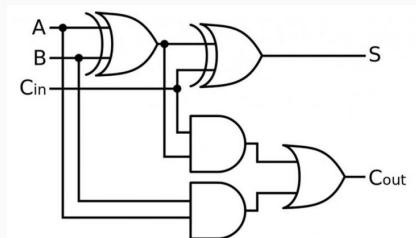
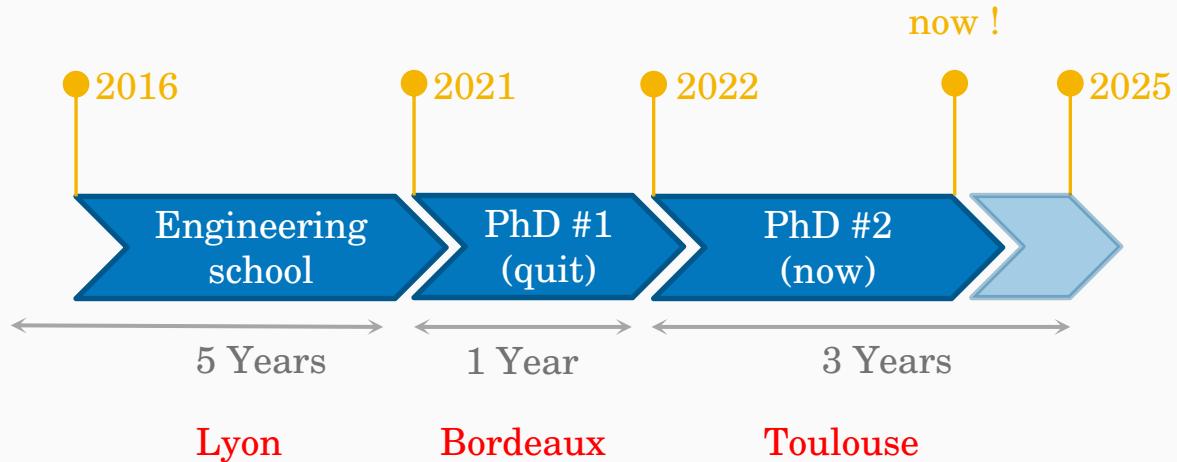


Modelling the Dynamics of Sensory Neural Responses

For low-level modelling of the brain

Ulysse Rançon
ulysses.rancon@cnrs.fr

My background



Outline

- I. What is a model ?
- II. Models of neurons / Spiking Neural Networks (SNNs)
- III. Neuromorphic computing and sensing
- IV. Conclusion

Little to no maths

Large overview

Main keywords



Starting point for self-study !

What is modelling (“modélisation”) ?

Taking a step back

A very difficult question : *What is a model ?*

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Essentially a **description of reality**

A “model” can be... just **anything** !

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***“The more I drink
coffee, the less I sleep”***

*even just an
idea...!*

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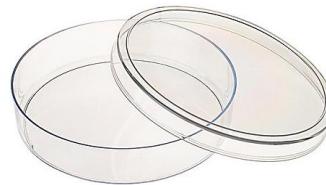
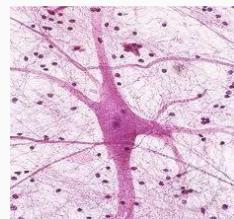
a computer simulation of many small agents thinking they have a life on their own...

$$\Delta U = Q - W$$

a physics formula...



a live animal...



***in vitro* neurons** in a petri dish, extracted from animals (therefore killing them)...

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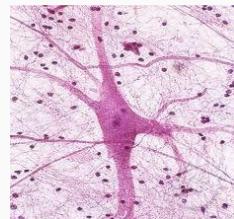
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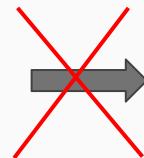
***in vitro* neurons** in a petri dish, extracted from animals (therefore killing them)...

How to choose my model ?

Depends on what you are working on...

“The more I drink coffee, the less I sleep”

*even just **an idea...**!*



NO !

$$\Delta U = Q - W$$

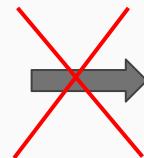
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“The more I drink coffee, the less I sleep”

*even just **an idea...**!*



NO !

$$\Delta U = Q - W$$

*a **physics formula...***

A GOOD model:

- provides a **quantitative description** of a feature, a phenomenon
- a **qualitative description**
- **inside and outside the scope** of what served to conceive it

It must be also:

- as **simple** as possible (*Occam's razor*)
- easily **expandable**

Abstraction levels when modelling

...And how much detail you want to capture !

"The more I drink coffee, the less I sleep"



Because of caffeine



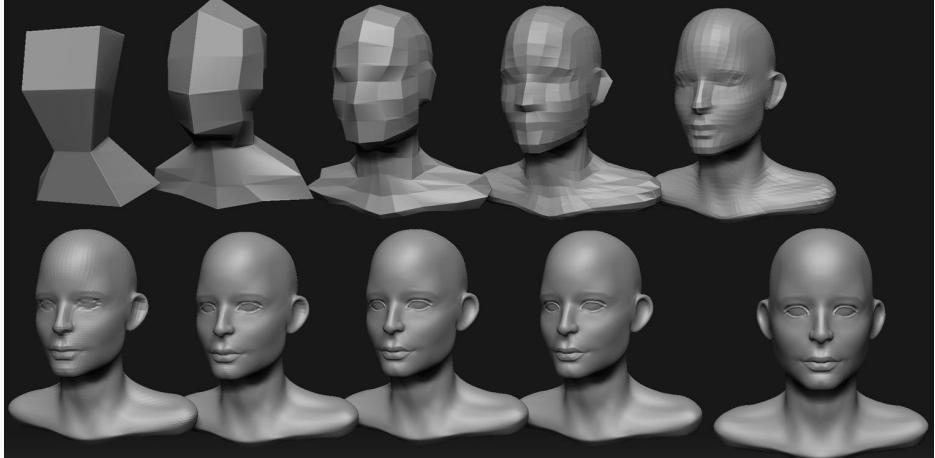
Theory of how caffeine is digested



Depends on many factors:

- ***amount in the coffee cup***
- ***person constitution***
- ***time of the day/night***
- ...

...
...



The essence of modelling: Question

“All models are wrong, but some are __(?)__”

George Box (1919-2013)



“What I cannot __(?)__, I cannot understand”

Richard Feynman (1918-1988)

The essence of modelling: Answers

*“All models are wrong, but some are **useful**”*

George Box (1919-2013)



*“What I cannot **create**, I cannot understand”*

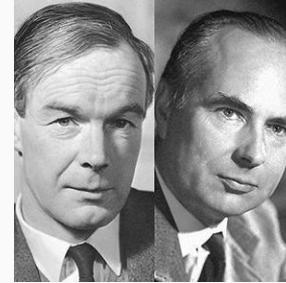
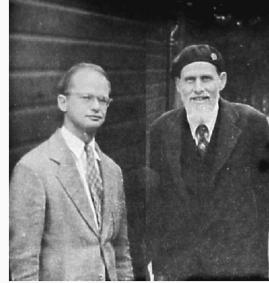
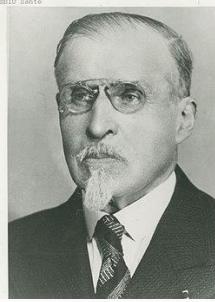
Richard Feynman (1918-1988)

Models of Biological Neurons /

Spiking Neural Networks (SNNs)

According to you, what does this mean ?

A short history of computational neuroscience



now !



1906



1907



1943



1952

...



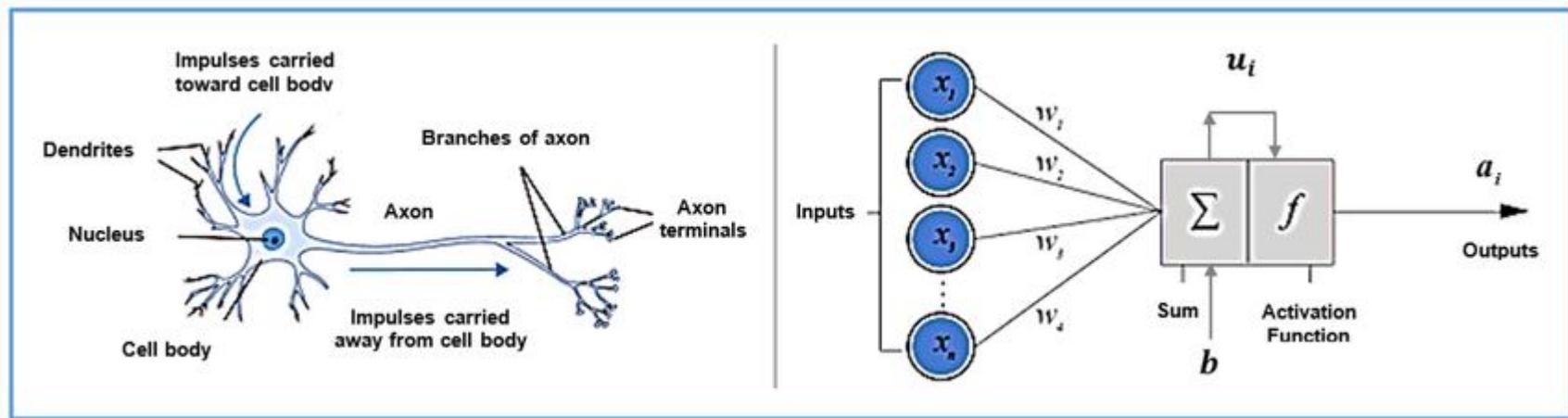
Ramon y Cajal
discovery of neurons

McCulloch & Pitts
the Perceptron

Louis Lapicque
Integrate-and-Fire
(IF) model

Hodgkin & Huxley
Eponymous model

The McCulloch & Pitts model



Supposed to mimick how actual neurons work:

- receive weighted contributions of several presynaptic inputs (electrical currents)
- **integrates** (i.e. sum) them
- outputs a (nonlinear) activation

The McCulloch & Pitts model

Q: Who can write the equation for this model ?

The McCulloch & Pitts model

Q: Who can write the equation for this model ?

$$a = f(\sum_i w_i x_i + b)$$

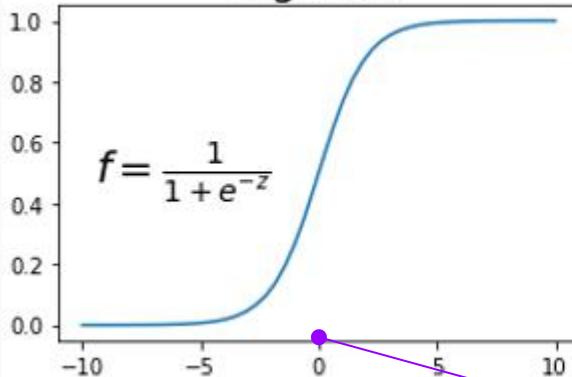
The McCulloch & Pitts model

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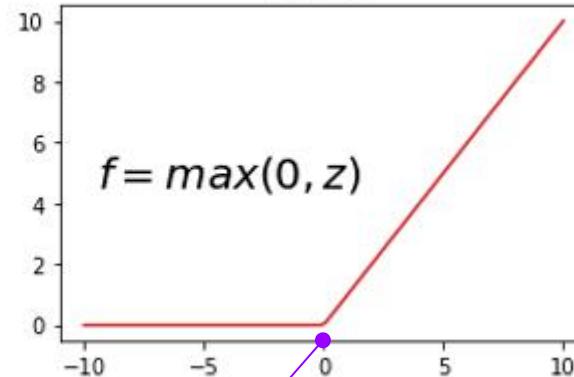
$$a = f\left(\sum_i w_i x_i + b\right)$$

in previous classes / in deep learning, f was / is a **sigmoid** or **ReLU**

Sigmoid



ReLU



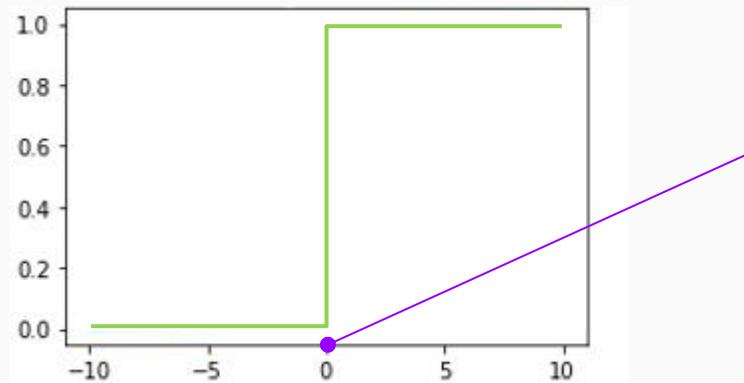
change of behavior

The McCulloch & Pitts model

Q: Who can write the equation for this model ?

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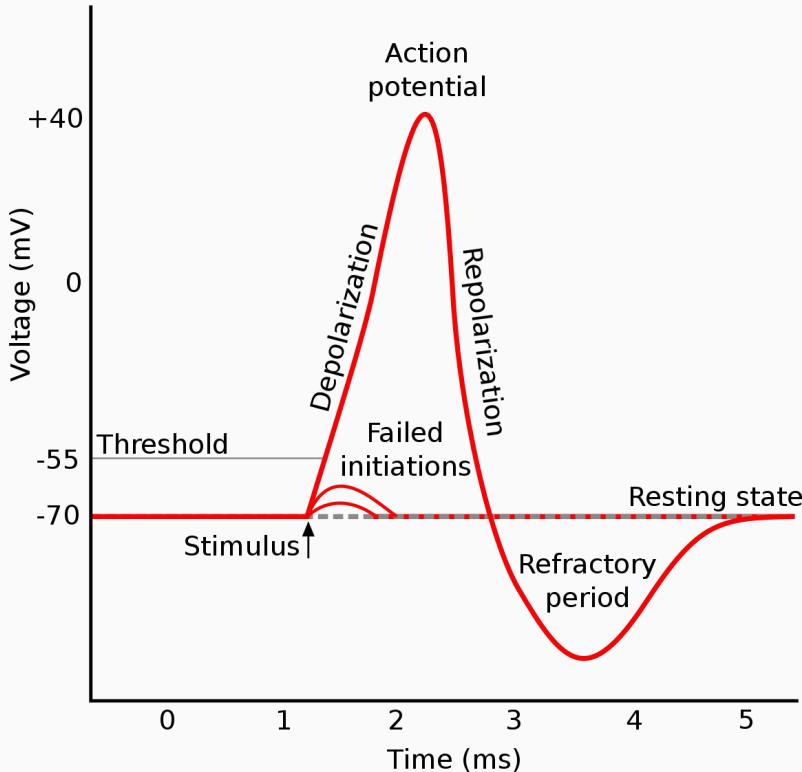
in the MCP model, it is a **Heaviside** function !



change of behavior (again) at a certain
threshold θ (here: 0)

The output is **All or nothing** / 1 or 0 !

Spikes / Action potentials

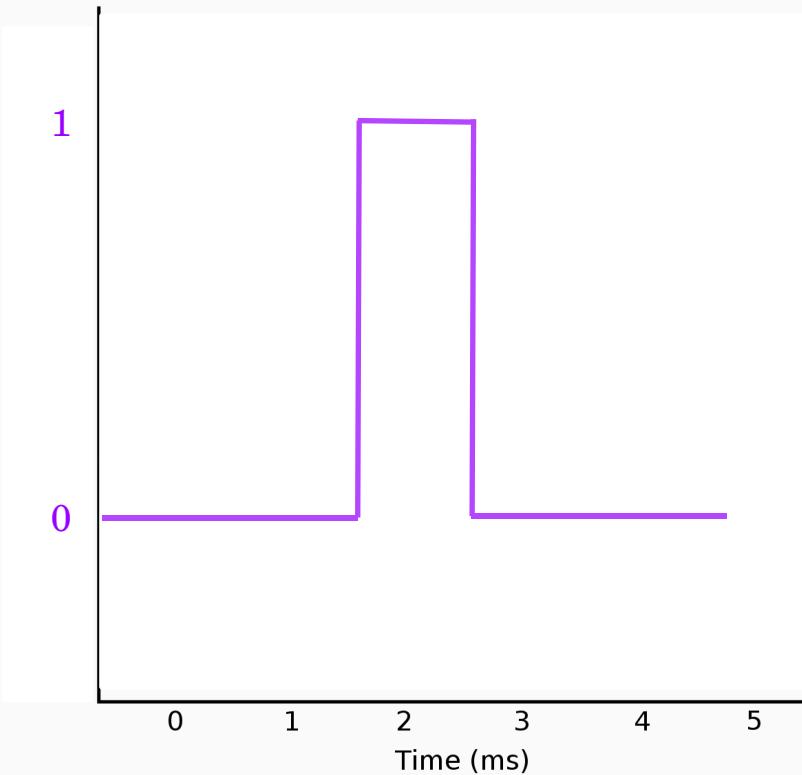
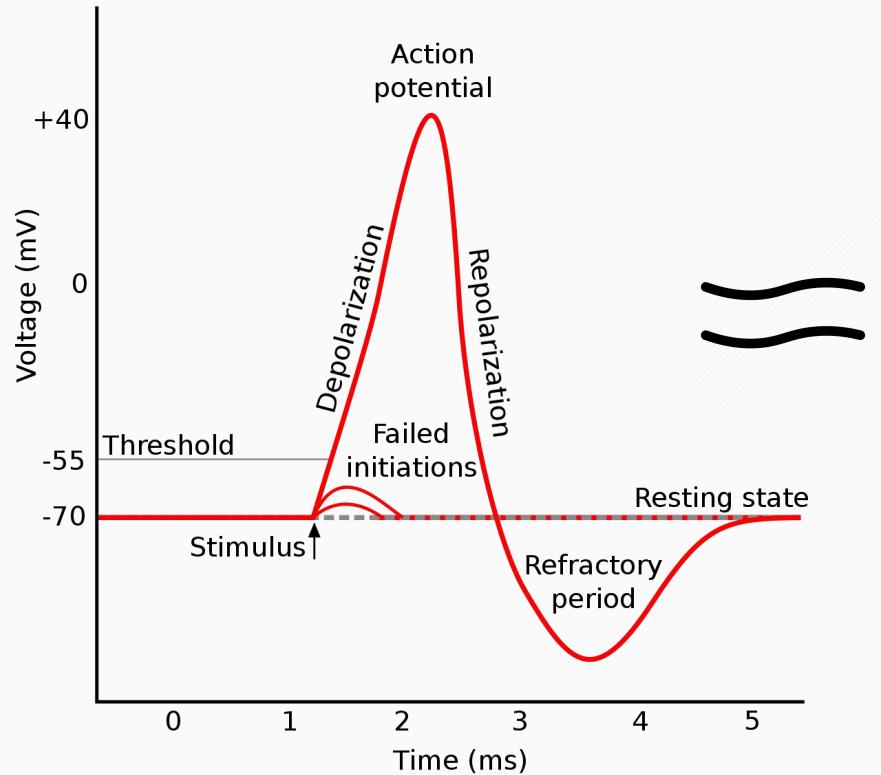


Real biological neurons emit **spikes**: stereotyped electrical impulses (“all-or-none”) emitted when a neuron is sufficiently stimulated

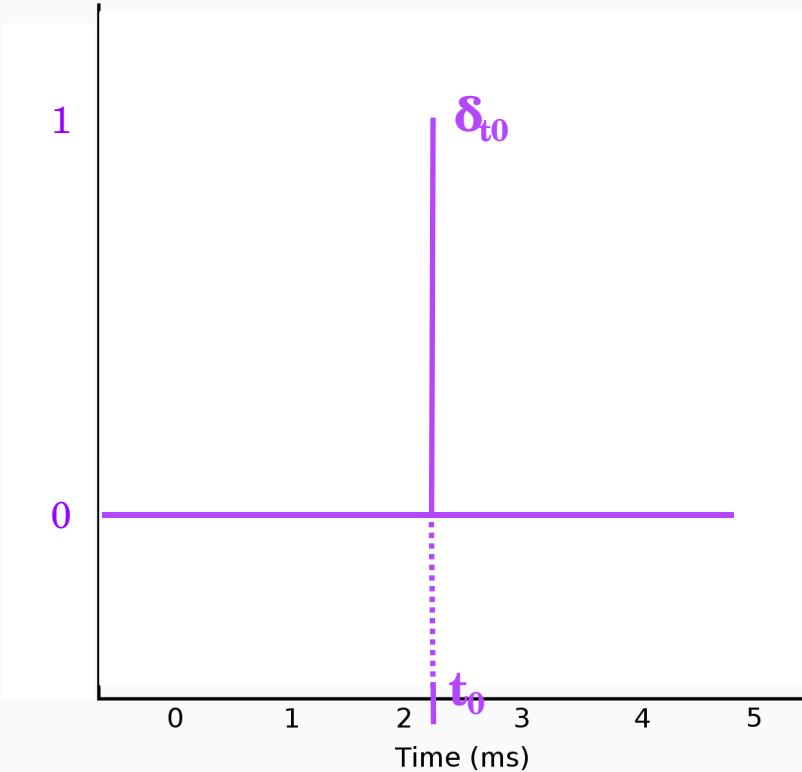
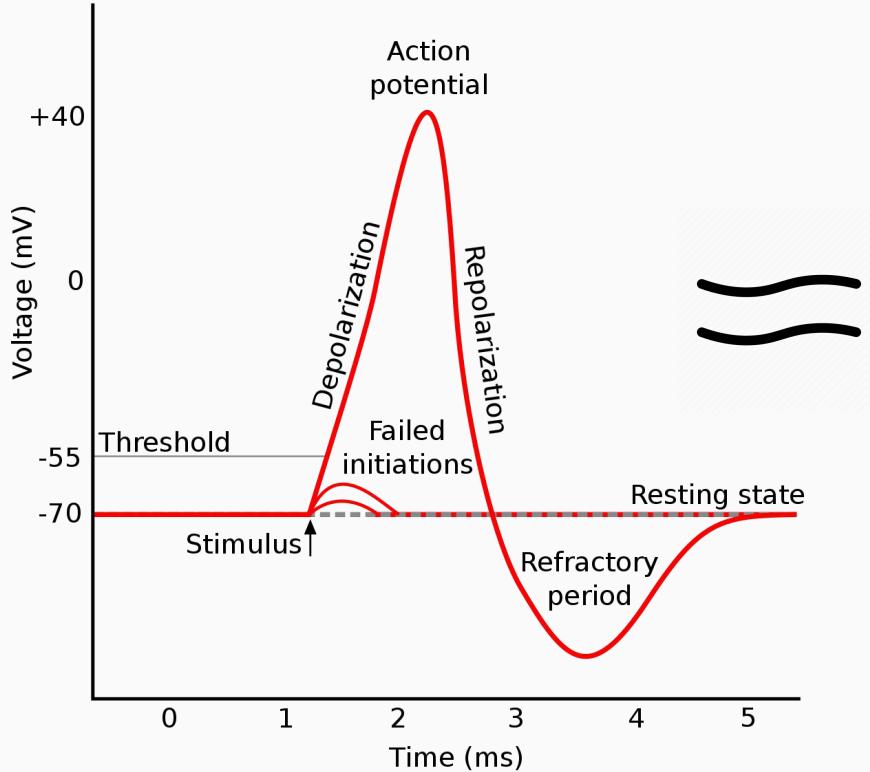
Spikes propagate along the **axons** without attenuation (“active propagation”).

Neurons can only exchange information via binary spikes

Spikes / Action potentials



Spikes / Action potentials



The Integrate and Fire (IF) neuron model

What was lacking in the MCP model, is a **memory trace**

The state of a neuron at a given instant directly depends on its previous state (makes sense, no ?), i.e. they are **recurrent**

In reality, biological neurons are characterized by the **membrane potential** V which has a **resting value** V_{rest}

Let's complexify the MCP model a bit:

(Potential update)

$$V_t = V_{t-1} - \sum_i w_i x_i$$

(Spike at time t)

$$S_t = H(V_t - \theta)$$

(Reset condition)

$$V_t > \theta \longrightarrow V_t = V_{rest}$$

*Integrate-and-Fire (IF) spiking model
(discrete time equation)*

Complexifying the IF with a refractory period

Real neurons have a **refractory period**:

their membrane potential is maintained to V_{rest} during T time-steps after a spike

$$V_t = V_{t-1} - \sum_i w_i x_i$$

$$S_t = H(V_t - \theta)$$

$$V_t > \theta \longrightarrow V_t = V_{rest}$$

$$t - t_{\text{last spike}} < T \longrightarrow V_t = V_{rest}$$

(Refractoriness)

refractory IF

Towards the Leaky-Integrate and Fire (LIF) neuron model

In real neurons, the membrane potential **leaks** back to its rest value :
their membrane potential is maintained to V_{rest} during T time-steps after a spike

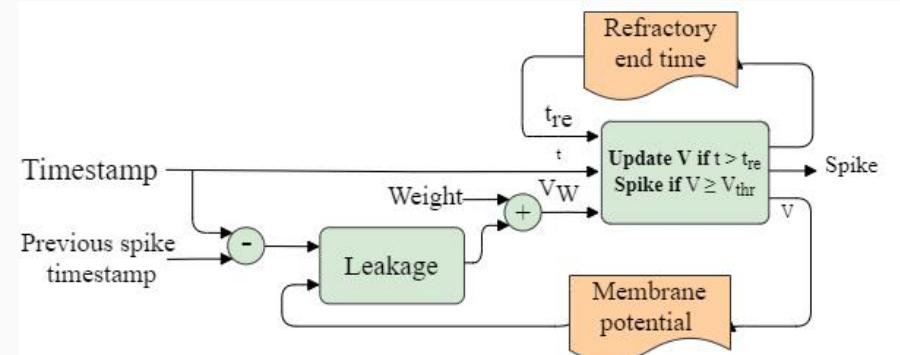
refractory LIF

$$V_t = V_{t-1} + \sum_i w_i x_i - \frac{1}{\tau} V_{t-1}$$

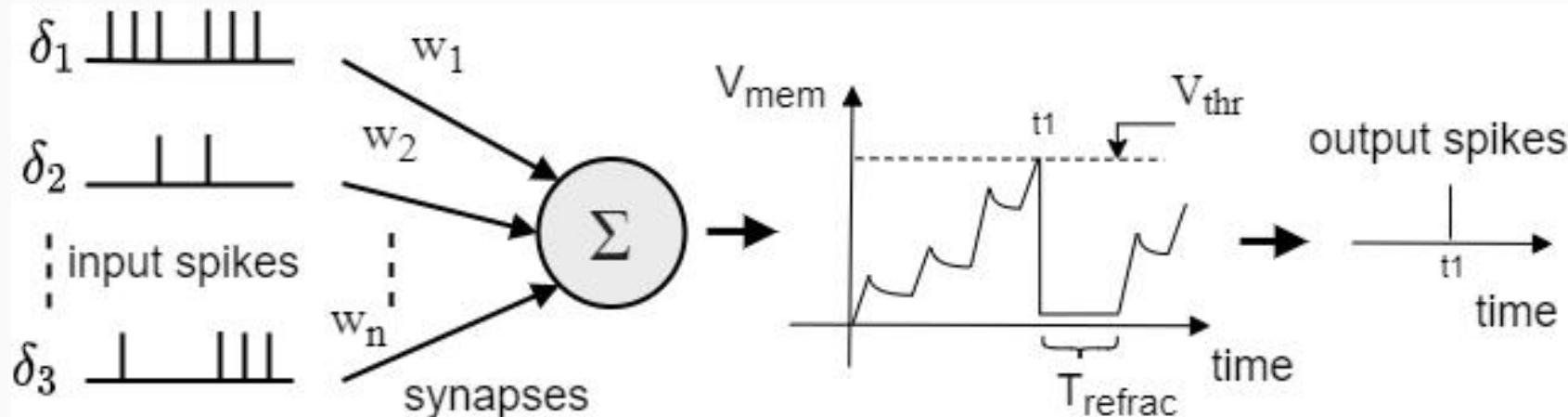
$$S_t = H(V_t - \theta)$$

$$V_t > \theta \rightarrow V_t = V_{rest}$$

$$t - t_{\text{last spike}} < T \rightarrow V_t = V_{rest}$$



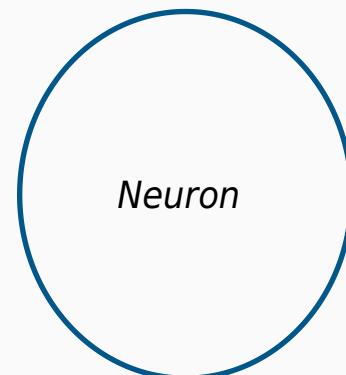
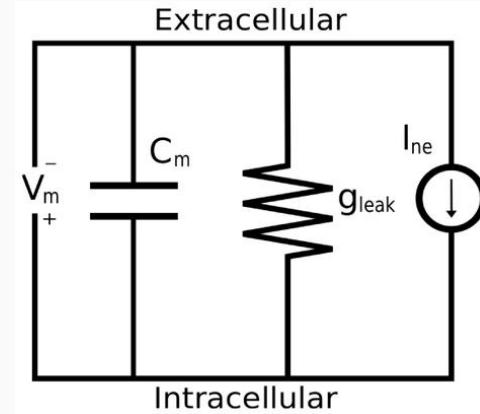
Example LIF behavior



Electrical analogy

The LIF model comes from **biophysics** !

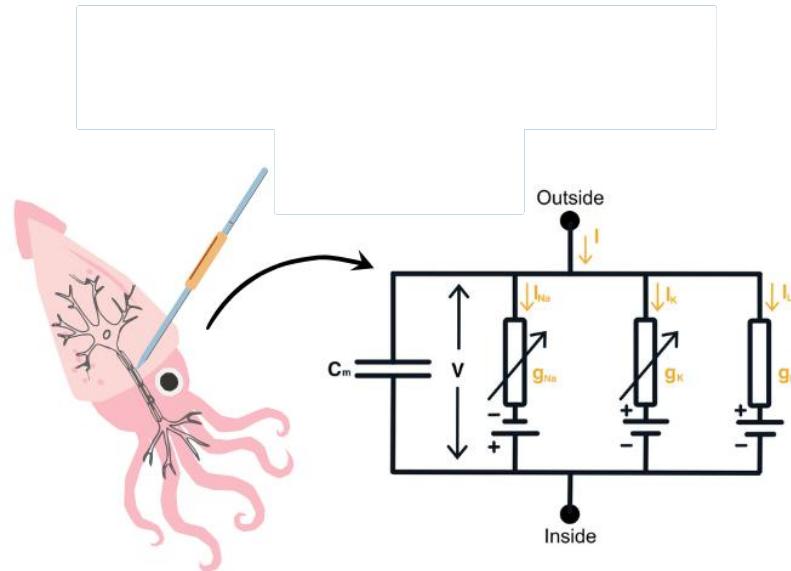
- Biological neurons are **electrically charged**: difference in potential between the inside and the outside of the cell = membrane potential
- **Ion channels** act as a Resistance
- Act as a **RC circuit** (Resistive & Capacitive)



The Hodgkin-Huxley model

1952:

- H&H experiment on the giant squid axon
- Elaboration of a model with 3 ionic channels



<https://perceptron.blog/hodgkin-huxley/>

1963:

Nobel prize in Physiology or Medicine



The Hodgkin-Huxley model

$$C \frac{dV}{dt} = -G_L(V - V_L) - G_{Na}m^3h(V - E_{Na}) - G_Kn^4(V - E_K) + I_e, \quad (13)$$

where V is the membrane potential, I_e is an external current and the gating variables m , n and h obey the first-order ODEs

$$\frac{dm}{dt} = \alpha_m(V)(1 - m) - \beta_m(V)m, \quad (14)$$

$$\frac{dh}{dt} = \alpha_h(V)(1 - h) - \beta_h(V)h, \quad (15)$$

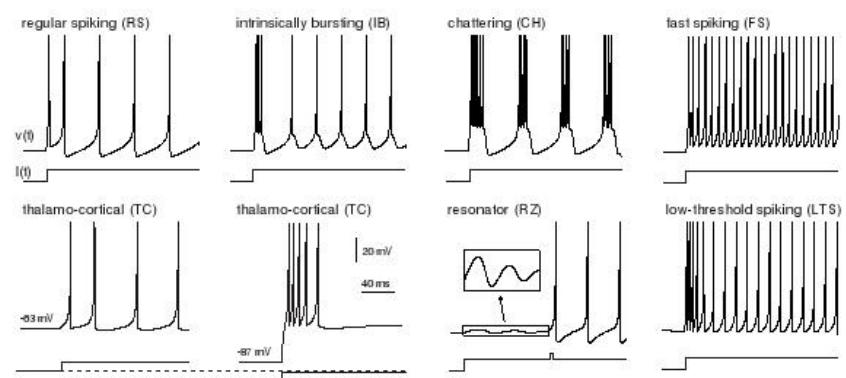
$$\frac{dn}{dt} = \alpha_n(V)(1 - n) - \beta_n(V)n, \quad (16)$$

with transition rates $\alpha(V)$ and $\beta(V)$ given by

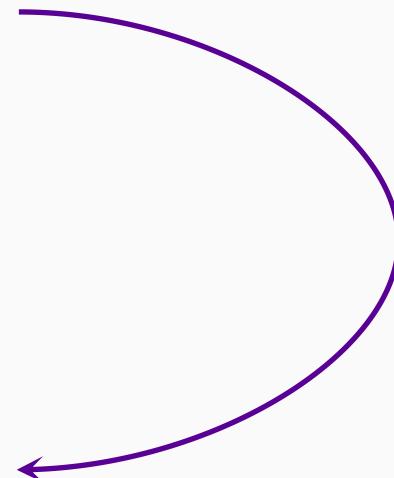
$$\alpha_m(V) = \frac{0.1(V + 40)}{1 - e^{-0.1(V + 40)}}; \quad \beta_m(V) = 4e^{-0.0556(V + 65)}, \quad (17)$$

$$\alpha_h(V) = 0.07e^{-0.05(V + 65)}; \quad \beta_h(V) = \frac{1}{1 + e^{-0.1(V + 35)}}, \quad (18)$$

$$\alpha_n(V) = \frac{0.01(V + 55)}{1 - e^{-0.1(V + 55)}}; \quad \beta_n(V) = 0.125e^{-0.0125(V + 65)}. \quad (19)$$



A very complex and precise model...

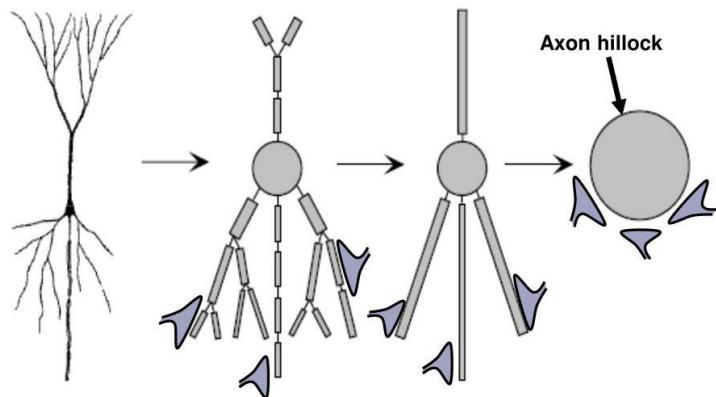


...capable of much more than the LIF !

Point vs Compartmental models

*Compartmental models take into account the neuron's **2d or 3d morphology**.*

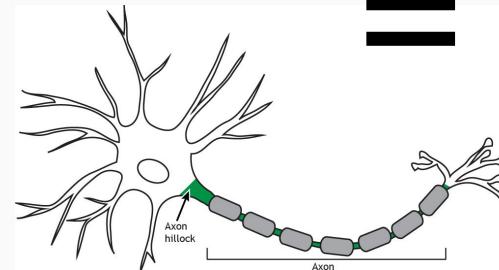
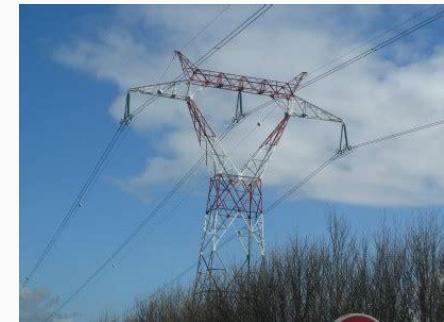
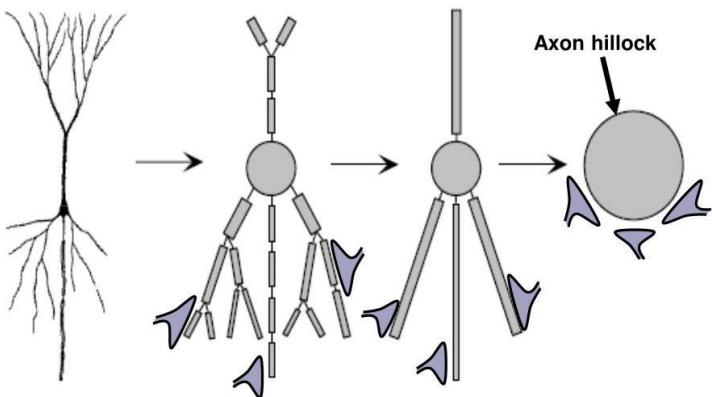
- **discretize** the axon and dendrites into N small compartments
- presynaptic neurons can be anywhere along these axes



Point vs Compartmental models

*Compartmental models take into account the neuron's **2d or 3d morphology**.*

- **discretize** the axon and dendrites into N small compartments
 - presynaptic neurons can be anywhere along these axes
 - apply the **laws of physics** (wave equation, telegrapher's equations)
- > propagation of the AP !!!

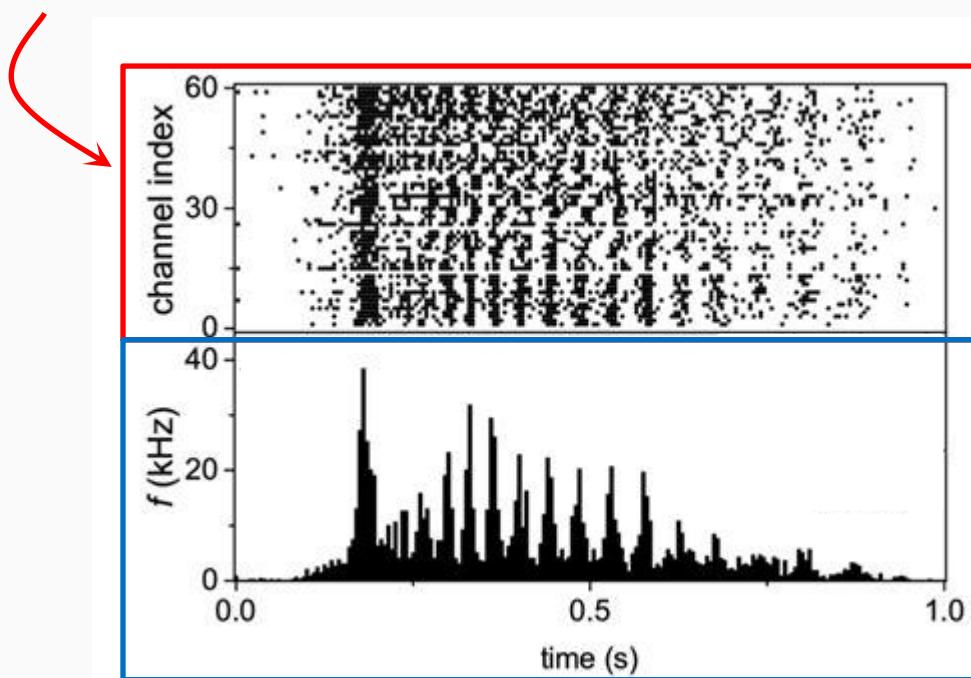


Raster plots and derivatives

Raster plot

To represent the simultaneous spiking activity (spike trains) of:

- several neurons in a population
- a single neuron over repeated trials of the same condition

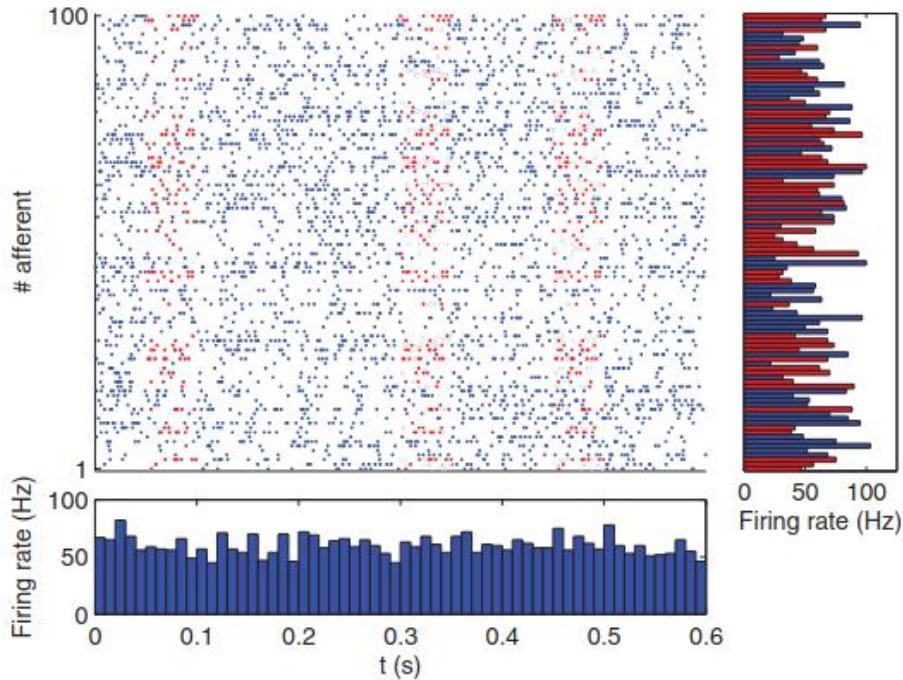


Spike histogram

Sum or average spikes over channels to give:

- population activity
- the target neuron's firing probability or firing rate

Coincidence detectors / Spike patterns

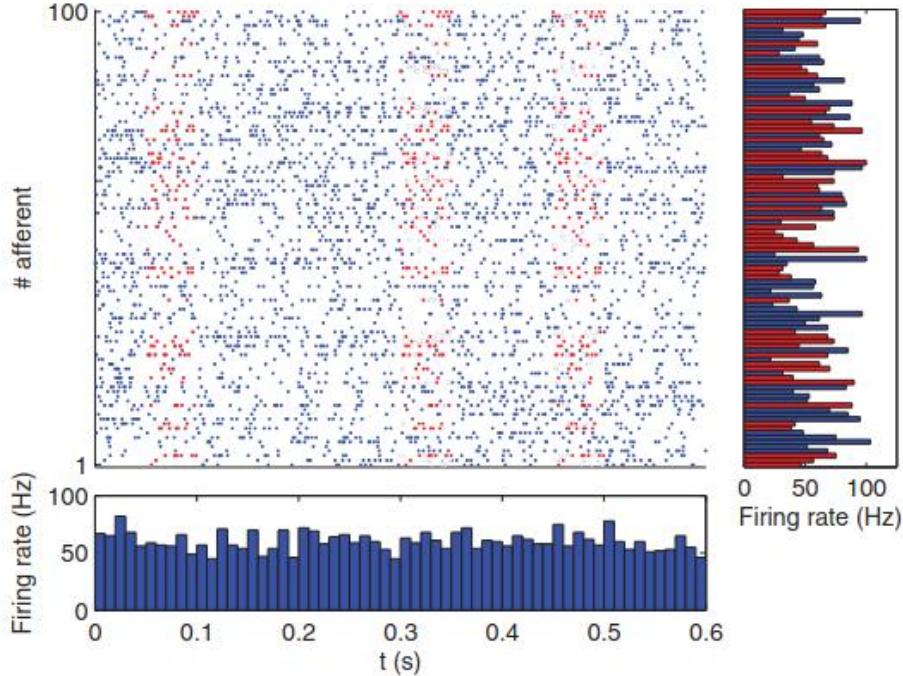


For a given action / thought / stimulus, a **pattern of spikes** are repeated, with more or less **variability**.

Downstream (post-synaptic) neurons learn to **detect** (spike in response to) these patterns.

Masquelier et al. (2008) Spike Timing Dependent Plasticity Finds the Start of Repeating Patterns in Continuous Spike Trains, PLoS One

Coincidence detectors / Spike patterns



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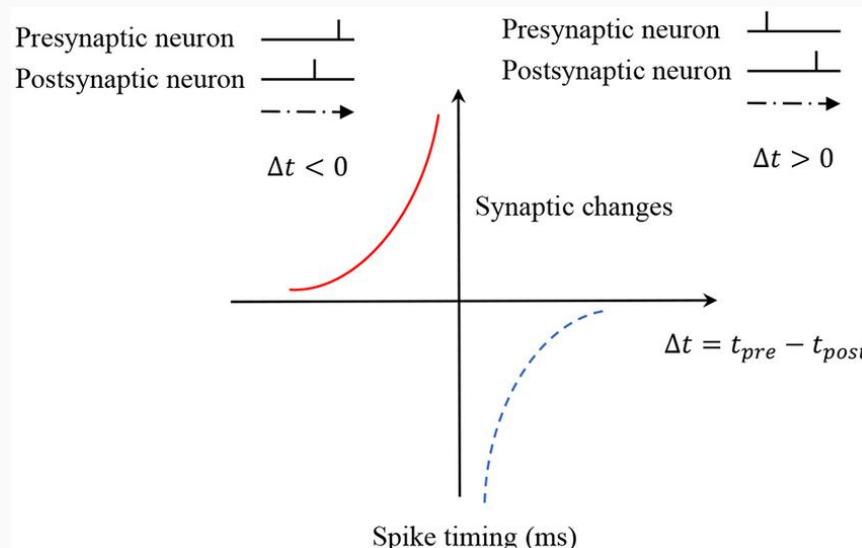
But how ?

Masquelier et al. (2008) Spike Timing Dependent Plasticity Finds the Start of Repeating Patterns in Continuous Spike Trains, PLoS One

Spike-Timing Dependent Plasticity (STDP)

A local, **Hebbian** learning rule:

“Neurons that fire together, wire together”



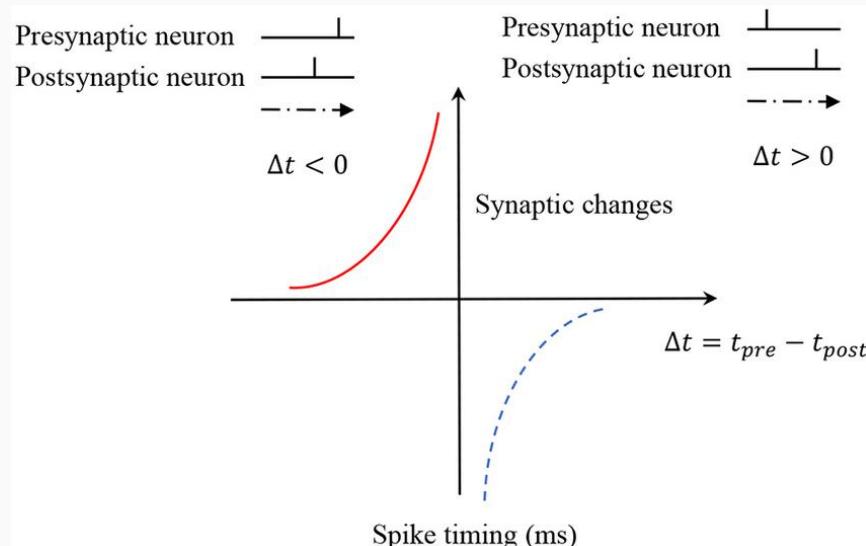
Features:

- local
- unsupervised
- biologically-plausible

Spike-Timing Dependent Plasticity (STDP)

A local, **Hebbian** learning rule:

“Neurons that fire together, wire together”



*between directly connected neurons only,
macroscopic behaviors emerge from microscopic changes*

Features:

- local
- unsupervised
- biologically-plausible

*observed in the brain,
experimental evidence*

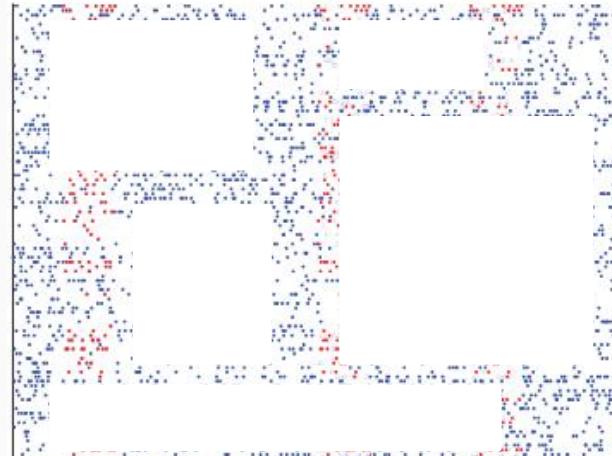
no label / groundtruth

Sparse coding

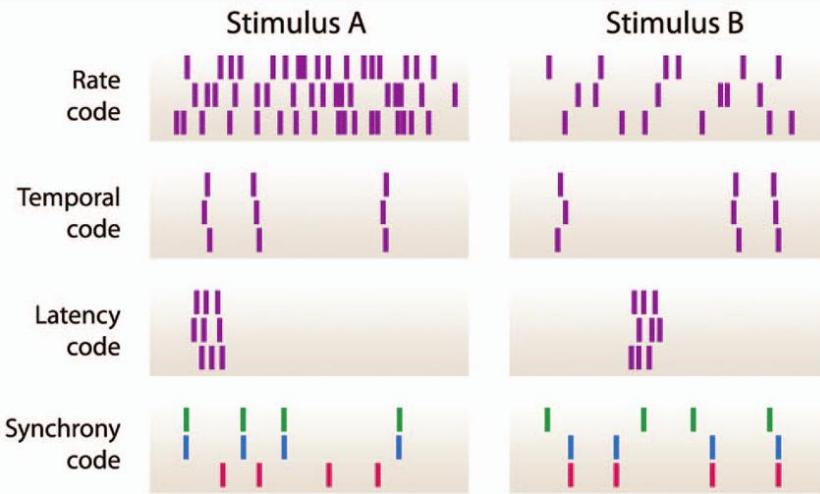
Generating action potentials consumes substantial energy.

To limit overconsumption, neurons in the brain use patterns with very few spikes: **sparse coding**

This is a form of **homeostasis**, under **evolutionary pressure**



Temporal vs Rate coding



There are many ways to encode (the same) information.

Biological neurons use 2 main types:

Temporal coding:

Information is encoded in the relative timing between presynaptic spikes

Rate coding:

Information is encoded in the firing rate (i.e. the number of incoming spikes)

SNNs vs ANNs

SNNs originated as low-level models of the brain.

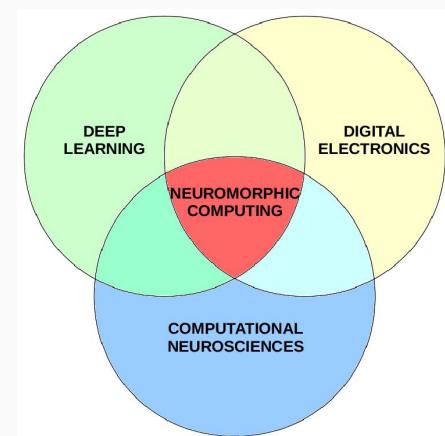
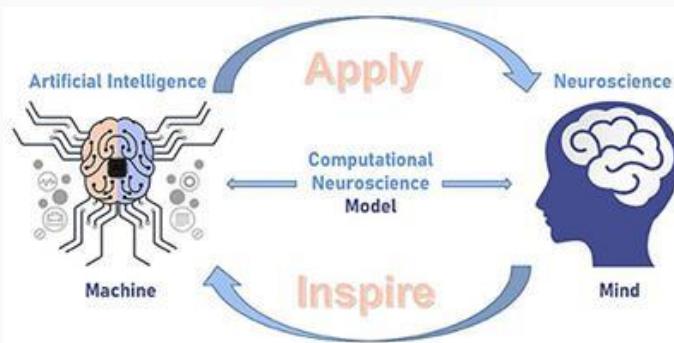
Contrarily to ANNs, SNNs only output binary spikes, not real values.

To obtain real values and to convey finer information, need:

- time as an additional dimension,
- to average across other neurons in the population (space)

BUT they can implement sparse coding for higher energy efficiency

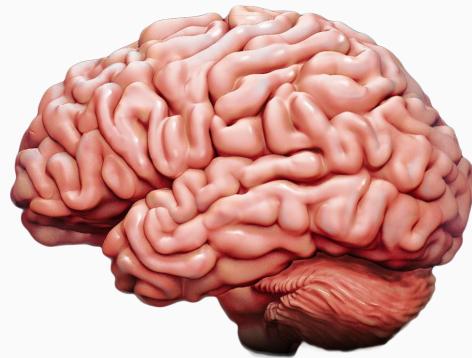
→ *take inspiration for engineering ?*



Neuromorphic computing and sensing

Brain-inspired AI

The energy efficiency of the brain



? W (Watt)



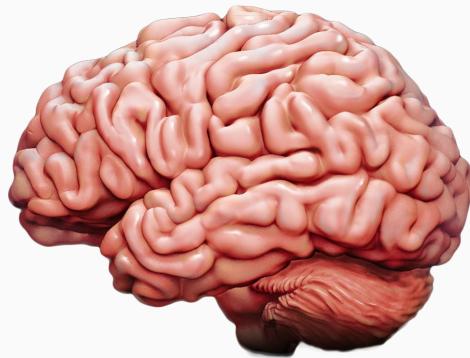
70 W



40 W

Q: How much is the brain's estimated power consumption ?

The **incredible** energy efficiency of the brain



20 W (Watt)

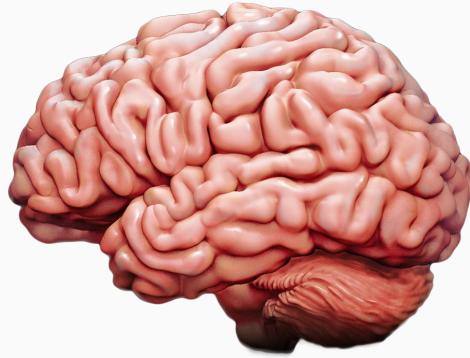


70 W



40 W

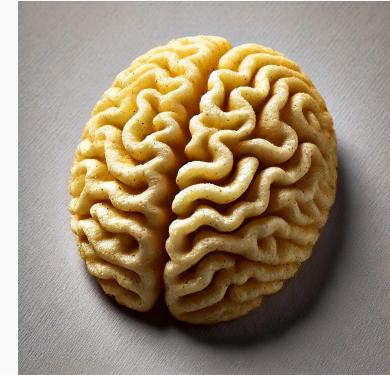
Neuromorphic chips



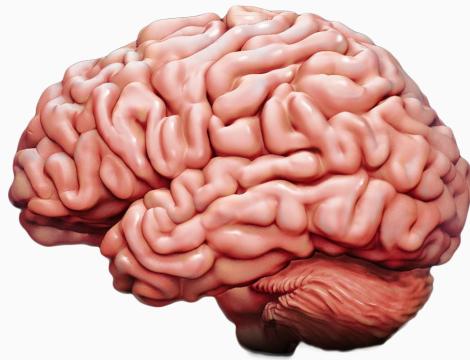
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Neuromorphic chips



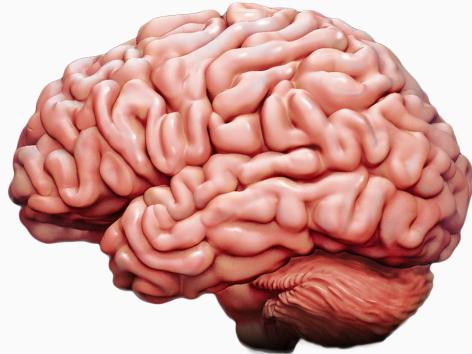
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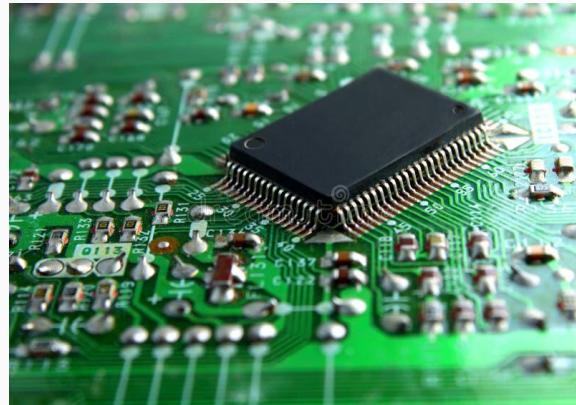
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Neuromorphic chips



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Electronic chips (“puces”) specially designed to emulate spiking neural networks (SNNs)

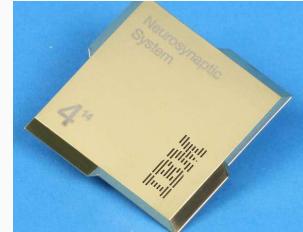
GPU / Graphics card --> gaming

Neuromorphic chips --> SNNs

Neuromorphic chips: main principle

Electronic chips (“puces”) specially designed to emulate spiking neural networks (SNNs)

Only consume power when generating a spike (like the brain)
Few spikes (sparse coding) ==> little energy consumption



IBM TrueNorth

Advantages (over regular computers/chips):

- **ultra low power** consumption
- **very fast**
- **asynchronous**

Industrial applications:

- Embedded systems
- IoT
- BCIs
- ...



HBP SpiNNaker



Intel Loihi 2



Brainchip Akida

Neuromorphic Retina: pros and cons

Also known as the **Dynamic Vision Sensor (DVS)** or **Event Camera**

Mimics how actual retinas work:

emit a spike only on big changes of luminance at a given pixel (location)

<https://youtu.be/MjX3z-6n3iA?si=IHiwIEPFFPPMySS6>

DAVIS346 Simultaneous events and frames 	DVXplorer Lite Discover event-based vision 	DVXplorer High resolution 	DVXplorer Mini Lightweight and compact 	DVXplorer S Duo Smart camera 
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The DV suite from Inivation,
<https://inivation.com/>

DVS event streams contain a lot of information !

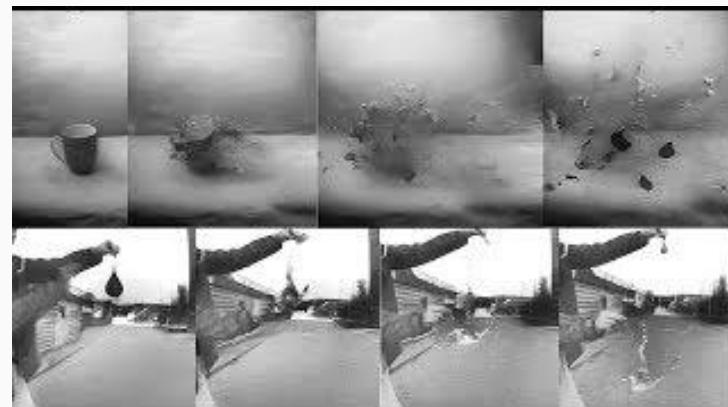
Proof: *quality grayscale images can be reconstructed from events thanks to deep neural networks !*

These **reconstructed videos inherit the benefits of event data**:

- events are not subject to motion blur → reconstructions cleaner than frame based cameras
- events have a higher dynamic range → same
- events have a high temporal resolution → reconstruction / information retrieval possible at high FPS rates

Many types of information can be retrieved:

- **intensity** (this work)
- **optical flow** (Javier's)
- **depth** (StereoSpike)



H. Rebecq, R. Ranftl, V. Koltun and D. Scaramuzza, "**High Speed and High Dynamic Range Video with an Event Camera**," in *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 43, no. 6, pp. 1964-1980, 1 June 2021, doi: 10.1109/TPAMI.2019.2962386

Neuromorphic Retina: pros and cons

Feature \ Camera type	Event-based	Frame-based	
Power consumption	Very low (~ mW)	~W	 Energy-efficient
Temporal resolution	Very high (~ μs)	60 FPS >~ 10 ms	 No motion blur !
Spatial Resolution	Low (<1 MPx), best 1280x720	Very High (>10 MPx), e.g. Huawei P20	
Dynamic Range	Very high (120 dB)	~50 dB	 Dim / Bright light ok !
Data efficiency	Sparse events, compact representation	Redundant information	
Mode	Asynchronous	Synchronous	 Fast
Price	High (several k €)	Low	

Neuromorphic Cochleas

Equivalent of the DVS but for audio: **Dynamic Audio Sensor (DAS)**

show raster plots

Conclusion

Outline

I. What is a model ?

II. Models of neurons / Spiking Neural Networks (SNNs)

III. Neuromorphic computing and sensing

IV. Conclusion

Little to no maths

Large overview

Main keywords



Starting point for self-study !

Going further... (Some exercises)

Exercise #1:

Code by yourself, in Python, a LIF neuron in discrete time: with $thresh=1$, $V_{rest}=0$, and $\tauau=10$

It should receive a constant input current $I=0.3$ between time-steps 10 and 30.

Simulate during 50 time-steps and plot the membrane potential and spikes.

You will iterate through time-steps with a for loop.

Exercise #2:

Add a refractory period of $T=5dt$ after each spike, during which potential is maintained to V_{rest} and launch a new simulation. Do you notice any differences ?

Exercise #3:

Play with the input current ! Change it to a ramp, and/or to a spike train, and see the difference in behavior on your neuron.

If you don't know where to start, you can use ChatGPT... BUT it's better if you do it yourself, and make sure you understand its answer !



Going further... (Programming / coding / modelling)



The Brian2 spiking neuron simulator
(Python, with tutorials)



<https://brian2.readthedocs.io/en/stable/>

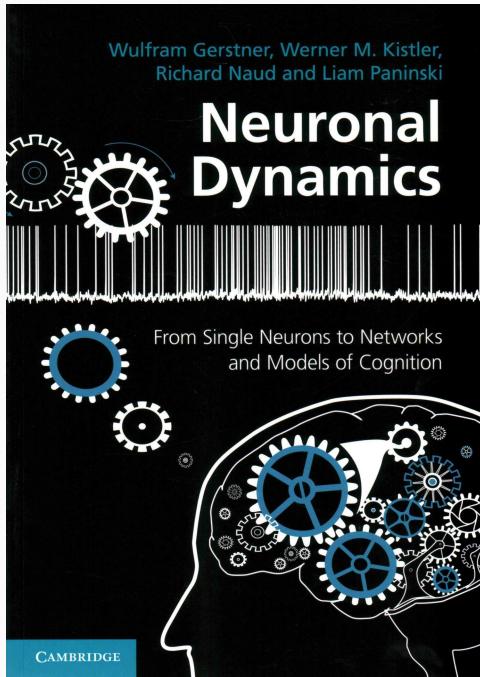
The NEST simulator
(Python, tutorials)



<https://nest-simulator.readthedocs.io/en/stable/>

Going further... (Selected materials 1/2)

Free book and online course by
Wulfram Gerster (EPFL)



<https://neuronaldynamics.epfl.ch/>

Artem Kirsanov's YT channel



Artem Kirsanov •
@ArtemKirsanov • 207 k abonnés • 36 vidéos
I'm a computational neuroscience student and researcher. On this channel we seek to ...plus
x.com/ArtemKRSV et 1 autre lien
S'abonner

Pour vous

Generalizing knowledge • 630 k vues • il y a 1 an
How Your Brain Organizes Information

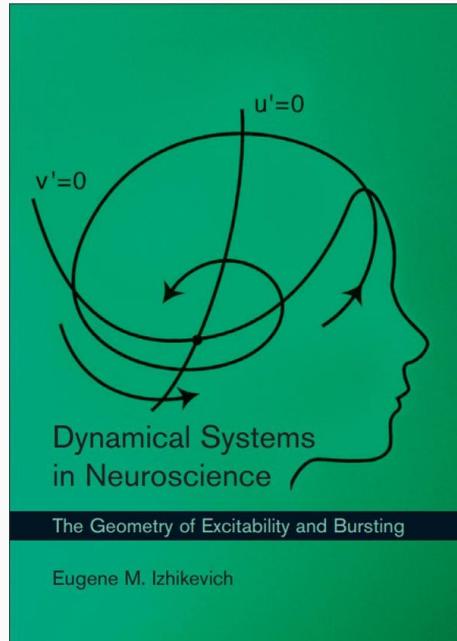
Boltzmann Machine • 104 k vues • il y a 2 mois
Generative Model That Won 2024 Nobel Prize

Hopfield networks • 132 k vues • il y a 3 mois
A Brain-Inspired Algorithm For Memory

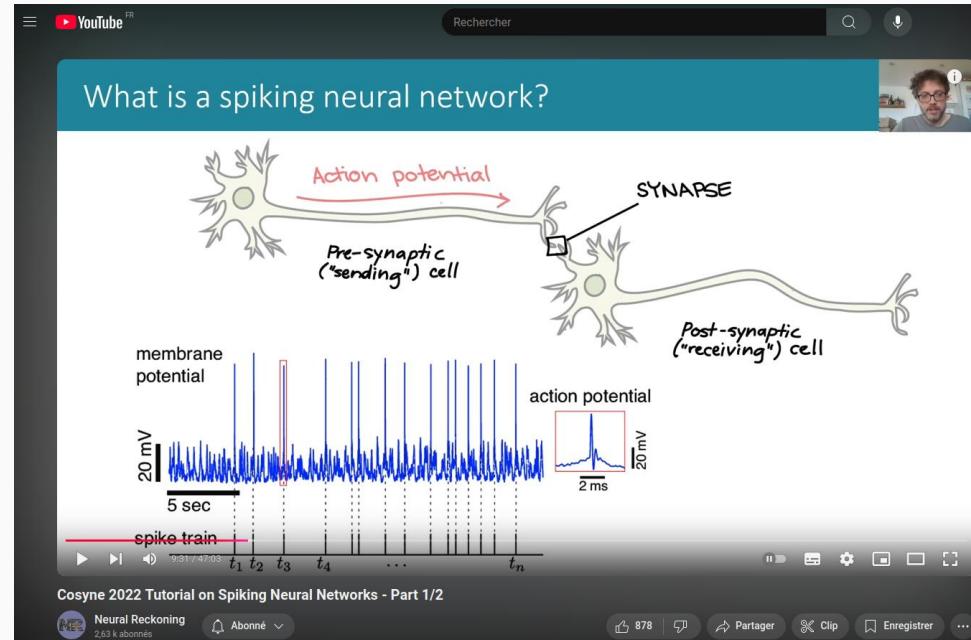
<https://www.youtube.com/@ArtemKirsanov>

Going further... (Selected materials 2/2)

Eugene Izhikevich's textbook

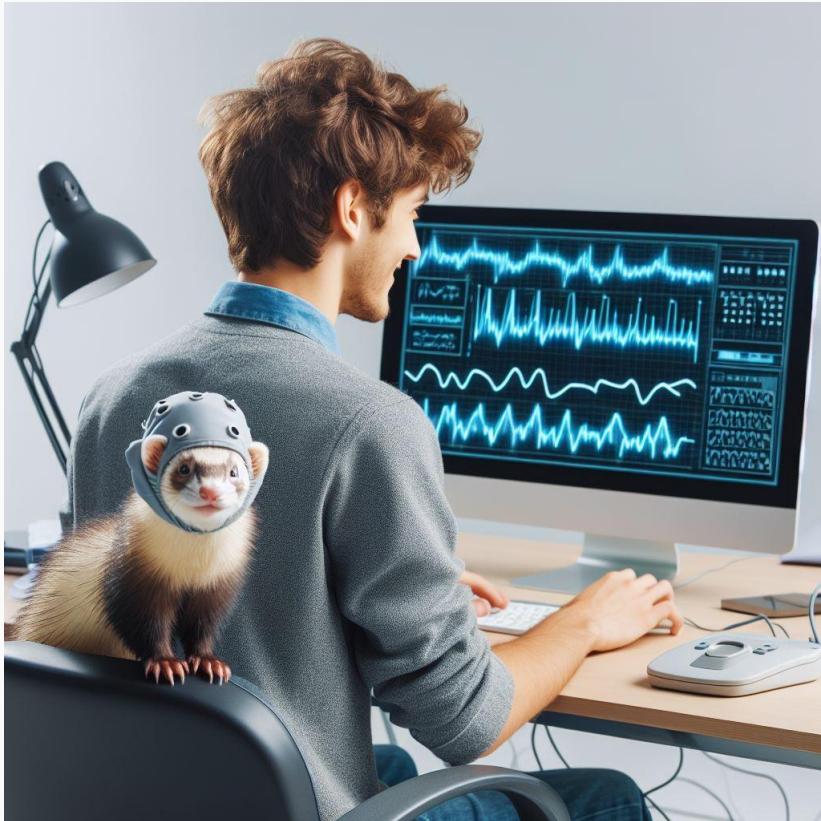


Cosyne 2022 Tutorial on Spiking Neural Networks
(Dan Goodman, YouTube)



https://youtu.be/GTXTQ_sOxak?si=5BDwA02QHEjatV7t

Thank you for your attention !



Ask your questions now, or send me an email
(ulysse.rancon@cnrs.fr)