

# Machine Learning and Pattern Recognition Practice

## Session V: Neural Networks

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# Overview

- 1 Perceptron
- 2 Activation function
- 3 Network architectures
- 4 Loss functions

# Perceptron

# Parametrized supervised learning

optimization problem in supervised learning

$$\hat{y} = f_w(x)$$

$$\hat{w} = \operatorname{argmin}_w L(y, \hat{y}) = \operatorname{argmin}_w L(y, f_w(x))$$

# Perceptron classifier

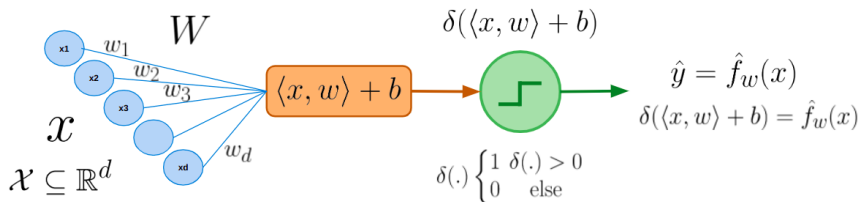


Figure: The perceptron pipeline

## The perceptron model

The model gets  $d$ -dimensional input vectors where each input variable is linearly combined to a weight vector  $w$ . After the linear combination  $\langle x, w \rangle$  an activation function is used to discretize the output value.

# Activation function

## activation function

$$f_i = \sigma_i(W_i X_{i-1} + b_i)$$

where  $\sigma$  is the activation function or "neuron" which input is a linear combination of weights and random variable  $X$ . There are multiple activation functions such as

- Identity
- Relu
- Sigmoid
- TanH

# Activation function

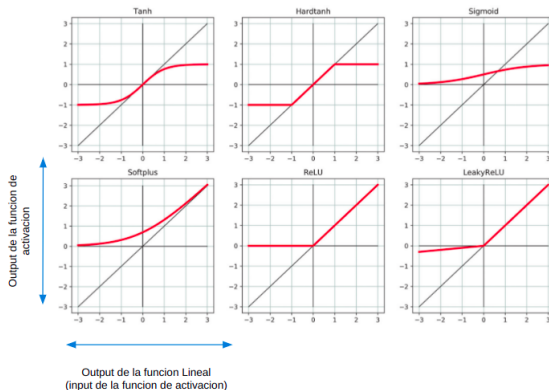


Figure: The landscape of activation functions

Some activation functions saturate when  $x \rightarrow \infty$  and others not.



# Activation function

## sigmoid

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

## TanH

$$\tanh(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} = \frac{1 - e^{-2x}}{1 + e^{-2x}}$$

## Softmax

$$\sigma(z_i) = \frac{e^{z_i}}{\sum_{j=1}^K e^{z_j}} \quad \text{for } i = 1, 2, \dots, K$$

## Softmax

$$\text{Relu}(z) = \max(0, z)$$

# Network architectures

# single neuron and single layer neural network

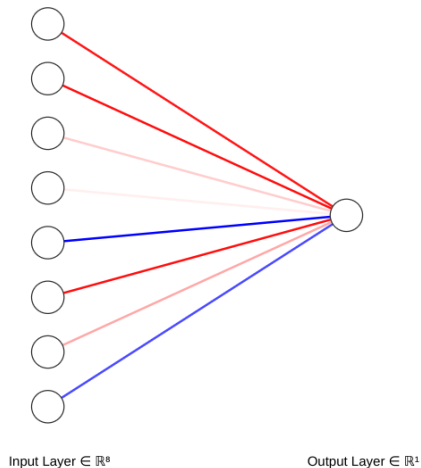


Figure: Neural network of 1 neuron and 1 layer

# two neuron and single layer neural network

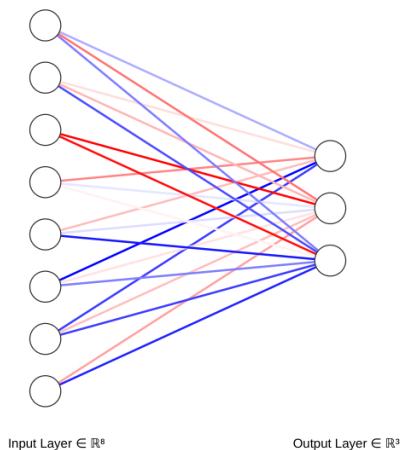
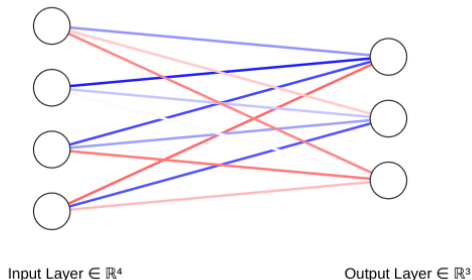


Figure: Neural network of 2 neuron and 1 layer

# Matrix notation to Neural Nets

if  $x \in \mathbb{R}^d$  with  $d = 4$  and a output label  $z \in \mathbb{Z}^p$  with  $p = 3$  then  
 $\mathbf{W}X + b = z$

$$\sigma \left( \begin{bmatrix} w_{11} & w_{12} & w_{13} & w_{14} \\ w_{21} & w_{22} & w_{23} & w_{24} \\ w_{31} & w_{32} & w_{33} & w_{34} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix} + \begin{bmatrix} b_1 \\ b_2 \\ b_3 \end{bmatrix} \right) = \begin{bmatrix} z_1 \\ z_2 \\ z_3 \end{bmatrix}$$



# Multilayer perceptron

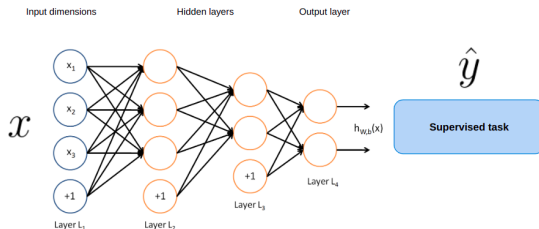


Figure: Neural network of multiple hidden MLP layers

## Multilayer perceptron stacked layers equation

$$y = \sigma(W_n(\dots \sigma(W_2(\sigma(W_1x + b_1) + b_2)) \dots + b_n))$$

# Loss functions

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## Classification: cross entropy

Binary classification

$$-(y \log(p) + (1 - y) \log(1 - p))$$

Multiclass:

$$-\sum_{c=1}^M y_{o,c} \log(p_{o,c})$$

## Mean Squared Error

For regression

$$\sum_{i=1}^N |x_i - y_i|$$



# Loss landscape

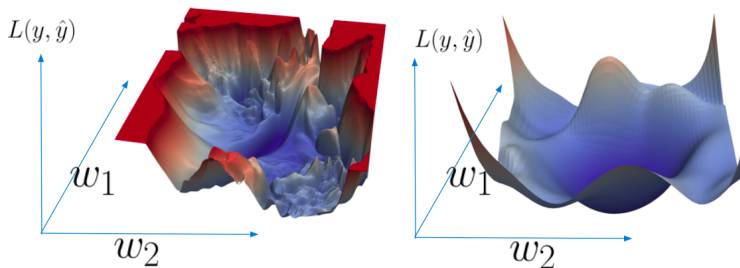


Figure: Loss landscape. Source: <https://www.jeremyjordan.me>

The loss landscape is conditioned to the dataset  $\mathbf{X}$ , the model architecture and the type of loss function. Via a non-convex optimization problem using Stochastic Gradient Descent a  $\hat{w}$  coordinate weight parameter is determined to solve the optimization problem in a local minima.

# Loss across training epochs

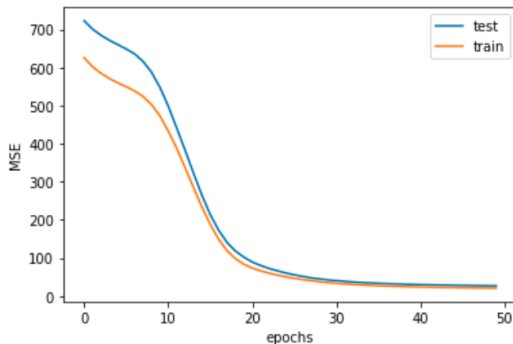


Figure: Loss

At each epoch the weight parameters are updated in order to minimize the value of the objective loss function.



Stevens, E., Antiga, L., & Viehmann, T. (2020). Deep learning with PyTorch. Manning Publications.



Shawe-Taylor, J., Cristianini, N. (2004). Kernel methods for pattern analysis. Cambridge university press.