160 + 136 + 9 = 305$$
- $f: \mathbb{R}^p \rightarrow \mathbb{R}^1$

# Biological Analogy / Architecture Diagram

→ Each layer has  $d_n$  neurons. Each neuron receives stimulus from the input  $X$  or neurons in preceding layers. Each neuron is either excited or not, and passes this information to neurons in succeeding layers.

