ALMA MATER STUDIORUM
UNIVERSITÀ DI BOLOGNA
CAMPUS DI FORLÌ

# 91258 / B0385
# Natural Language Processing

## Lesson 11. "More than One" Neuron

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# Previously

- The perceptron
- Intro to neural networks

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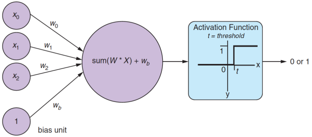
Chapter 5 of Lane et al. (2019)

# Backpropagation (brief)

# Weight Updating

Learning in a "simple" perceptron[1] vs a fully-connected network




(Lane et al., 2019, p. 158, 168)

[1]Remember: aka linear regression

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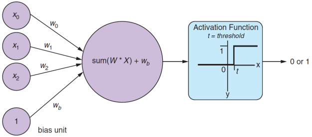


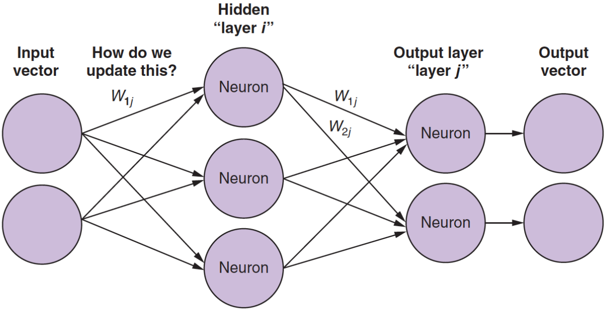


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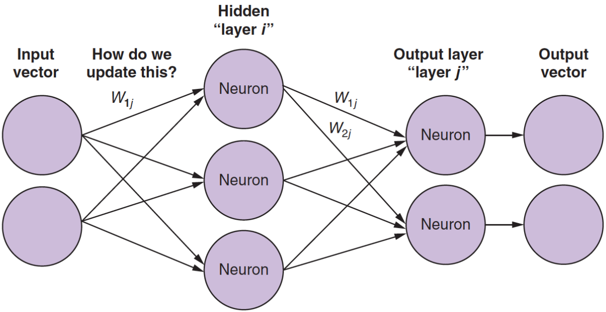
# Backpropagation (of the errors)

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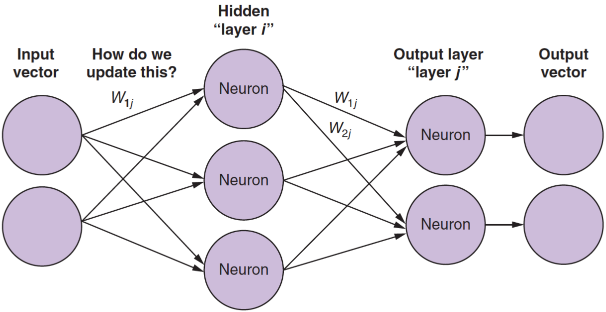


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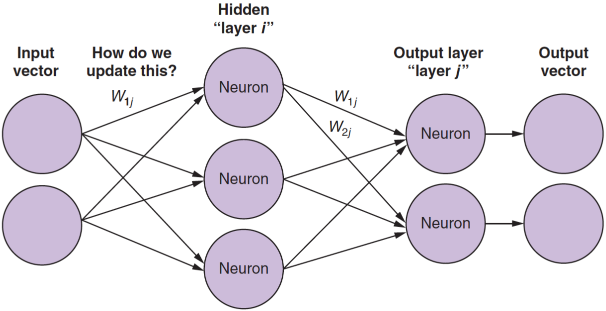


- The error is computed on the output vector
- How much error did $W_{1i}$ "contribute"?[2]
- "Path": $W_{1i} \rightarrow [W_{1j}, W_{2j}] \rightarrow \textit{output}$

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Step function: $f(\vec{x}) = \begin{cases} 1 & \text{if } \sum_{i=0}^{n} x_i w_i > \textit{threshold} \\ 0 & \text{otherwise} \end{cases}$

[3] The change of the output is not proportional to the change of the input.

# Backpropagation (of the errors)

## A better activation function

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Sigmoid function: non-linear[3] and continuously differentiable

$$S(x) = \frac{1}{1 + e^{-x}} \tag{1}$$

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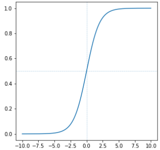


Non-linear $\rightarrow$ model non-linear relationships

Continuously differentiable $\rightarrow$ partial derivatives wrt various variables to update the weights

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## Squared error[4]

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With (4) we can find the derivative of the actfunct ∀ unit wrt its input.
Plain words: find the contribution of a weight to the error and adjust it!

(no further math)

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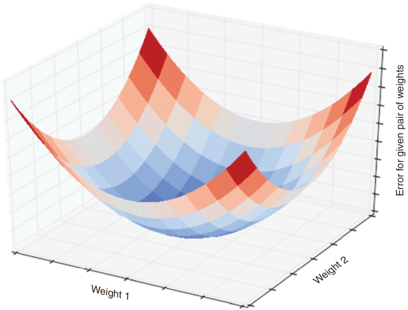
# Backpropagation (of the errors)

## ∼Gradient descent: minimising the error




Convex error curve

(Lane et al., 2019, p. 173–174)

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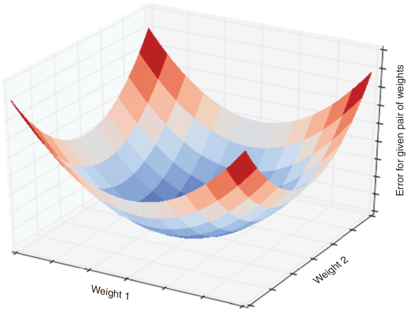


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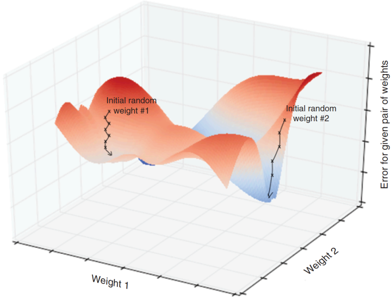


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Important parameter: learning rate $\alpha$
A parameter to define at what extent should we "correct" the error

# Keras

# Some Popular Libraries

There are many high- and low-level libraries in multiple languages

- PyTorch
  Community-driven; https://pytorch.org/
- TensorFlow
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We will use Keras; `https://keras.io/`

# What is Keras

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- A high-level wrapper with an accessible API for Python
- It gives access to three alternative backends
  - TensorFlow
  - CNTK (MS)

# Keras

## Logical exclusive OR (XOR) in Keras

| input | | output |
|---|---|---|
| 0 | 0 | 0 |
| 0 | 1 | 1 |
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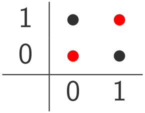

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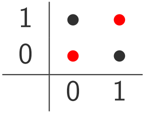


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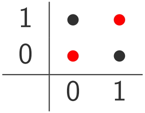


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- 30 parameters

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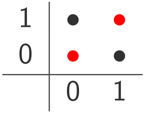


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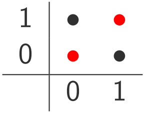


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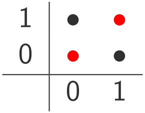


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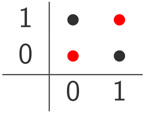


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Now we can compile the model

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## Some Guidelines

# Design Decisions

## Activation functions

Sigmoid

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tanh Hyperbolic tangent

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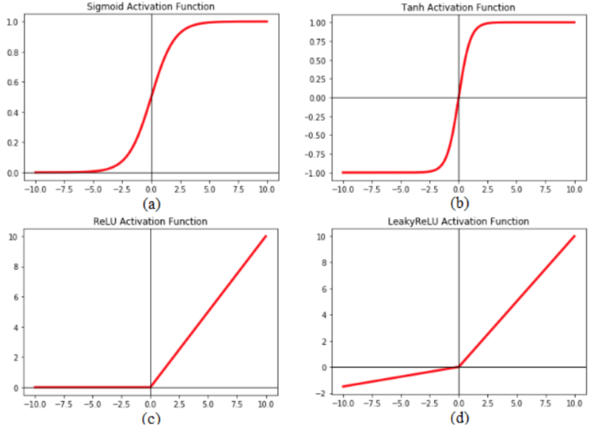


Figure source: (Kandel and Castelli, 2020)

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## Regularisation

- Dampen a weight from growing/shrinking too far from the rest to prevent overfitting

# Normalisation

**Example** House classification.

- **Input** number of bedrooms, last selling price
- **Output** Likelihood of selling
- **Vector** `input_vec = [4, 12000]`

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NLP typically uses TF–IDF, one-hot encoding, word2vec (already normalised)

# References

Kandel, I. and M. Castelli
2020. Transfer learning with convolutional neural networks for diabetic retinopathy image classification. a review. *Applied Sciences*, 10(6).

Lane, H., C. Howard, and H. Hapkem
2019. *Natural Language Processing in Action*. Shelter Island, NY: Manning Publication Co.