

Artificial neural networks and backpropagation

E. Decencière

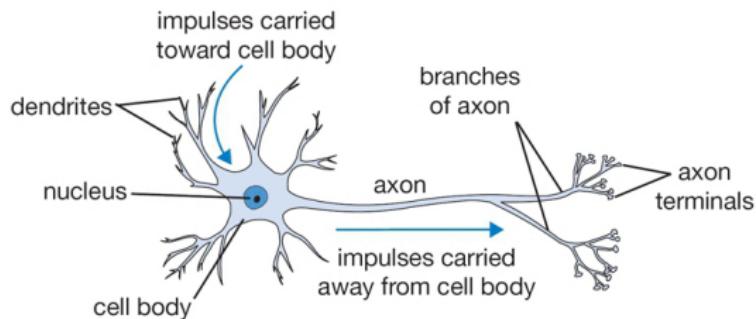
Mines Paris
PSL Research University
Center for Mathematical Morphology



Contents

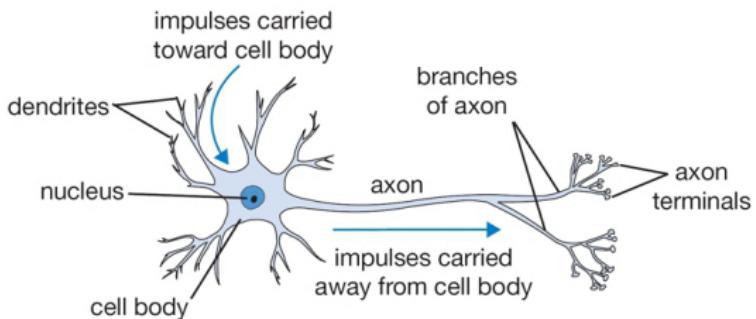
- 1 Artificial neurons
- 2 Artificial neural networks
- 3 Training a neural network
- 4 Conclusion

Biological neuron



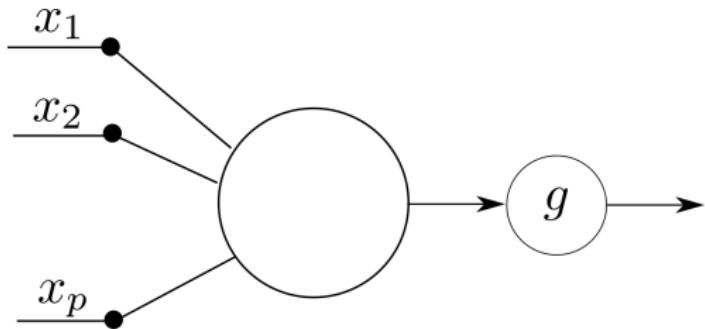
- A human neuron can have several thousand dendrites

Biological neuron



- A human neuron can have several thousand dendrites
- The neuron sends a signal through its axon if during a given interval of time the net input signal (sum of excitatory and inhibitory signals received through its dendrites) is larger than a threshold.

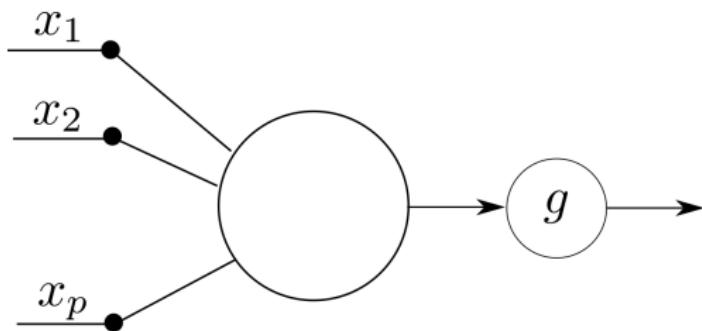
Artificial neuron



General principle

An artificial neuron takes p inputs $\{x_i\}_{1 \leq i \leq p}$, **combines** them to obtain a single value, and applies an **activation function** g to the result.

Artificial neuron

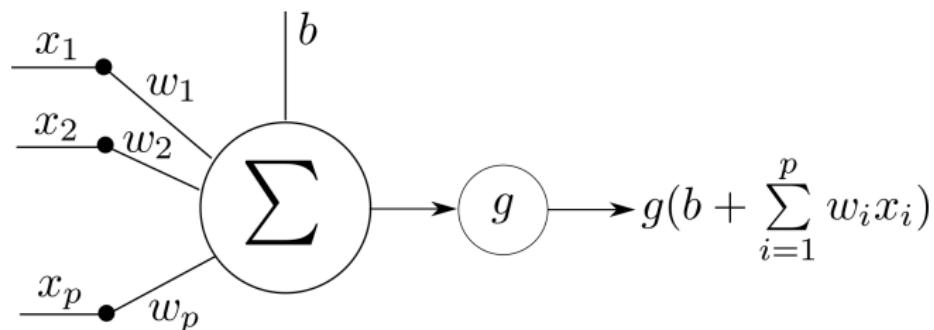


General principle

An artificial neuron takes p inputs $\{x_i\}_{1 \leq i \leq p}$, **combines** them to obtain a single value, and applies an **activation function** g to the result.

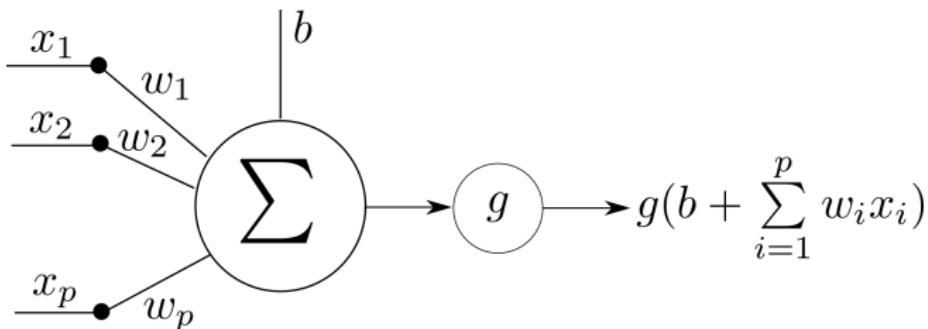
- The first artificial neuron model was proposed by [McCulloch and Pitts, 1943]
- Input and output signals were binary
- Input dendrites could be inhibitory or excitatory

Modern artificial neuron



- The neuron computes a linear combination of the **inputs** x_i
 - The **weights** w_i are multiplied with the inputs
 - The **bias** b can be interpreted as a threshold on the sum
- The **activation function** g somehow decides, depending on its input, if a signal (the neuron's **activation**) is produced

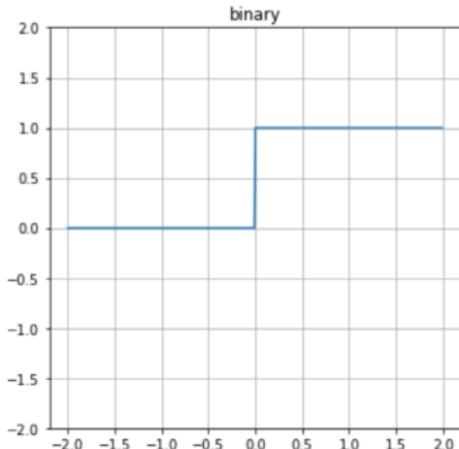
The role of the activation function



- The initial idea behind the activation function is that it works somehow as a gate
- If its input is “high enough”, then the neuron is activated, i.e. a signal (other than zero) is produced
- It can be interpreted as a source of abstraction: information considered as unimportant is ignored (or reduced)

Activation: binary

$$g(x) = \begin{cases} 1, & \text{if } x > 0 \\ 0, & \text{otherwise} \end{cases}$$

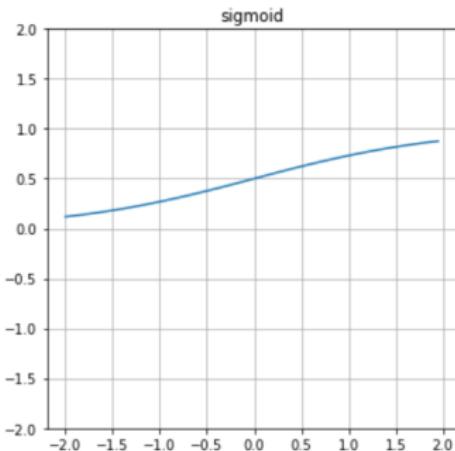


Remarks

- Biologically inspired
- + Simple to compute
- + High abstraction
- Gradient nil except on one point
- In practice, almost never used

Activation: sigmoid

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

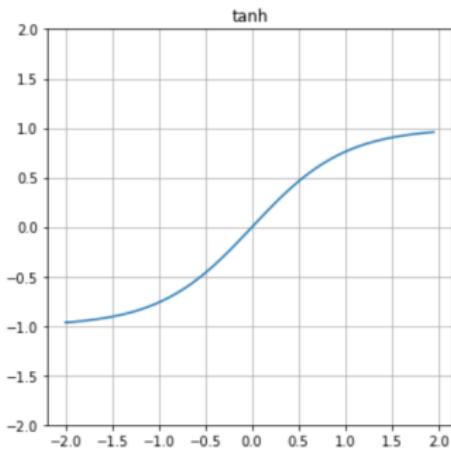


Remarks

- + Similar to binary activation, but with usable gradient
- Bijection between \mathbb{R} and $]0, 1[$: no loss of information
- Gradient tends to zero as we get away from zero
- More computationally intensive

Activation: hyperbolic tangent

$$g(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}}$$

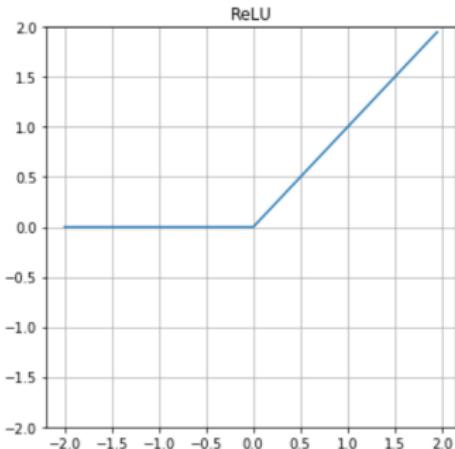


Remarks

- Similar to sigmoid

Activation: rectified linear unit (ReLU)

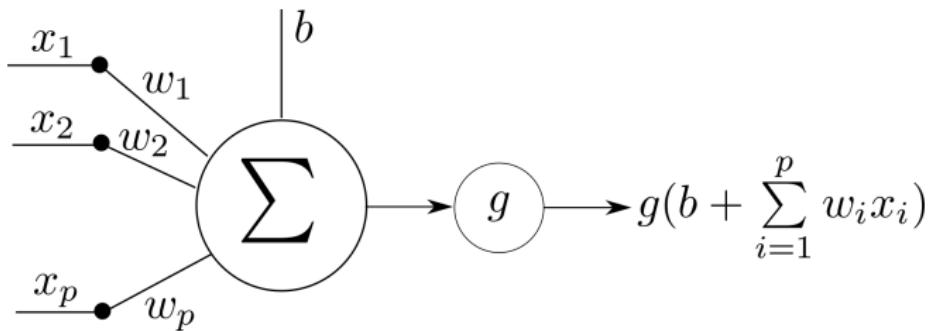
$$g(x) = \begin{cases} x, & \text{if } x > 0 \\ 0, & \text{otherwise} \end{cases}$$



Remarks

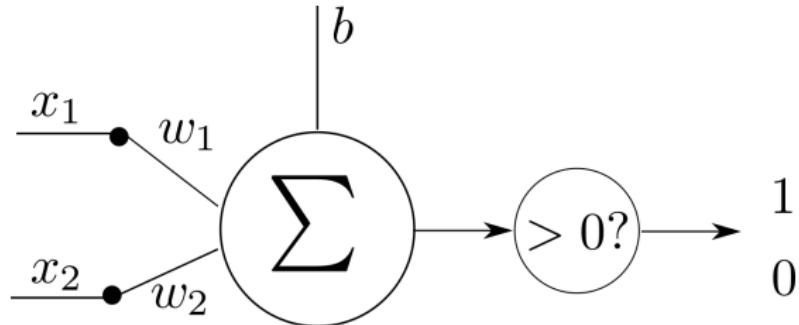
- + Usable gradient when activated
- + Fast to compute
- + High abstraction

What can an artificial neuron compute?



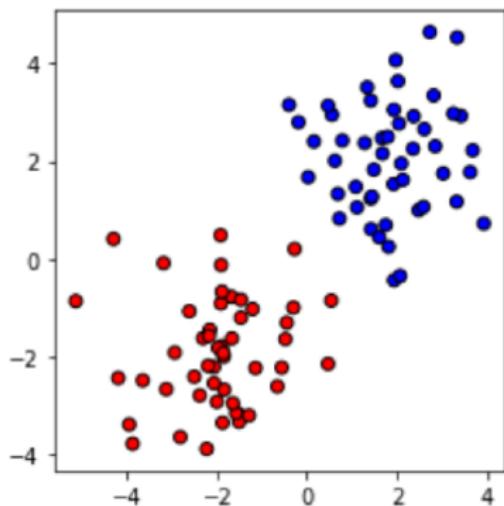
In \mathbb{R}^p , $b + \sum_{i=1}^p w_i x_i = 0$ corresponds to a hyperplane H . For a given point $\mathbf{x} = \{x_1, \dots, x_p\}$, decisions are made according to the side of the hyperplane it belongs to.

Example in 2D

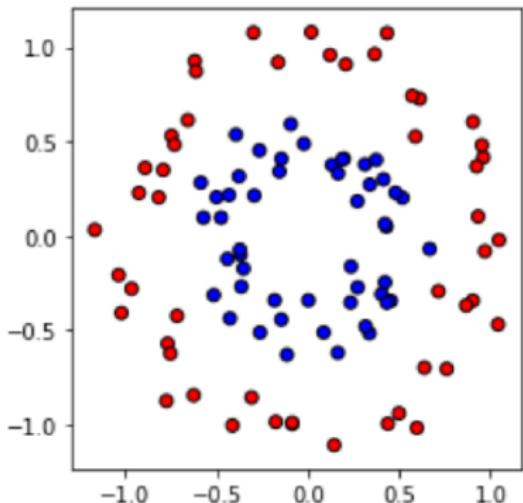


- $p = 2$: 2-dimensional inputs (can be represented on a screen!)
- Activation: binary
- Classification problem

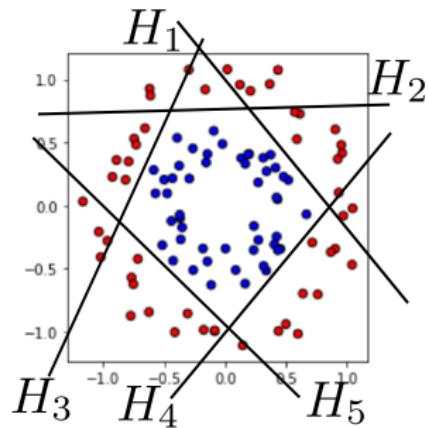
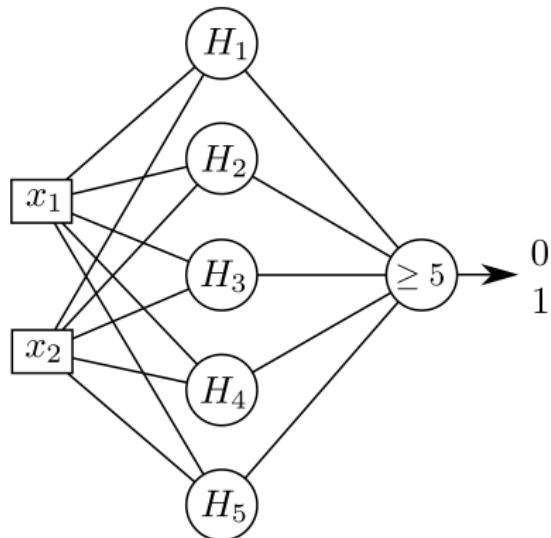
Gaussian clouds



Circles



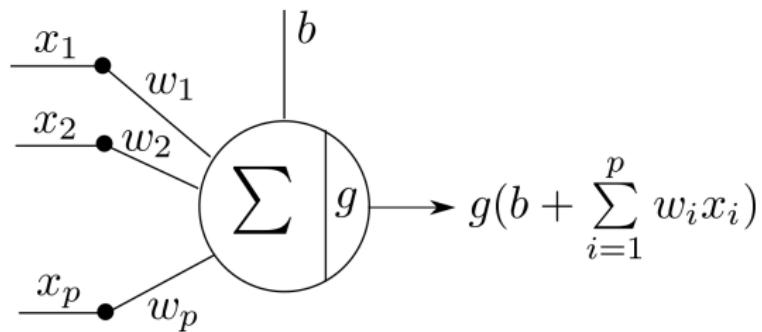
Solution with a simple neural network



Intuition

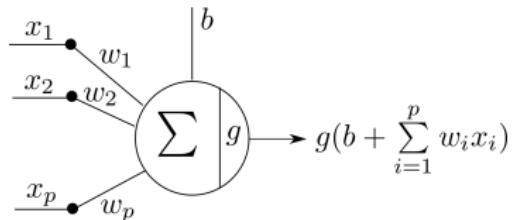
Combining several neurons one can build complex classifiers.

Compact representation



Notations

With



$$\mathbf{w} = \begin{pmatrix} w_1 \\ \vdots \\ w_p \end{pmatrix} = (w_1, \dots, w_p)^T$$

and

$$\mathbf{x} = \begin{pmatrix} x_1 \\ \vdots \\ x_p \end{pmatrix} = (x_1, \dots, x_p)^T$$

We can simply write:

$$g(b + \sum_{i=1}^p w_i x_i) = g(b + \mathbf{w}^T \mathbf{x})$$

Contents

1 Artificial neurons

2 Artificial neural networks

- Computational graph
- First architectures
- Modelling power

3 Training a neural network

4 Conclusion

Contents

1 Artificial neurons

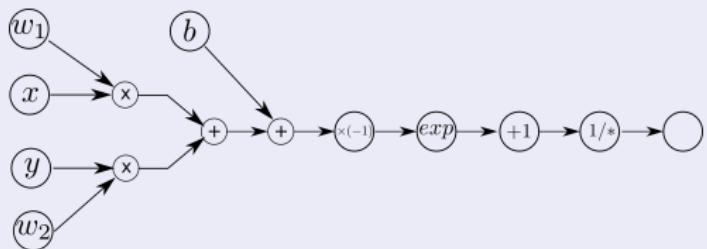
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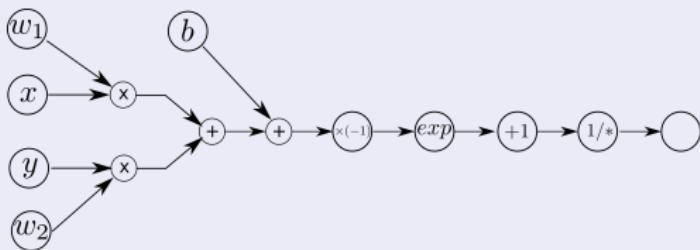
3 Training a neural network

4 Conclusion

Computational graph



Computational graph

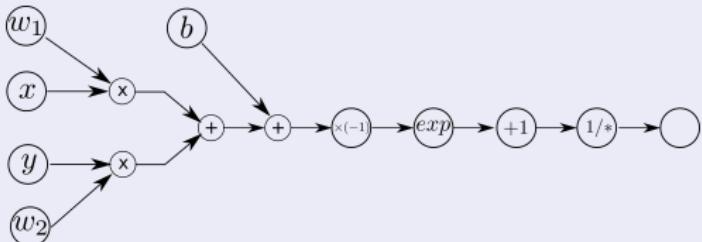


Definition

A computational graph is an acyclic directed graph such that:

- A node is a mathematical operator
- To each edge is associated a value
- Each node can compute the values of its output edges from the values of its input edges
 - Nodes without input edges are *input nodes*. They represent the input values of the graph.
 - Similarly, output values can be held in the *output nodes*.

Computational graph



- In this course, we will only consider *acyclic* computational graphs.
- Computing a *forward pass* through the graph means choosing its input values, and then progressively computing the values of all edges.

Computational graph example

Computational graph of:

$$\sigma(w_1x + w_2y + b)$$

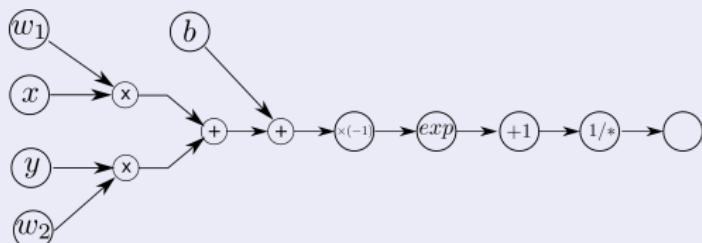
where σ is the sigmoid function: $\sigma(x) = \frac{1}{1+e^{-x}}$

Computational graph example

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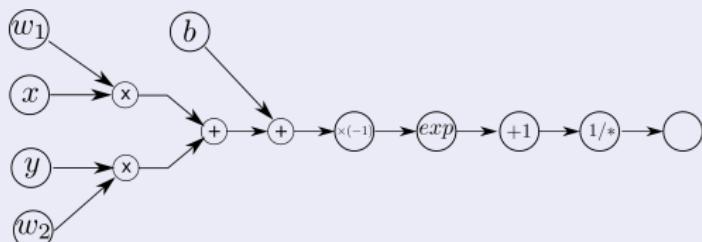


Computational graph example

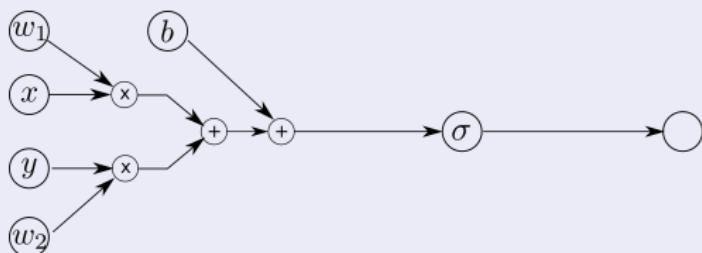
Computational graph of:

$$\sigma(w_1x + w_2y + b)$$

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The graph can be represented at different levels of detail:



Contents

1 Artificial neurons

2 Artificial neural networks

- Computational graph
- First architectures
- Modelling power

3 Training a neural network

4 Conclusion

Neural network (NN)

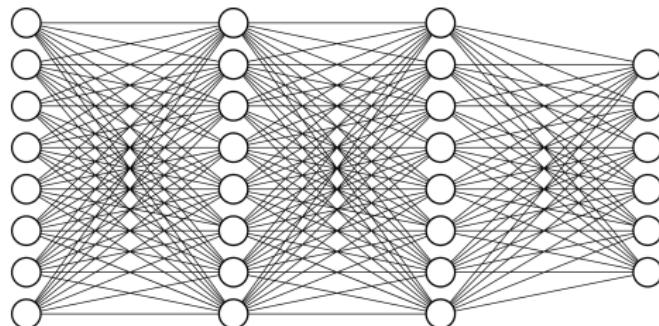
Definitions

- An artificial neural network is a computational graph, where the nodes are artificial neurons
- The **input layer** is the set of neurons without incoming edges.
- The **output layer** is the set of neurons without outgoing edges.

Network layers

Definition

- Neurons are usually organized in **layers**
- Any layers other than input and output layers are called **hidden layers**



Other types of neural networks

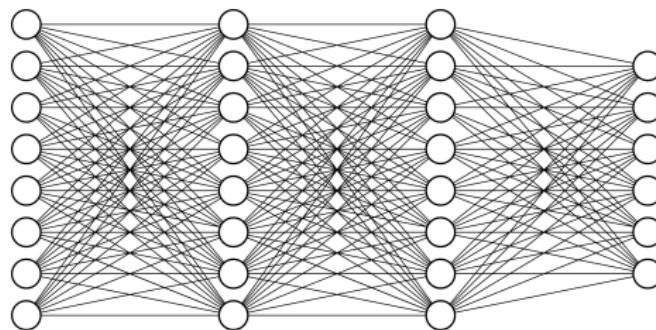
In the following of this course, except when otherwise specified, all NNs will be feed-forward. Indeed, this is the preferred type of NN for image processing.

What about other architectures?

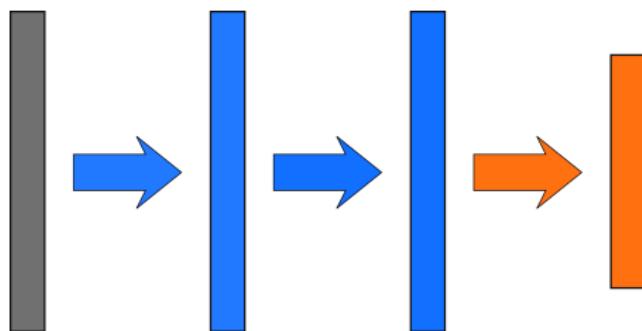
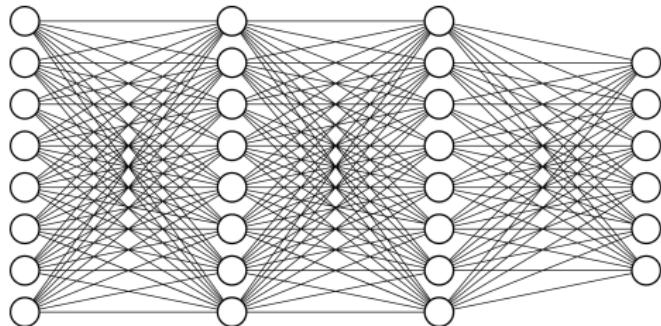
- Recurrent neural networks (RNN)
 - Long short-term memory networks (LSTM)
-
- + More powerful than feed-forward NNs
- Complex dynamics; more difficult to train
 - Mainly used for processing temporal data

Fully-connected layer

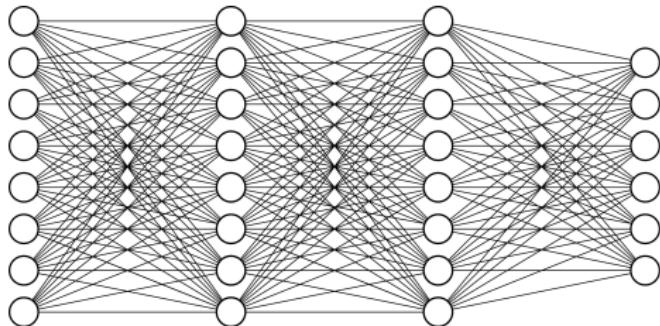
- A layer is said to be fully-connected (FC) if each of its neurons is connected to all the neurons of the previous layer
- If a FC layer contains r neurons, and the previous layer q , then its weights are a 2D dimensional array (a matrix) of size $q \times r$



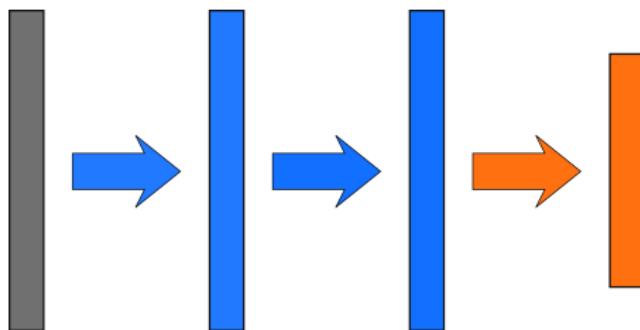
Graphical representation of NNs



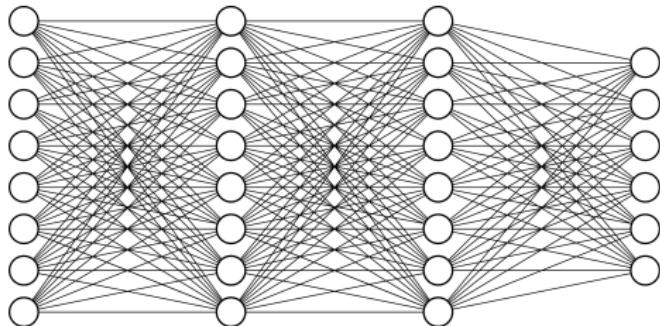
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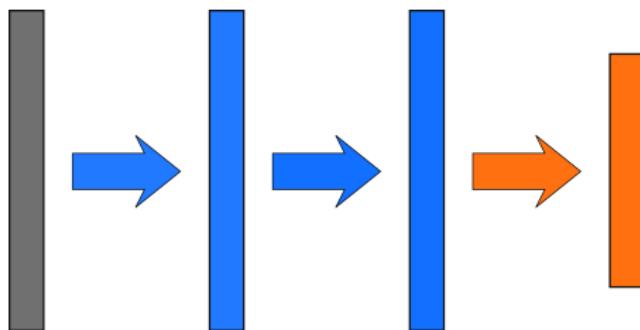
- Data is organized into arrays, linked with operators



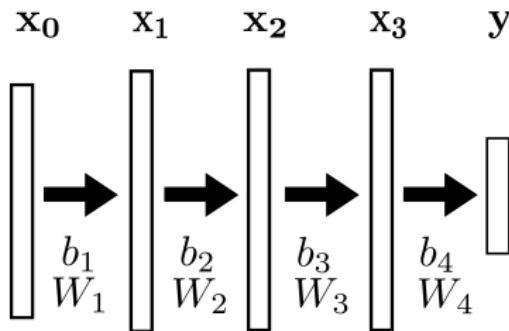
Graphical representation of NNs



- Data is organized into arrays, linked with operators
- A layer corresponds to an operator between arrays.



The equations of a fully connected neural network

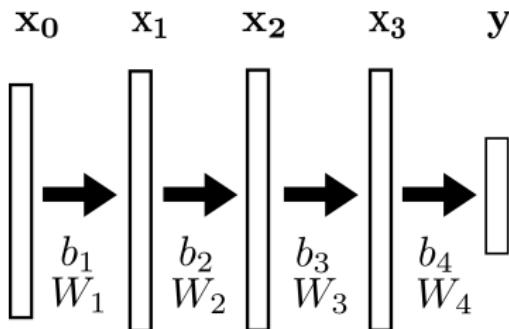


For $i \in \{1, 2, 3\}$:

$$\mathbf{x}_i = g_i(\mathbf{x}_{i-1}^t \mathbf{W}_i + \mathbf{b}_i)$$

$$\mathbf{y} = g_4(\mathbf{x}_3^t \mathbf{W}_4 + \mathbf{b}_4)$$

The equations of a fully connected neural network



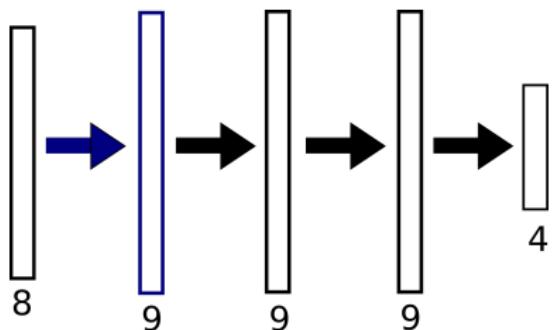
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What would happen if all activation functions g_i were equal to the identity function?

Number of parameters



- How many parameters does the above network contain?
A/ 270
B/ 274
C/ 301
D/ 39

Batch processing

In a learning context, one may want to process n vectors of length p at the same time. They can be grouped into a matrix \mathbf{X} of size $n \times p$. The n corresponding outputs \mathbf{y}_i can also be grouped into a matrix \mathbf{Y} . The resulting equations are:

For $i \in \{1, 2, 3\}$:

$$\mathbf{X}_i = g_i(\mathbf{X}_{i-1} \mathbf{W}_i + \mathbf{b}_i)$$

$$\mathbf{Y} = g_4(\mathbf{X}_4 \mathbf{W}_4 + \mathbf{b}_4)$$

This can accelerate processing thanks to hardware architectures such as Graphical Processing Units (GPUs) but can also play an important role in optimization.

From neurons to arrays

- Neurons are organized into arrays (0-D, 1-D, 2-D, 3-D ...)
- Artificial neural networks can be seen as computational graphs processing arrays

Contents

1 Artificial neurons

2 Artificial neural networks

- Computational graph
- First architectures
- Modelling power

3 Training a neural network

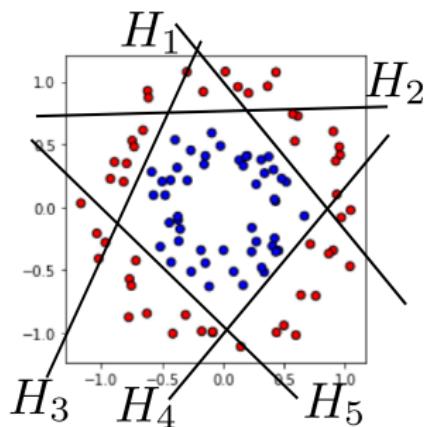
4 Conclusion

A composition of differentiable functions

- The functions composing an artificial neural network are differentiable (almost everywhere), so that it can be optimized via gradient descent. Therefore, an ANN is differentiable (almost everywhere).
- In fact, any continuous function on a closed bounded domain can be approached within any error margin by an artificial neural network.

Universal approximation theorem

- We have previously seen that a neuron can be used as a linear classifier and that combining several of them one can build complex classifiers
- We will see that this observation can be generalized



Universal approximation theorem

Let f be a **continuous** real-valued function of $[0, 1]^p$ ($p \in \mathbb{N}^*$) and ϵ a strictly positive real. Let g be a non-constant, increasing, bounded real function (*the activation function*).

Then there exists an integer q , real vectors $\{\mathbf{w}_i\}_{1 \leq i \leq q}$ of \mathbb{R}^p , and reals $\{b_i\}_{1 \leq i \leq q}$ and $\{v_i\}_{1 \leq i \leq q}$ such that for all \mathbf{x} in $[0, 1]^p$:

$$\left| f(\mathbf{x}) - \sum_{i=1}^q v_i g(\mathbf{w}_i \mathbf{x} + b_i) \right| < \epsilon$$

A first version of this theorem, using sigmoidal activation functions, was proposed by [Cybenko, 1989]. The version above was demonstrated by [Hornik, 1991].

Universal approximation theorem: what does it mean?

$$\left| f(\mathbf{x}) - \sum_{i=1}^q v_i g(\mathbf{w}_i \mathbf{x} + b_i) \right| < \epsilon$$

This means that function f can be approximated with a neural network containing:

- an input layer of size p ;
- a hidden layer containing q neurons with activation function g , weights \mathbf{w}_i and biases b_i ;
- an output layer containing a single neuron, with weights v_i (and an identity activation function).

Universal approximation theorem in practice

- The number of neurons increases very rapidly with the complexity of the function
- Empirical evidence has shown that **multi-layer architectures give better results**
- For learning tasks, the function to be modelled is only known on a finite number of points.

Universal approximation theorem in practice

- The number of neurons increases very rapidly with the complexity of the function
- Empirical evidence has shown that **multi-layer architectures give better results**
- For learning tasks, the function to be modelled is only known on a finite number of points.

A NN can potentially have a lot of parameters. How can we set them?

Contents

- 1 Artificial neurons
- 2 Artificial neural networks
- 3 Training a neural network
 - Loss functions
 - Gradient descent
 - Backpropagation
 - Weights initialization
- 4 Conclusion

Introduction

- We have seen that NNs have a lot of potential. However, how can the parameters $\theta = (\mathbf{W}_i, \mathbf{b}_i)$ be set?
- What is our objective ?

Supervised learning problem

We recall that our training set contains n samples:

$$(\mathbf{x}_i, y_i) \in \mathbb{R}^p \times \mathcal{Y}$$

Where $\mathcal{Y} = \mathbb{R}$ in the regression case and $\mathcal{Y} = \{0, 1\}$ in the binary classification case.

Supervised learning problem

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Where $\mathcal{Y} = \mathbb{R}$ in the regression case and $\mathcal{Y} = \{0, 1\}$ in the binary classification case.

We **choose** a loss function l and we **choose** a family f_{θ} of functions from \mathbb{R}^p into \mathbb{R} , depending on a set of parameters θ , and **find** the value θ^* of θ that minimizes:

$$\frac{1}{n} \sum_{i=1}^n l(f_{\theta}(\mathbf{x}_i), y_i)$$

Supervised learning problem

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For the sake of simplicity, we have dropped the regularization term.

Contents

1 Artificial neurons

2 Artificial neural networks

3 Training a neural network

- Loss functions
- Gradient descent
- Backpropagation
- Weights initialization

4 Conclusion

Choosing a loss function

- The choice of the loss function depends on the type of problem (regression or classification) and is tightly linked to the application.

The standard loss for regression problems: Squared error loss

In the regression case, we have $\mathcal{Y} = \mathbb{R}$.

Squared error loss

$$l(f_{\theta}(x), y) = (f_{\theta}(x) - y)^2$$

Binary cross-entropy

In the simplest classification case, we have $\mathcal{Y} = \{0, 1\}$.

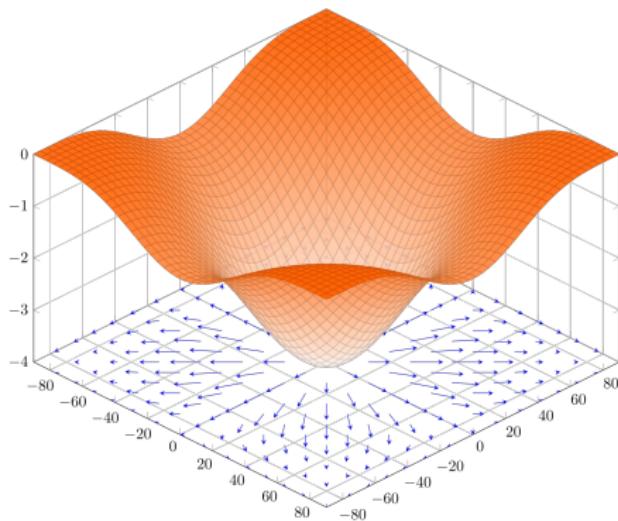
Binary cross-entropy loss

$$l(f_{\theta}(x), y) = -y \log(f_{\theta}(x)) - (1 - y) \log(1 - f_{\theta}(x))$$

- For this expression to be mathematically sound, $f_{\theta}(x)$ must belong to $]0, 1[$. In practice, in the case of NN, this can be achieved by using a sigmoid as last activation.
- Note that the expression above is equivalent to:

$$l(f_{\theta}(x), y) = \begin{cases} -\log(1 - f_{\theta}(x)) & \text{if } y = 0 \\ -\log(f_{\theta}(x)) & \text{if } y = 1 \end{cases}$$

How to minimize the loss?



Definition: gradient

Let L be a differentiable function from \mathbb{R}^n into \mathbb{R} . Its gradient ∇L is:

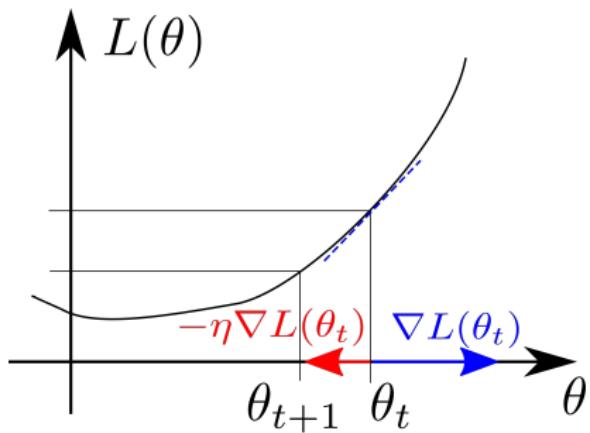
$$\nabla L(x) = \begin{pmatrix} \frac{\partial L}{\partial \mathbf{x}_1}(x) \\ \vdots \\ \frac{\partial L}{\partial \mathbf{x}_n}(x) \end{pmatrix}$$

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<https://commons.wikimedia.org/>

Contents

- 1 Artificial neurons
- 2 Artificial neural networks
- 3 Training a neural network
 - Loss functions
 - Gradient descent
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- 4 Conclusion

Gradient descent in the scalar case



$$\theta_{t+1} = \theta_t - \eta \nabla L(\theta_t)$$

L is called the **learning rate**.

Gradient descent

Definition

Gradient descent is an optimization algorithm. For a differentiable function L , a positive real η (the **learning rate**) and a starting point θ_0 , it computes a sequence of values:

$$\forall t \in \mathbb{N} : \theta_{t+1} = \theta_t - \eta \nabla L(\theta_t)$$

Property

For a given t , if η is small enough, then:

$$L(\theta_{t+1}) \leq L(\theta_t)$$

Gradient descent is an essential tool in optimization.

Gradient descent: stopping criteria

In practice:

$$\forall t \in [0, \dots, E - 1] : \quad \theta_{t+1} = \theta_t - \eta \nabla L(\theta_t)$$

- Choose E (the number of epochs) based on experience
- Track the quality of the model using a validation dataset and stop when the validation loss does not improve

Towards stochastic gradient descent

The loss function we initially defined depends on the whole training set:

$$L(\boldsymbol{\theta}) = \frac{1}{n} \sum_{i=1}^n l(y_i, f_{\boldsymbol{\theta}}(\mathbf{x}_i))$$

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- If n is very large, computing L is impractical.

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- If n is very large, computing L is impractical.
- A computation on the whole training set leads to a single update of the model parameters - convergence can therefore be slow.

Stochastic gradient descent

In **stochastic gradient descent**, the parameters are updated for each sample i .

- First, the loss is computed

$$L(\boldsymbol{\theta}_t) = l(y_i, f(\mathbf{x}_i, \boldsymbol{\theta}_t))$$

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- The gradient $\nabla L(\boldsymbol{\theta}_t)$ is computed and

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- Finally the parameters are updated:

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- The gradient $\nabla L(\boldsymbol{\theta}_t)$ is computed and
- Finally the parameters are updated:

$$\boldsymbol{\theta}_{t+1} = \boldsymbol{\theta}_t - \eta \nabla L(\boldsymbol{\theta}_t)$$

- Note that the learning rate η can have a different value than in classic gradient descent.

Mini-batch processing

- One can (and often does) choose an intermediate solution between the full gradient and the stochastic gradient: mini-batch gradient.

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Mini-batch processing

- One can (and often does) choose an intermediate solution between the full gradient and the stochastic gradient: mini-batch gradient.
- The training database is then separated into subsets containing m samples ($m < n$).
- This has a regularization effect on the optimization with respect to the stochastic gradient and speeds up computation thanks to the vectorization capacity of hardware architectures such as GPUs.

Contents

1 Artificial neurons

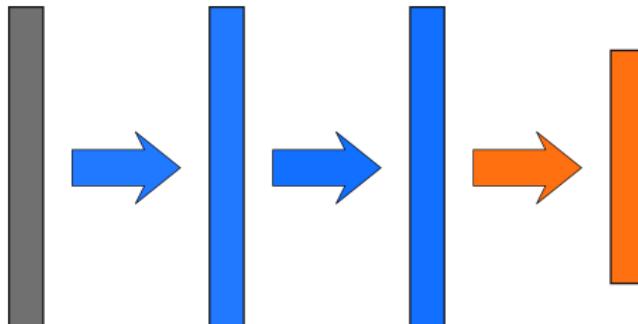
2 Artificial neural networks

3 Training a neural network

- Loss functions
- Gradient descent
- **Backpropagation**
- Weights initialization

4 Conclusion

Gradient descent applied to neural networks



- In the case of neural networks, the loss L depends on each parameter θ_i via the composition of several functions.
- Analytical derivation is possible, but complex - and has to be re-computed when the network architecture is modified
- Using the chain rule theorem leads to an efficient solution: **backpropagation**.

Chain rule theorem

Let f_1 and f_2 be two differentiable real functions ($\mathbb{R} \rightarrow \mathbb{R}$). Then for all x in \mathbb{R} :

$$(f_2 \circ f_1)'(x) = (f'_2 \circ f_1)(x) \cdot f'_1(x)$$

Leibniz notation

Let us introduce variables x , y and z :

$$x \xrightarrow{f_1} y \xrightarrow{f_2} z$$

Then:

$$\frac{dz}{dx} = \frac{dz}{dy} \cdot \frac{dy}{dx}$$

The backpropagation algorithm

- The backpropagation algorithm is used in a neural network to efficiently compute the partial derivatives of the loss with respect to each parameter of the network.
- One can trace the origins of the method to the sixties
- It was first applied to NN in the eighties
[Werbos, 1982, LeCun, 1985]

The backpropagation algorithm: intuition

- Given a computational graph, the main idea is to compute the local derivatives during a forward pass
- Then, during a backward pass, the partial derivatives of the loss with respect to each parameter are computed

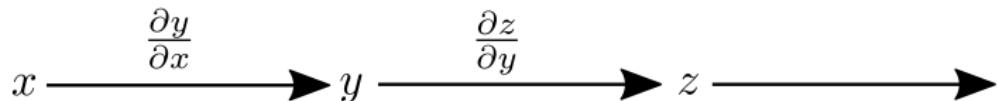
Simple backpropagation example



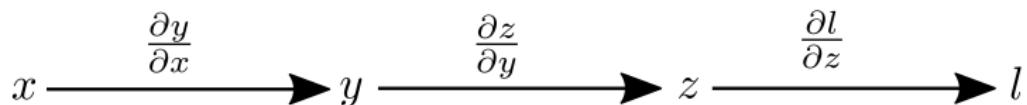
Simple backpropagation example



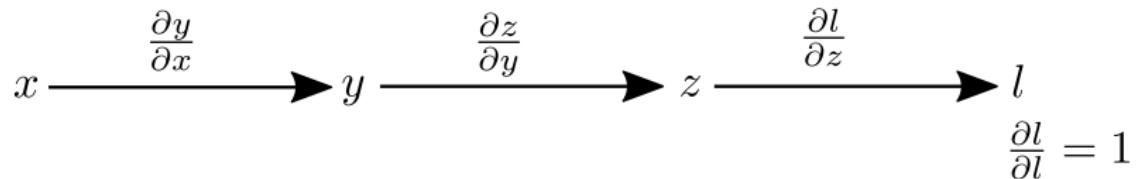
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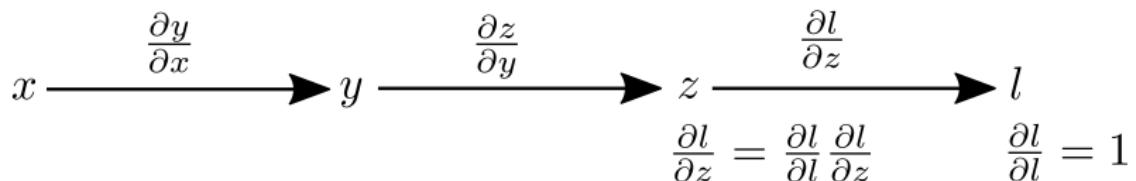
Simple backpropagation example



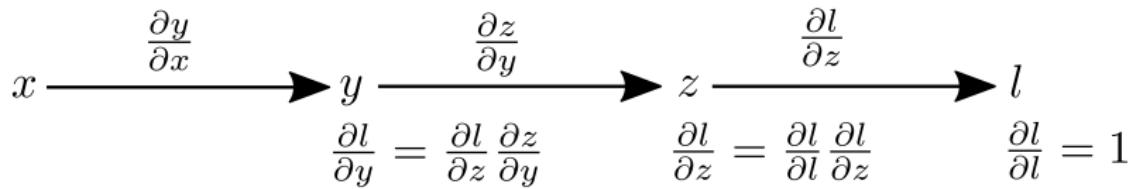
Simple backpropagation example



Simple backpropagation example



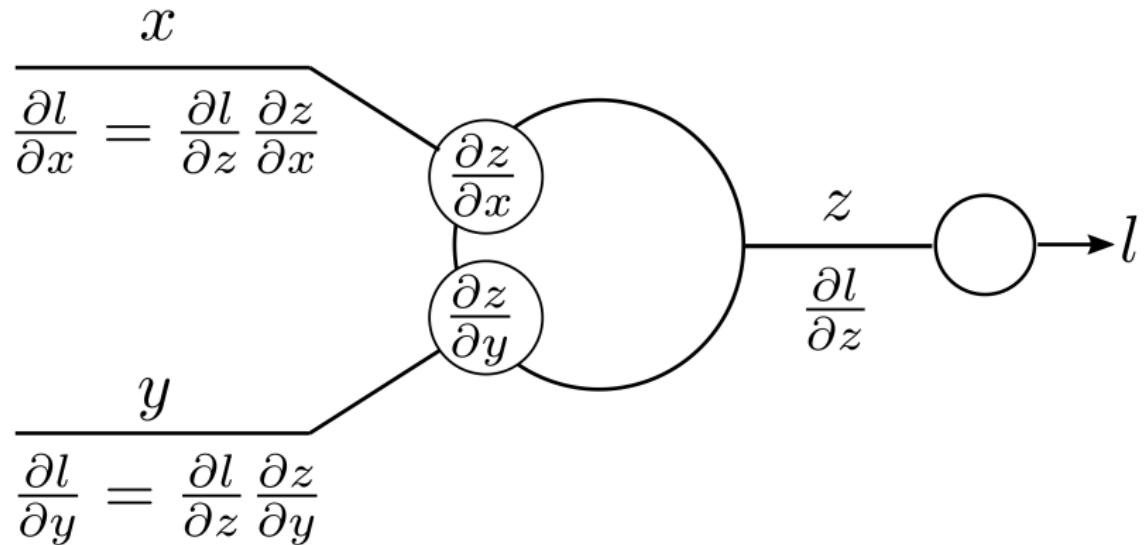
Simple backpropagation example



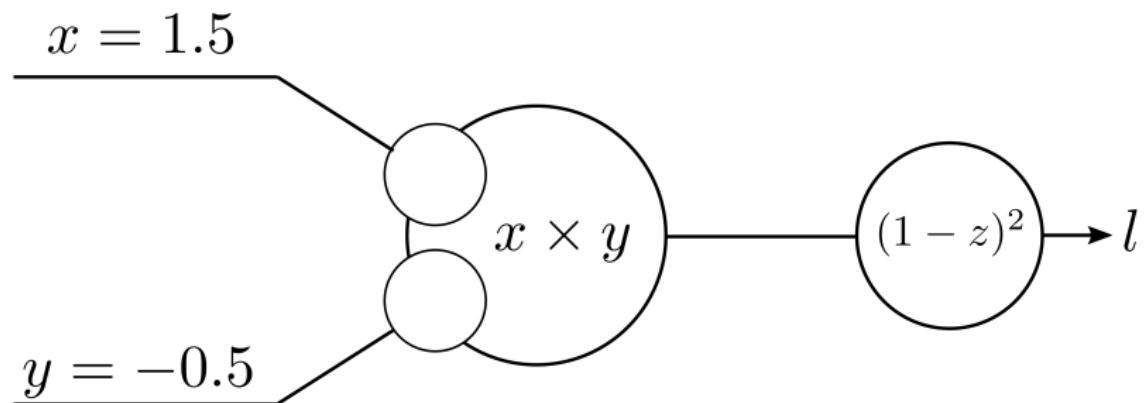
Simple backpropagation example

$$\begin{array}{ccccccc} & \frac{\partial y}{\partial x} & & \frac{\partial z}{\partial y} & & \frac{\partial l}{\partial z} & \\ x & \xrightarrow{\hspace{1cm}} & y & \xrightarrow{\hspace{1cm}} & z & \xrightarrow{\hspace{1cm}} & l \\ \frac{\partial l}{\partial x} = \frac{\partial l}{\partial y} \frac{\partial y}{\partial x} & & \frac{\partial l}{\partial y} = \frac{\partial l}{\partial z} \frac{\partial z}{\partial y} & & \frac{\partial l}{\partial z} = \frac{\partial l}{\partial l} \frac{\partial l}{\partial z} & & \frac{\partial l}{\partial l} = 1 \end{array}$$

Backpropagation through a neuron



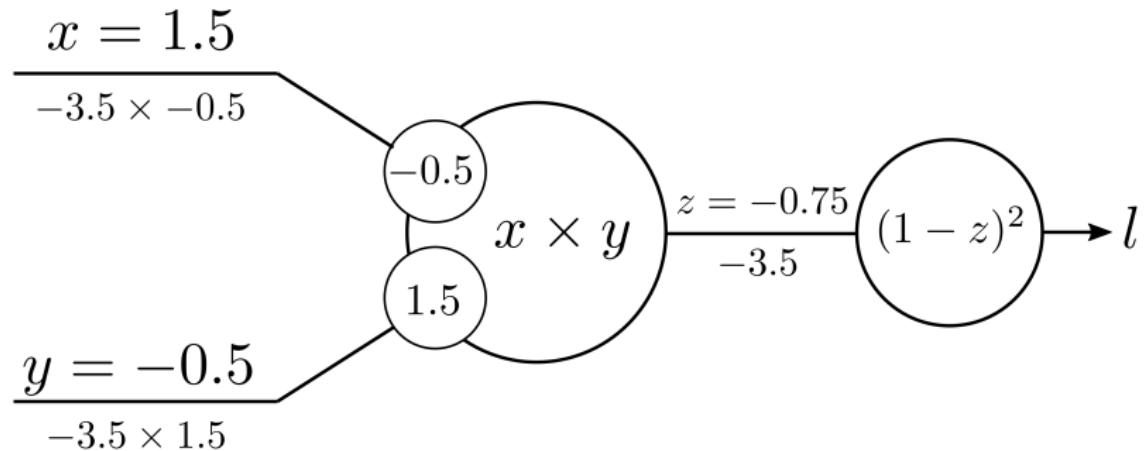
Exercise 1



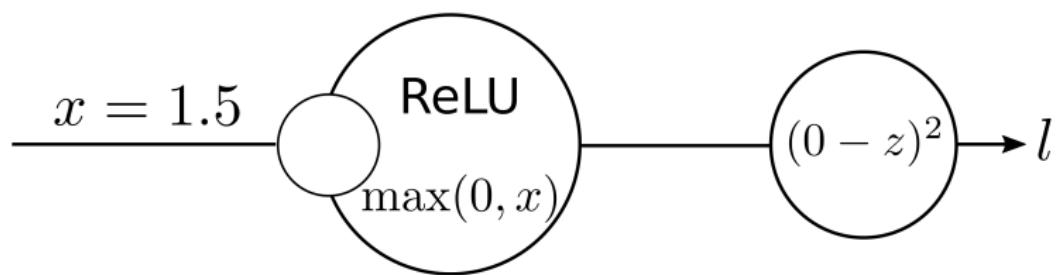
$\frac{\partial l}{\partial x}$ is equal to:

- A/ 1.75
- B/ -2.25
- C/ -1.5
- D/ 0.75

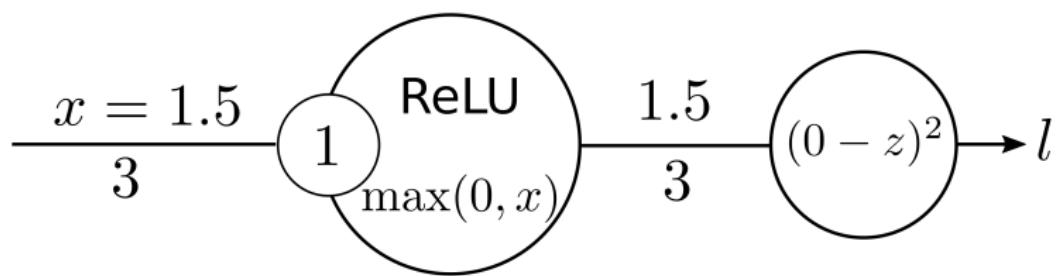
Exercise 1: solution



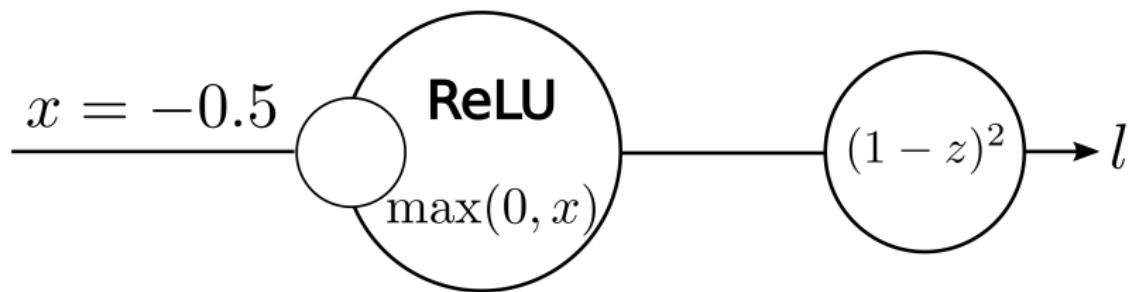
Exercise 2



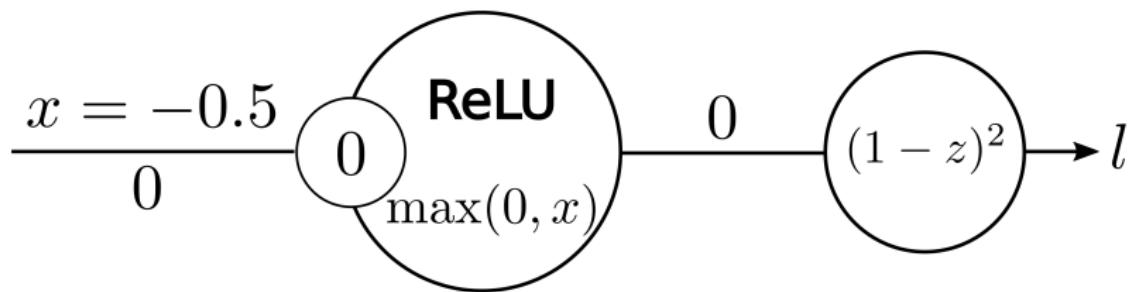
Exercise 2: solution



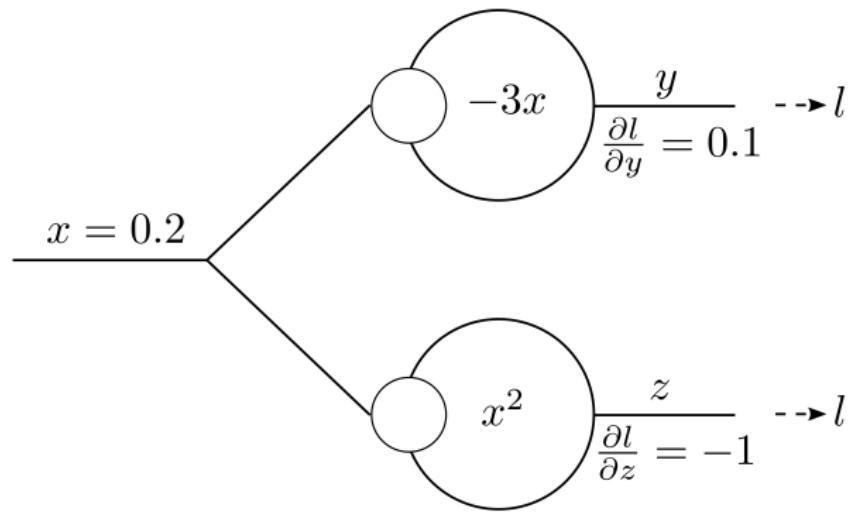
Exercise 3



Exercise 3: solution



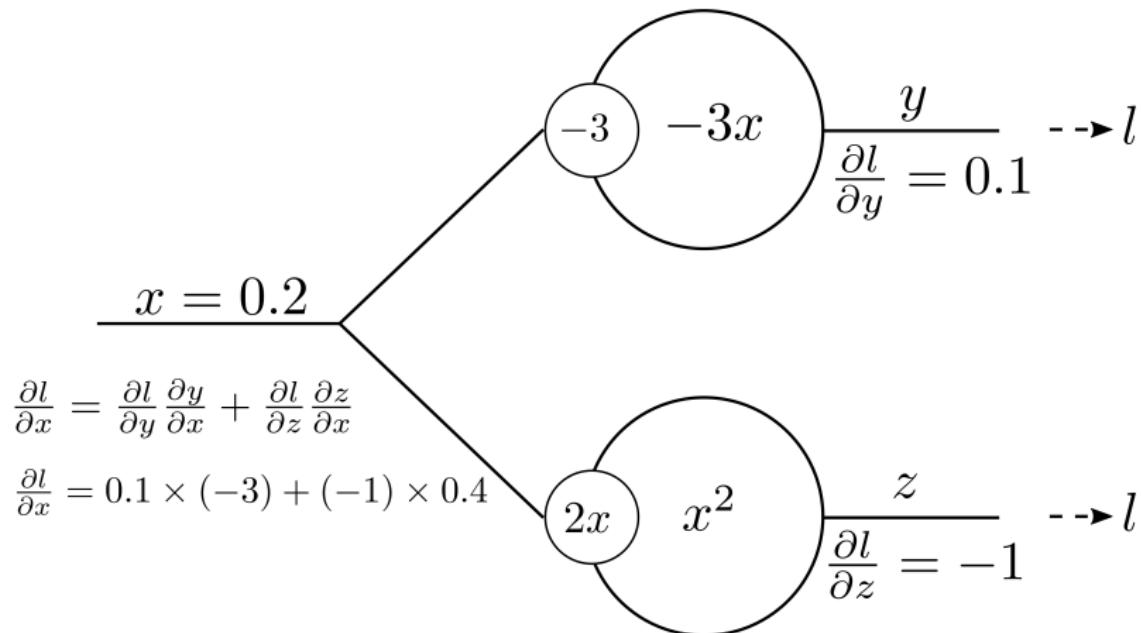
Exercise 4



Quizz

What's the value of $\frac{\partial l}{\partial x}$?

Exercise 4: solution



Vector calculus

- L and V are differentiable functions.

$$L : \mathbb{R}^n \longrightarrow \mathbb{R}$$

$$\mathbf{x} \longmapsto L(\mathbf{x})$$

Gradient

$$\nabla_{\mathbf{x}} L = \frac{\partial L}{\partial \mathbf{x}} = \left(\frac{\partial L}{\partial x_1}, \dots, \frac{\partial L}{\partial x_n} \right)$$

Vector calculus

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Gradient

$$\nabla_{\mathbf{x}} L = \frac{\partial L}{\partial \mathbf{x}} = \left(\frac{\partial L}{\partial x_1}, \dots, \frac{\partial L}{\partial x_n} \right)$$

$$V : \mathbb{R}^p \longrightarrow \mathbb{R}^q$$

$$\mathbf{y} \longmapsto V(\mathbf{y})$$

Jacobian

$$J(V) = \frac{\partial V}{\partial \mathbf{y}} = \begin{pmatrix} \frac{\partial V_1}{\partial y_1} & \cdots & \frac{\partial V_1}{\partial y_p} \\ \vdots & \ddots & \vdots \\ \frac{\partial V_q}{\partial y_1} & \cdots & \frac{\partial V_q}{\partial y_p} \end{pmatrix}$$

Matrix calculus

- Function \mathcal{M} is differentiable.

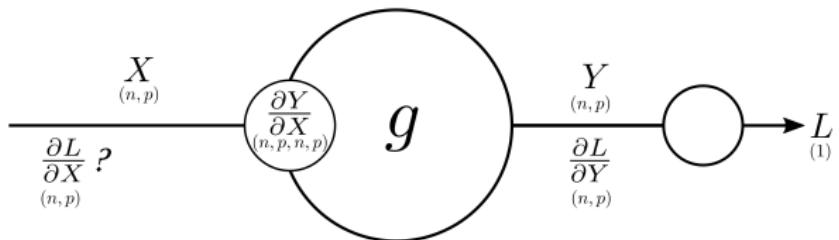
$$\mathcal{M} : \mathbb{R}^{(m,n)} \longrightarrow \mathbb{R}^{(p,q)}$$

$$\mathbf{X} \longmapsto \mathcal{M}(M)$$

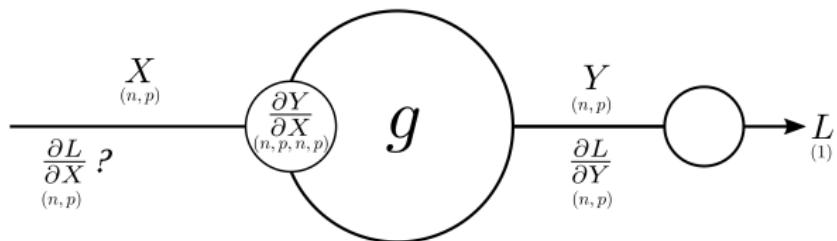
$$\frac{\partial \mathcal{M}}{\partial \mathbf{X}} = \begin{pmatrix} \frac{\partial \mathcal{M}_{1,1}}{\partial \mathbf{X}} & \dots & \frac{\partial \mathcal{M}_{1,q}}{\partial \mathbf{X}} \\ \vdots & \ddots & \vdots \\ \frac{\partial \mathcal{M}_{p,q}}{\partial \mathbf{X}} & \dots & \frac{\partial \mathcal{M}_{p,q}}{\partial \mathbf{X}} \end{pmatrix}$$

This is an array of size (m, n, p, q) .

Backpropagation through an activation function g

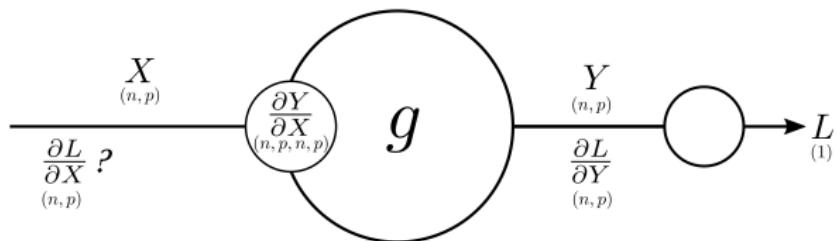


Backpropagation through an activation function g



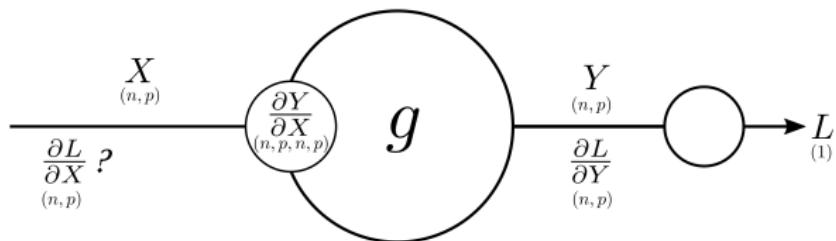
- Computing the full matrix $\frac{\partial \mathbf{Y}}{\partial \mathbf{X}}$ is impractical

Backpropagation through an activation function g



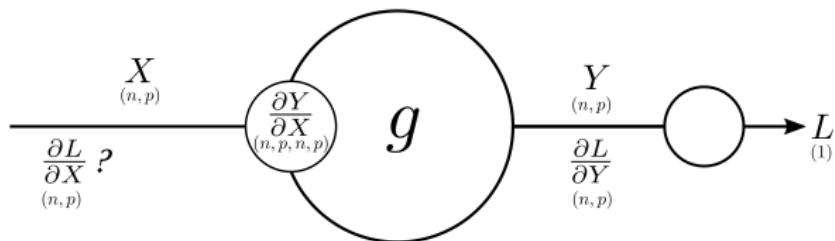
- Computing the full matrix $\frac{\partial \mathbf{Y}}{\partial \mathbf{X}}$ is impractical
- But here $Y_{i,j}$ only depends on $X_{i,j}$: $Y_{i,j} = g(X_{i,j})$

Backpropagation through an activation function g



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- Therefore: $\frac{\partial \mathbf{Y}_{i,j}}{\partial \mathbf{X}_{i,j}} = g'$.

Backpropagation through an activation function g

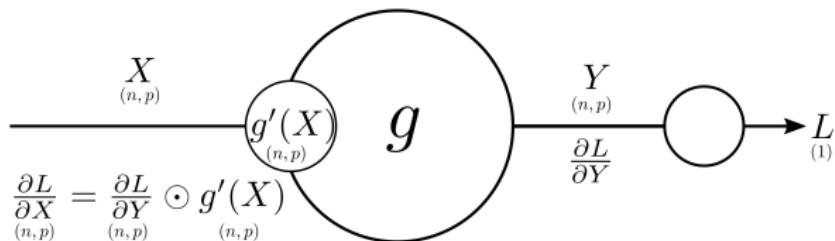


- Computing the full matrix $\frac{\partial \mathbf{Y}}{\partial \mathbf{X}}$ is impractical
- But here $Y_{i,j}$ only depends on $X_{i,j}$: $Y_{i,j} = g(X_{i,j})$
- Therefore: $\frac{\partial \mathbf{Y}_{i,j}}{\partial \mathbf{X}_{i,j}} = g'$.
- Finally:

$$\frac{\partial L}{\partial \mathbf{X}} = \frac{\partial L}{\partial \mathbf{Y}} \odot g'(\mathbf{X}),$$

where \odot is the term by term matrix multiplication or Hadamard matrix multiplication.

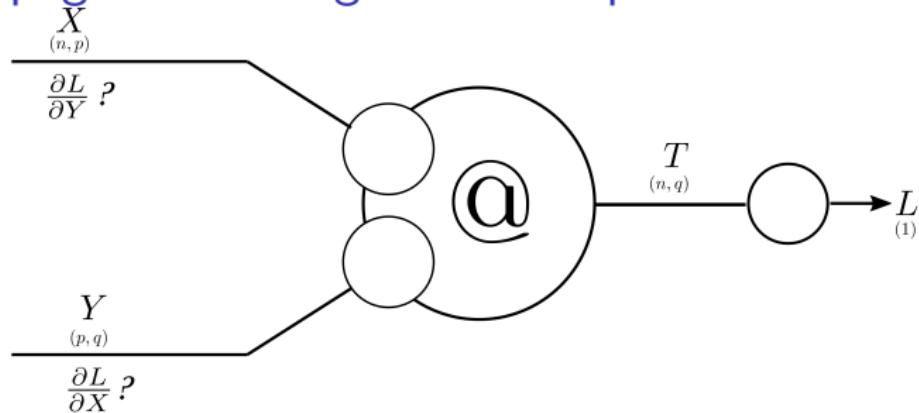
Backpropagation through an activation function g



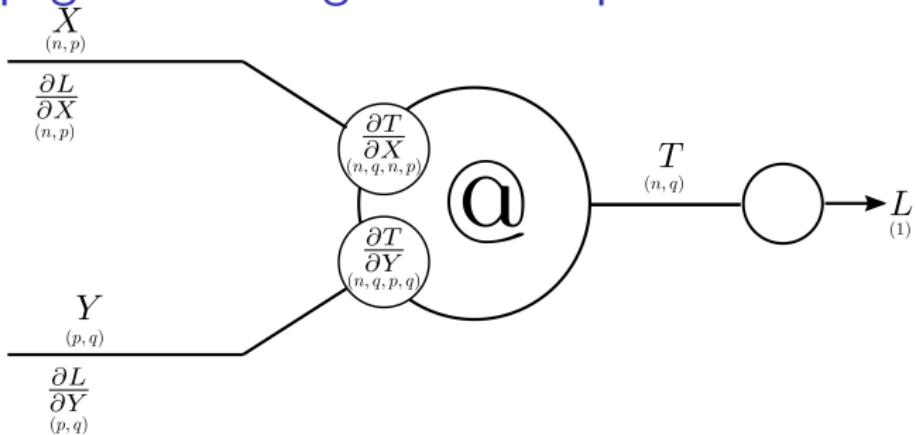
We will abusively write:

$$\frac{\partial \mathbf{Y}}{\partial \mathbf{X}} = \mathbf{g}'(\mathbf{X})$$

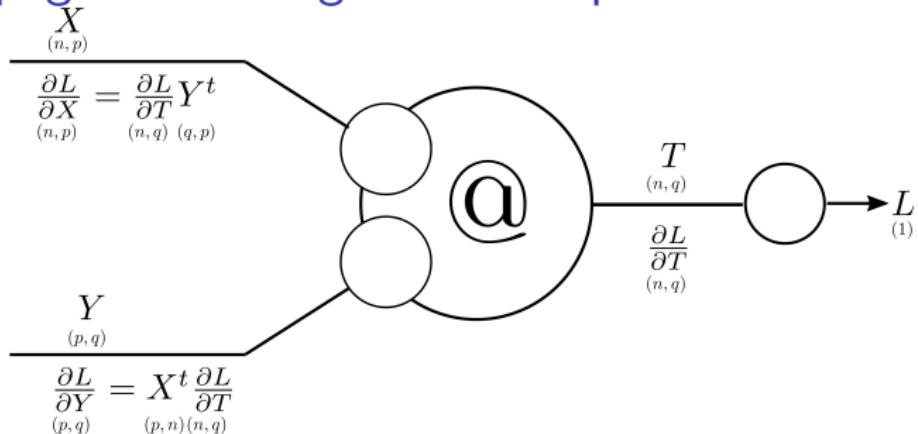
Backpropagation through a matrix product



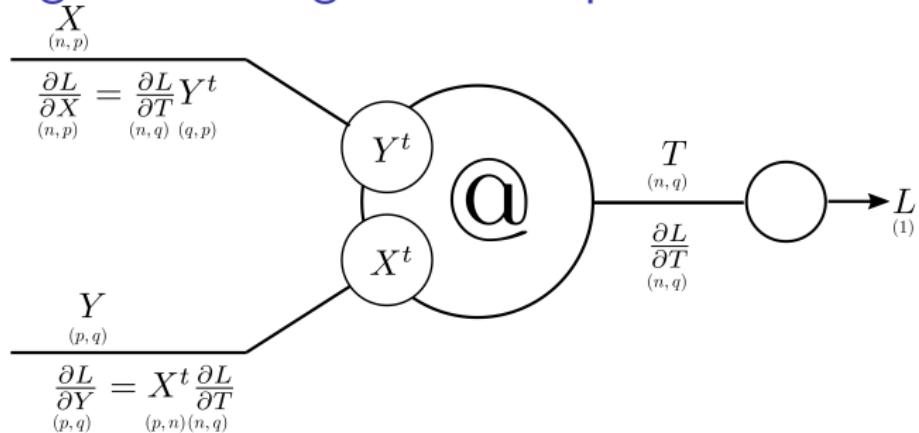
Backpropagation through a matrix product



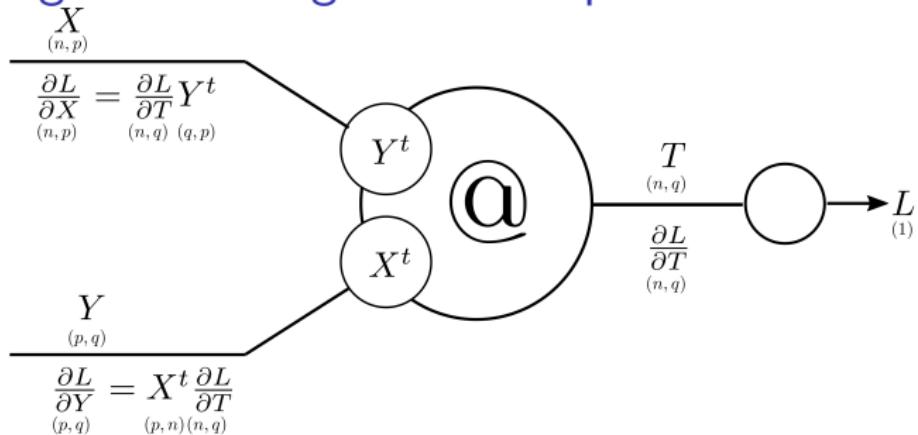
Backpropagation through a matrix product



Backpropagation through a matrix product

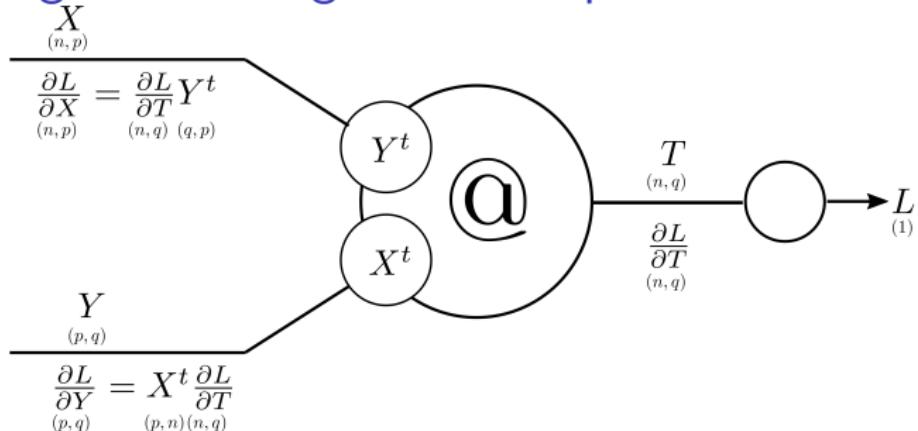


Backpropagation through a matrix product



In fact this is the only way you can make the shapes match.

Backpropagation through a matrix product



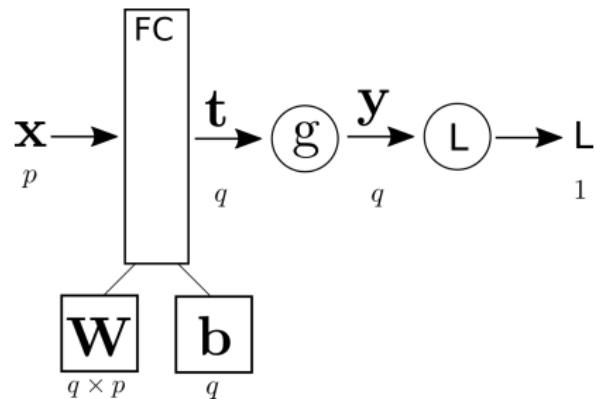
In fact this is the only way you can make the shapes match.

We will abusively write, **only for matrix multiplication**:

$$\frac{\partial \mathbf{T}}{\partial \mathbf{X}} = \mathbf{Y}^t$$

$$\frac{\partial \mathbf{T}}{\partial \mathbf{Y}} = \mathbf{X}^t$$

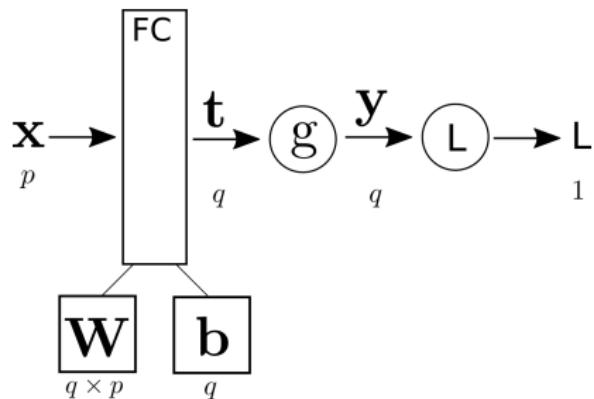
Backpropagation through a fully connected layer



Setup:

$$p, q \in \mathbb{N}^*$$
$$\mathbf{x} \in \mathbb{R}^p$$
$$\mathbf{W} \in \mathbb{R}^q \times \mathbb{R}^p$$
$$\mathbf{b}, \mathbf{t}, \mathbf{y} \in \mathbb{R}^q$$
$$L \in \mathbb{R}$$

Backpropagation through a fully connected layer



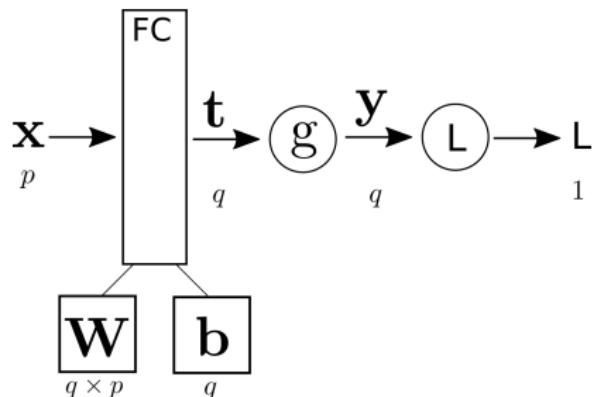
Forward pass:

$$\mathbf{t} = \mathbf{W}\mathbf{x} + \mathbf{b}$$

$$\mathbf{y} = g(\mathbf{W}\mathbf{x} + \mathbf{b})$$

$$L = L(\mathbf{y})$$

Backpropagation through a fully connected layer



Local gradients:

Forward pass:

$$\mathbf{t} = \mathbf{W}\mathbf{x} + \mathbf{b}$$

$$\mathbf{y} = g(\mathbf{W}\mathbf{x} + \mathbf{b})$$

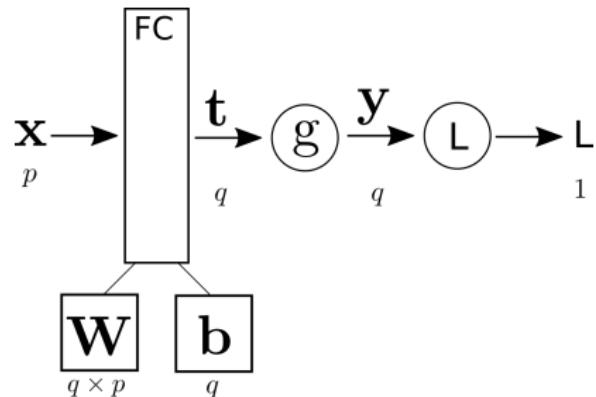
$$L = L(\mathbf{y})$$

$$\frac{\partial \mathbf{t}}{\partial \mathbf{W}} = \mathbf{x}^t$$

$$\frac{\partial \mathbf{t}}{\partial \mathbf{b}} = Id_{(q)}$$

$$\frac{\partial \mathbf{y}}{\partial \mathbf{t}} = g'(\mathbf{t})$$

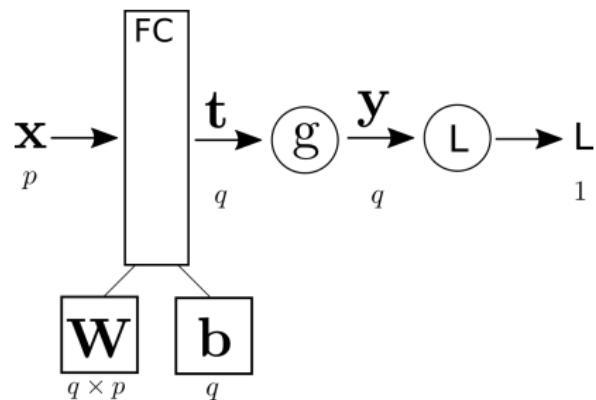
Backpropagation through a fully connected layer



Backpropagation:

$$\begin{aligned}\frac{\partial L}{\partial \mathbf{t}} &= \frac{\partial L}{\partial \mathbf{y}} \cdot \frac{\partial \mathbf{y}}{\partial \mathbf{t}} \\ &= \frac{\partial L}{\partial \mathbf{y}} \odot g'(\mathbf{t})\end{aligned}$$

Backpropagation through a fully connected layer



Backpropagation:

$$\begin{aligned}\frac{\partial L}{\partial \mathbf{W}} &= \frac{\partial L}{\partial \mathbf{t}} \cdot \frac{\partial \mathbf{t}}{\partial \mathbf{W}} \\ &= \frac{\partial L}{\partial \mathbf{y}} \odot g'(\mathbf{t}) \cdot \mathbf{x}^t\end{aligned}$$

$$\begin{aligned}\frac{\partial L}{\partial \mathbf{b}} &= Id^t \cdot \frac{\partial L}{\partial \mathbf{t}} \\ &= \frac{\partial L}{\partial \mathbf{y}} \odot g'(\mathbf{t})\end{aligned}$$

Contents

1 Artificial neurons

2 Artificial neural networks

3 Training a neural network

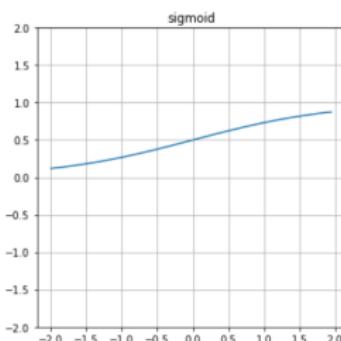
- Loss functions
- Gradient descent
- Backpropagation
- Weights initialization

4 Conclusion

Network parameters initialization

General idea

Inputs of activation functions should be in a range such that gradients are high.



- Bias are set to zero
- If weights are also initialized to zero, then in each layer the activations will remain equal – symmetry will never be broken
- Empirical solutions are based on a gaussian distribution of the weights, with *small* standard deviation.

Network parameters initialization: current practice

- [Glorot and Bengio, 2010]: they empirically show that a standard deviation of $1/\sqrt{n}$ gives good results (where n is the number of inputs of a neuron)
- [He et al., 2015]: in the case of ReLU activations, they recommend a $2/\sqrt{n}$ standard deviation

Contents

- 1 Artificial neurons
- 2 Artificial neural networks
- 3 Training a neural network
- 4 Conclusion

Conclusion

We have seen:

- What is an artificial neuron and an artificial neural network (NN)
- The (potential) power of a NN
- The backpropagation algorithm
- NN learning basics

Next step:

- Application to images

References |

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