

# Deep Learning course

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Session 5 – Multi-layer perceptron (MLP)

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# Outline

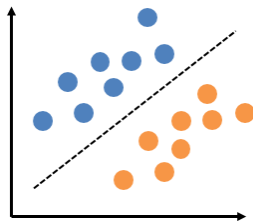
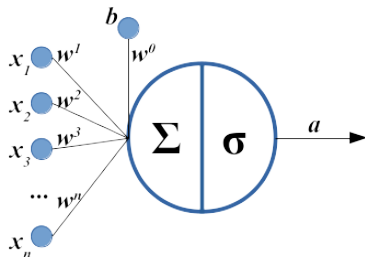
Perceptron

Multi-layer perceptron

Activations

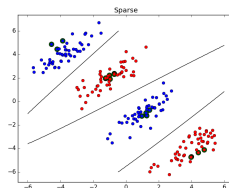
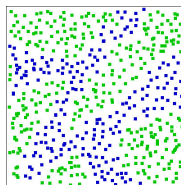
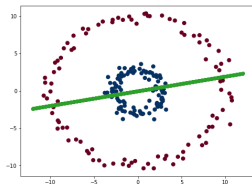
## Perceptron

- ▶ The simplest ANN, inspired by the neuron.
- ▶ Often using step or sigmoid activation functions  $\sigma(\cdot)$ .
- ▶ Linear classifier. Good enough for binary classification.
- ▶ Also good for linear regression.



## Perceptron

- ▶ Limited when dealing with non-linear separations.
- ▶ Also for multi-class problems (one perceptron per class).
- ▶ Difficult to guess whether a problem is linearly separable.  
e.g., Iris dataset classification performance.



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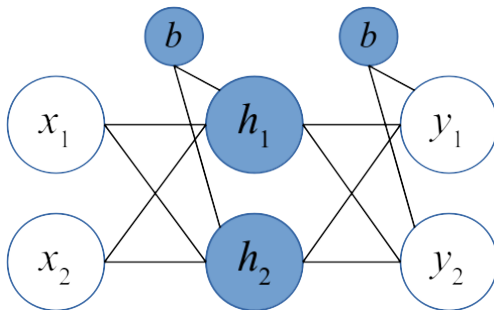
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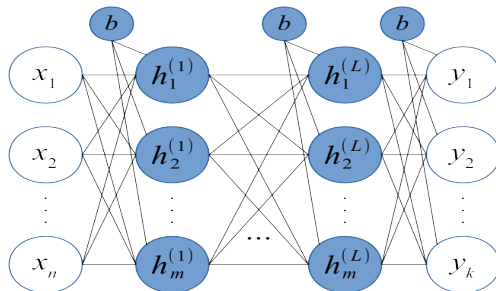
## MLP Network

- ▶ Arrangement of artificial neurons (a.k.a., units, nodes).
- ▶ Arranged within consecutive layers.
- ▶ Vanilla: input layer, hidden layers, output layer.
- ▶ Layers provide a hierarchically representation.



## MLP Network

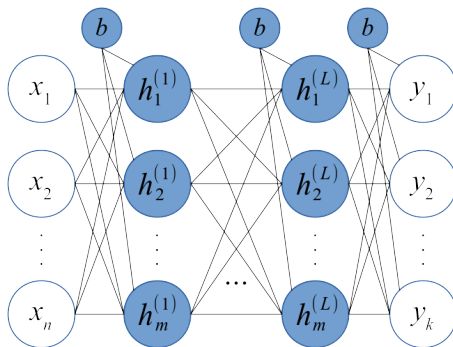
- ▶ Architecture: specific arrangement of the layers and nodes.
- ▶ Size: number of nodes in the model.
- ▶ Width: number of nodes in a specific layer.
- ▶ Depth: number of layers in a neural network.
- ▶ Capacity: function that the network can learn.





## Number of parameters

Fully connected network.



$$n_{paramL} = \Omega^{(L)}.shape[0] \times \Omega^{(L)}.shape[1] + \Omega^{(L)}.shape[0]$$

## Bias terms

- ▶ One per unit.
- ▶ One node ( $b^{(l)} = 1$ ) per layer, and
- ▶ multiple weights:  $\omega_{[m \times 1]}^{(l)}$ .

## How many layers and nodes?

Who knows?

- ▶ Input layer: one placeholder per feature.
- ▶ First hidden layer: one node per hyperplane.
- ▶ Output layer: one node per class.
- ▶ Intermediate layers: as many nodes as needed to (combine hyperplanes, induce sparsity, be robust, avoid overfitting, have enough capacity, reduce dimensionality, etc).
- ▶ Same for the number of intermediate layers: special attention on capacity.

## How many layers and nodes?

- ▶ Experimentation.
- ▶ Intuition.
- ▶ Keep it deep.
- ▶ Imitate the masters.

# Outline

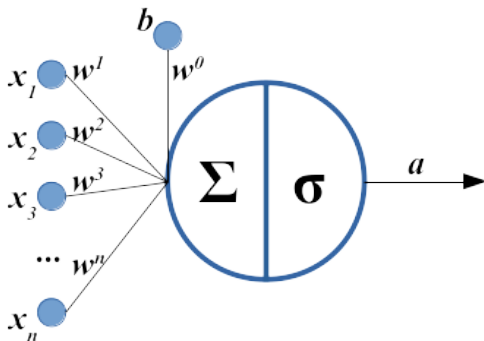
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## Activation function

Remember activation functions inside each unit.

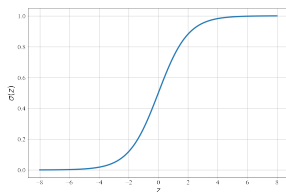


## Activation function

- ▶ Non linearity.
- ▶ Continuously differentiable.
- ▶ Finite range.
- ▶ Monotonic.
- ▶ Approximate identity near the origin.

## Logistic sigmoid (sigmoid)

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



- ▶ Positive real numbers within  $[0.0, 1.0]$ .
- ▶ Large negative numbers  $\rightarrow 0$ , and large positive numbers  $\rightarrow 1$ .
- ▶ Provides a notion of probability.
- ▶ *cons*: saturates, i.e., gradient close to 0.

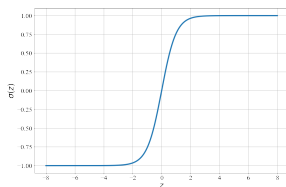
Derivative:

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



## Hyperbolic tangent (tanh)

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



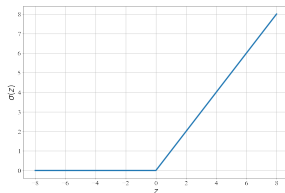
- ▶ Alternative to sigmoid.
- ▶ Real numbers within  $[-1.0, +1.0]$ .
- ▶ Negative numbers will remain negative.
- ▶ Zero centered.
- ▶ *cons*: saturates, i.e., gradient close to 0.

Derivative:

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

# ReLU

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



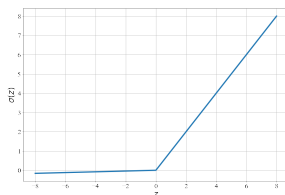
- ▶ Alternative to sigmoid.
- ▶ Positive real numbers within  $[0.0, \infty)$ .
- ▶ Much faster for optimization.
- ▶ *cons*: might saturate on the left.

Derivative:

$$\sigma'(z) = \begin{cases} 0, & z < 0 \\ 1, & z \geq 0. \end{cases}$$

## Leaky ReLU

$$\sigma(z) = \max(0.01z, z)$$



- ▶ Minimizes the risk of saturating on the left.
- ▶ Real numbers within  $[\approx 0.01z, \infty)$ .
- ▶ Faster enough for optimization.

Derivative:

$$\sigma'(z) = \begin{cases} 0.01, & z < 0 \\ 1, & z \geq 0. \end{cases}$$

## Soft-max

$$\sigma(z_i) = \frac{\exp(z_i)}{\sum_k \exp(z_k)}$$

- ▶ Suitable for last layer.
- ▶ Maps a vector onto a pdf.
- ▶ Real numbers within  $[\approx 0.01z, \infty)$ .

Derivative:

$$\sigma'(z_i) = \begin{cases} \sigma(z_i)(1 - \sigma(z_i)), & i = j \\ -\sigma(z_j)\sigma(z_i), & i \neq j. \end{cases}$$

## Most used activations

- ▶ ReLU [variants] (all hidden layers).
- ▶ Sigmoid (output layer for regression and binary classification).
- ▶ Softmax (output layer for multi-class classification).

# Suggested readings

- ▶ [http://peterroelants.github.io/posts/neural\\_network\\_implementation\\_intermezzo02](http://peterroelants.github.io/posts/neural_network_implementation_intermezzo02)
- ▶ DL Book. Goodfellow.

Thank you.

Q&A