Computational Intelligence & Machine Learning
http://www.di.unipi.it/groups/ciml
Dipartimento di Informatica
Università di Pisa - Italy

Neural Modeling and Computational Neuroscience

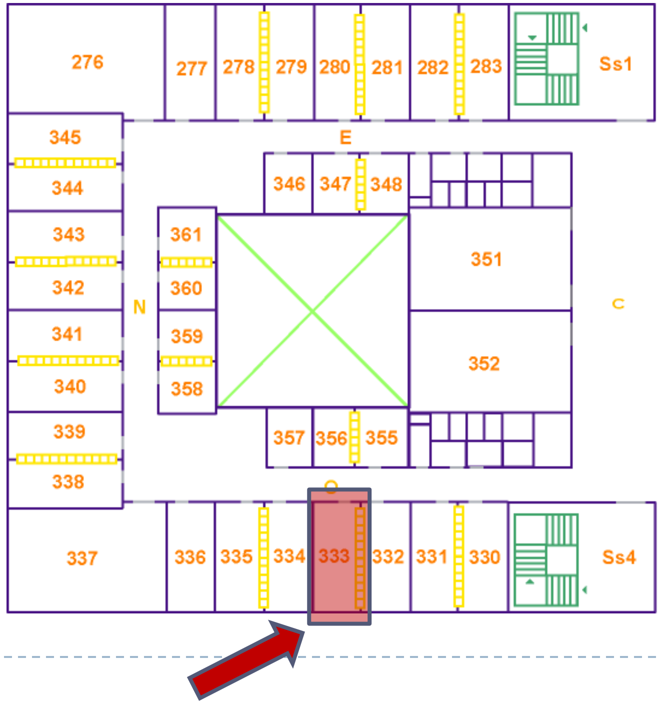
Claudio Gallicchio

Contact Information

Claudio Gallicchio, Ph.D.
PostDoc Research Fellow
Computational Intelligence and Machine Learning Group
http://www.di.unipi.it/groups/ciml/

Dipartimento di Informatica - Universita' di Pisa
Largo Bruno Pontecorvo 3, 56127 Pisa, Italy – Polo Fibonacci

web: www.di.unipi.it/~gallicch
email: gallicch@di.unipi.it
tel.:+390502213145



CNS mailing list

- **Please**, send asap to Prof. Alessio Micheli (micheli@di.unipi.it) an email:
  - **Subject:** [CNS-2017] student
  - **Corpus (email text):**
    - Name Surname
    - Master degree programme (Bionics eng. or Computer Science?)
    - Any note you find useful for us

Thank you.

Neuroscience modeling

- Introduction to basic aspects of brain computation
- Introduction to neurophysiology
- Neural modeling:
  - Elements of neuronal dynamics
  - Elementary neuron models
  - Neuronal Coding
  - Biologically detailed models: the Hodgkin-Huxley Model
  - Spiking neuron models, spiking neural networks
  - Izhikevich Model
- Introduction to Reservoir Computing and Liquid State Machines
- Introduction to glia and astrocyte cells, the role of astrocytes in a computational brain, modeling neuron-astrocyte interaction, neuron-astrocyte networks,
- The role of computational neuroscience in neuro-biology and robotics applications.

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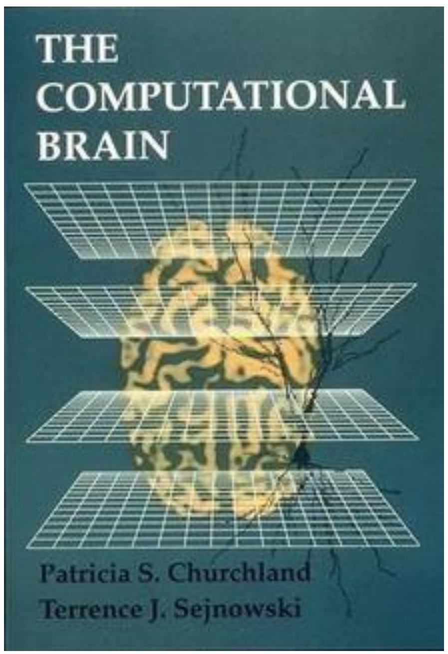
References

P. Churchland, T.J. Sejnowski. The computational brain. MIT press, 1992.

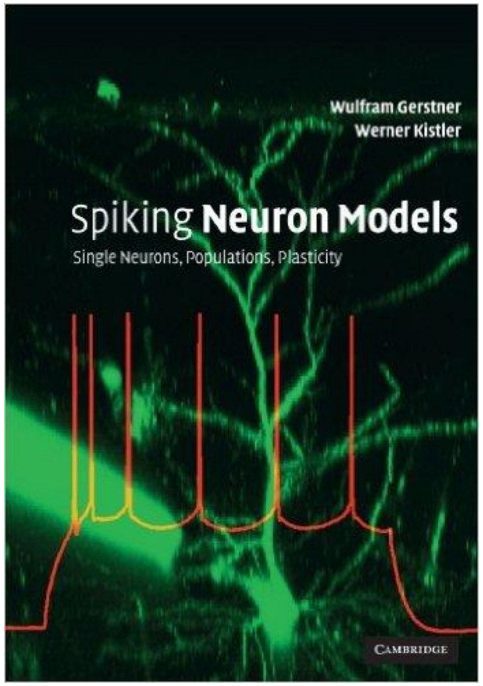


Chapters 1, 2

References

W. Gerstner and W.M. Kistler, Spiking Neuron Models: Single Neurons, Population, Plasticity. Cambridge Univ. Press, 2002

on-line at: http://lcn.epfl.ch/~gerstner/SPNM/SPNM.html

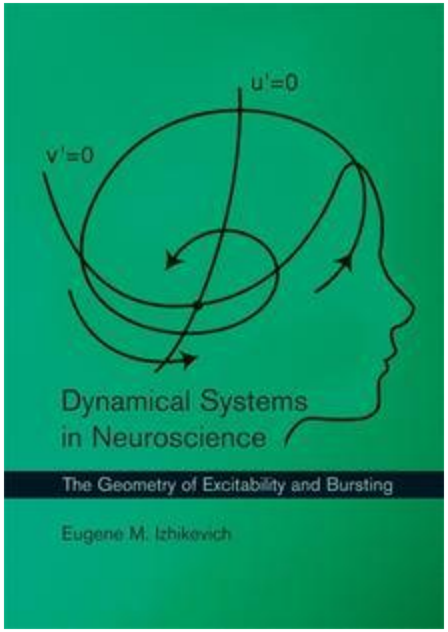


Chap. 1

Chap. 2 – Sect. 2.1

References

E.M. Izhikevich, Dynamical Systems in Neuroscience: The Geometry of Excitability and Bursting. The MIT press, 2007

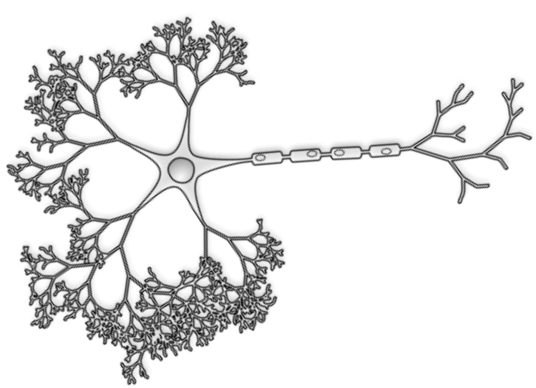


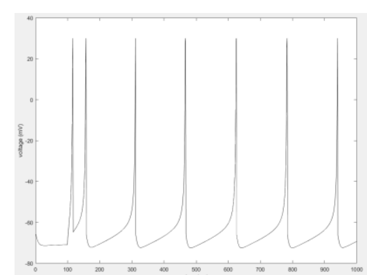
Sections 1.1, 2.1

The Computational Brain and Neurophysiology

Computational Neuroscience

- **Aim**
  - Discover and study the properties that characterize the mechanisms of data processing that take place in the brain.
  - Study how networks of neurons can produce complex effects, such as vision, learning, memory,…
- **Focus** on neurons
  - Brains are aggregations of neurons, cells with the peculiar ability to communicate by means of voltage propagation

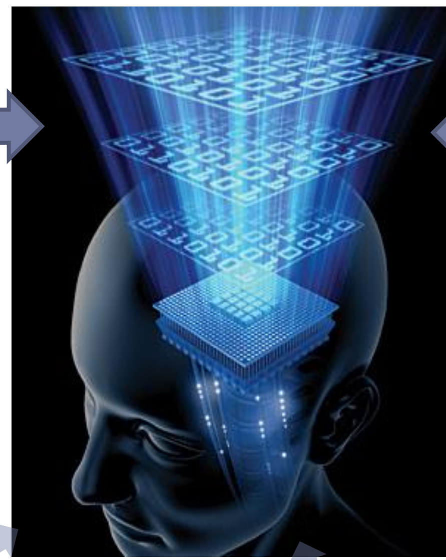




Computational Neuroscience

Interdisciplinary subject

Neuroscience



Computer Science

Psychology

Philosophy

Design of Neural Networks/Interdisciplinarity

Neurobiological Analogy – Neural Networks

- From neurobiological point of view:
  - look at Artificial Neural Networks as a research tool to interpret neurobiological phenomena
- From a Machine Learning point of view:
  - look at neurobiology for new ideas to solve problems
- Aim
  - Study biologically plausible mathematical models able to simulate neural dynamics

The Computational Brain

- The brain itself can be viewed as a computer
  - Organic constitution, complex, non-linear, parallel data processing
  - A collection of highly specialized interconnected computational sub-systems
  - Plasticity allows to adapt the nervous system to its environment
  - Not only a cognitive device:
    needs to cope with thermoregulation, growth, reproduction, respiration, regulation of hunger and thirst, sleep-awake control, etc.
  - Limitations and constraints:
    time (computation needs to be fast!), space, energy consumption, etc.

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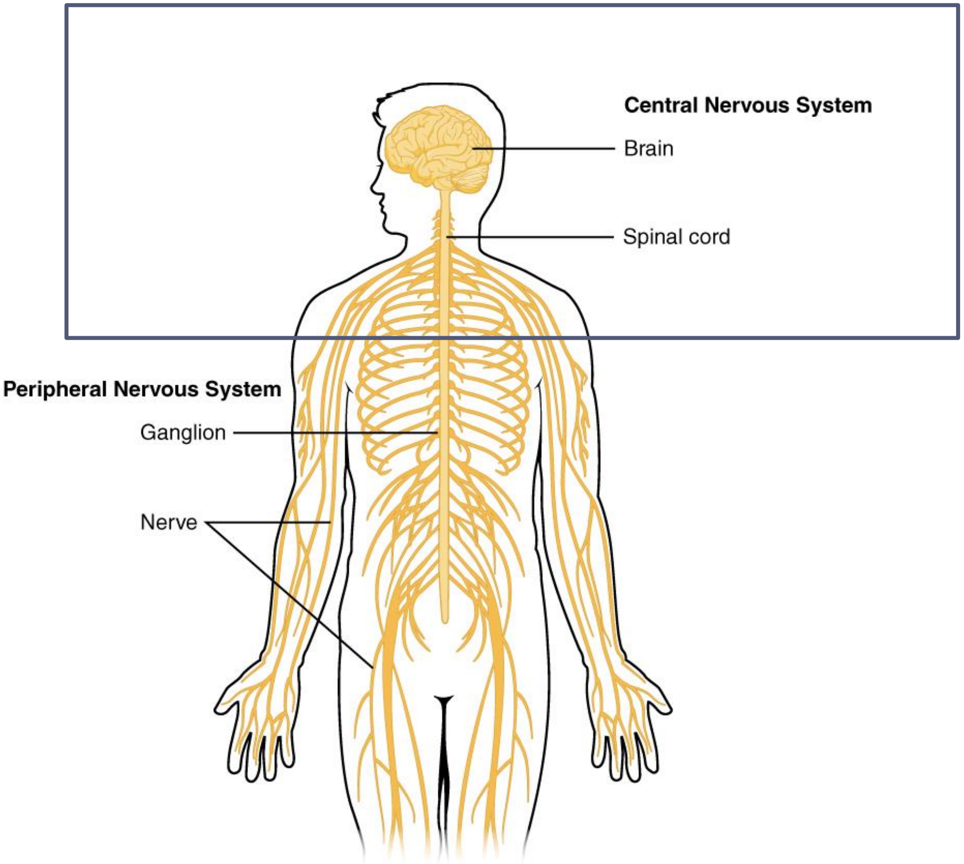
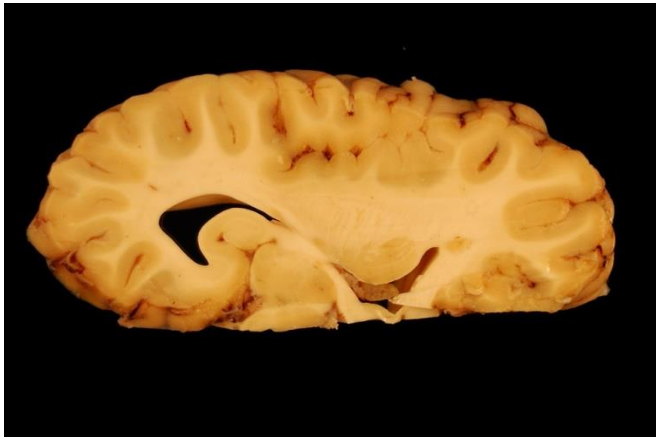
The "living" proof that neural networks are effective

Central Nervous System





Gray Matter

- Neurons' body cells

White Matter

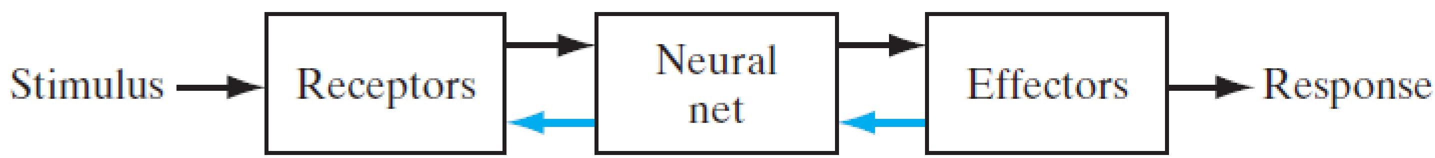
- Neurons' axons

Cerebral cortex

- Outer layer of the neural tissue in the brain

Model of the Central Nervous System

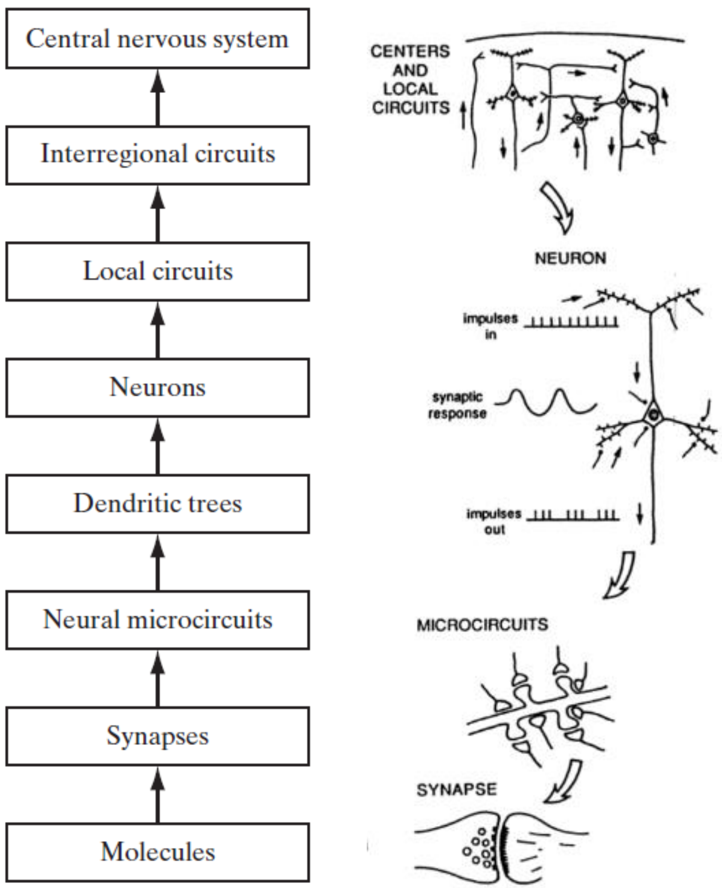
- Brain/CNS – Neural Net
  - Continually receives and processes information
- PNS - Receptors/Effectors
  - Converts external stimuli into electrical pulses
  - Convert electrical pulses into discernible responses



- Feed-forward / Feedback transmission of the information

Basic Facts on the Brain

Hierarchical Organization



Exploit Geometric properties in the elaboration: spatial proximity allows to efficiently organize the elaboration of the information

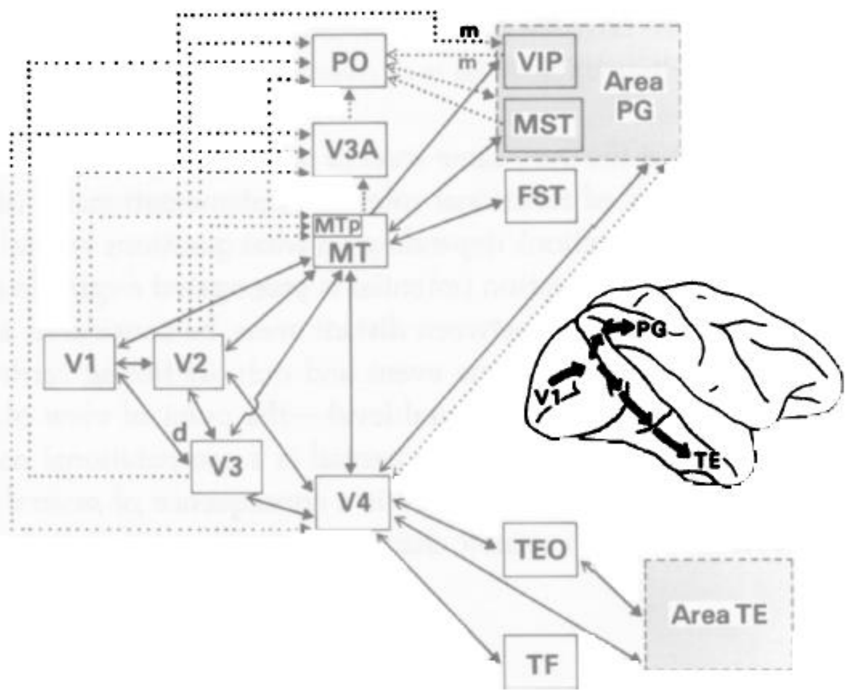
Hierarchical Processing

- Layered Organization
- From an anatomical point of view:
  - The higher the distance from the sensorial input, the higher the abstract level of processing of information

Basic Facts on the Brain

Feedback connections

- Hierarchical processing <u>with feedback</u>
  - Reciprocal connections among different areas

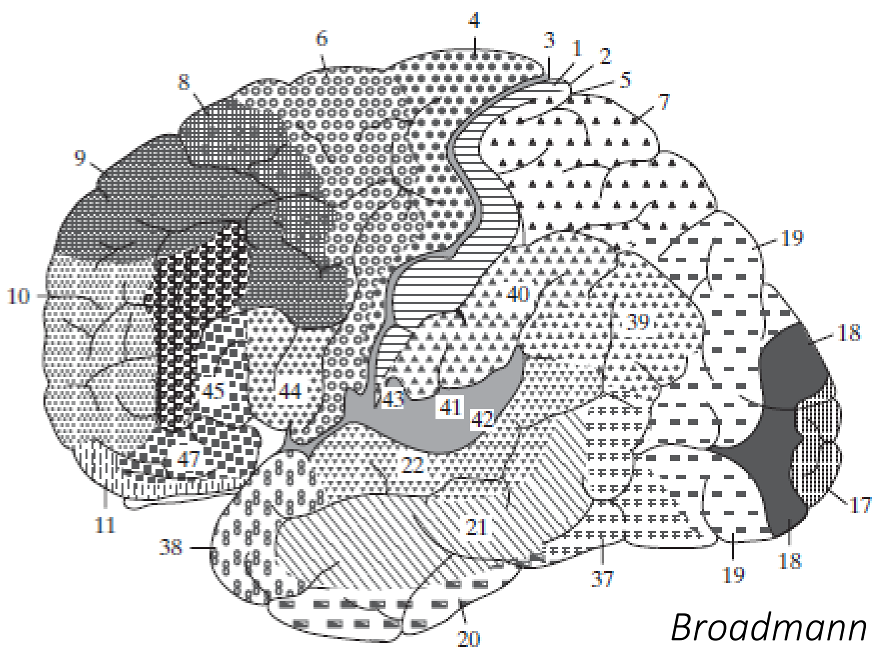


Reciprocal connections among some of the visual cortex areas

Basic Facts on the Brain

Specialization of Functions

- Different regions of the nervous system are specialized to different functions



Broadmann Areas

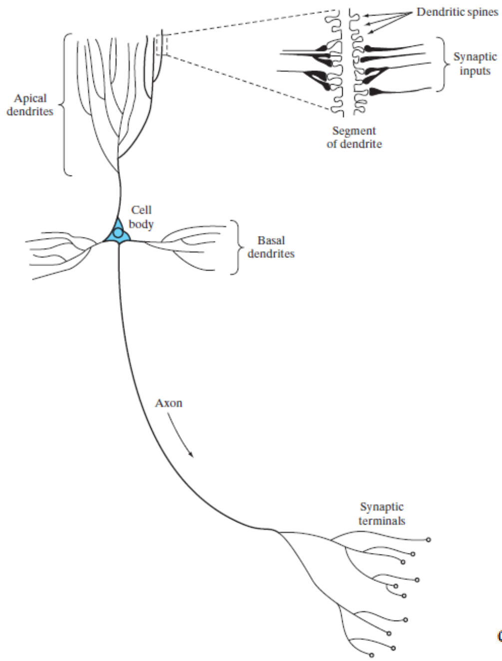
Basic Facts on the Brain

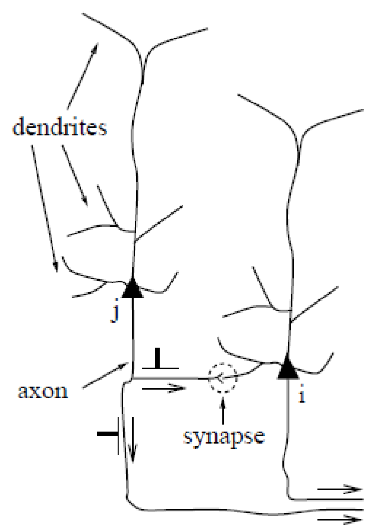
Numbers

- 10^{12} neurons in a human nervous system
- 10^{15} synapses
- In a mm^3 of cortical tissue:
  - 10^5 neurons and 10^9 synapses (≈1 synapse/μm^3)
- Each cortical neuron is connected to 3% of the neurons in the surrounding mm^3

Neural Modeling: Basics

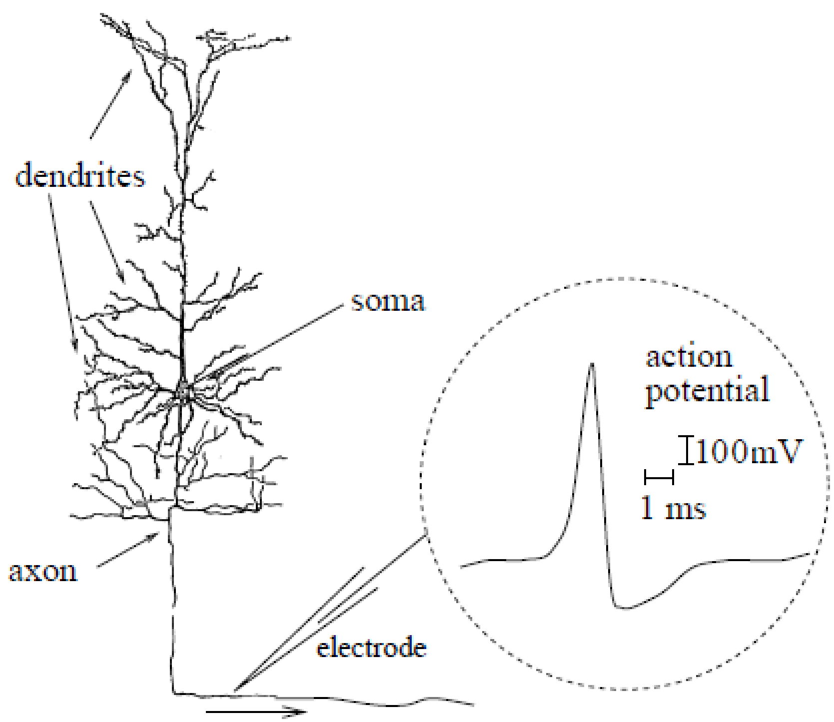
The Ideal Spiking Neuron





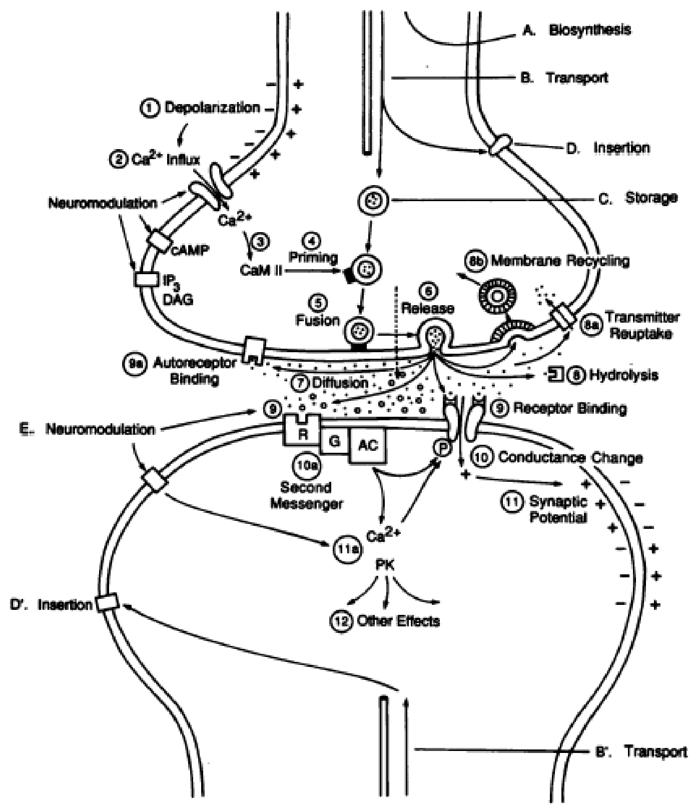
- Three functionally distinct parts:
  - **Dendrites**: input devices
  - **Soma**: central processing unit
  - **Axon**: output device
- Synapse
  - Junction between a pre-synaptic neuron and a post-synaptic neuron

Action Potentials or Spikes



- Spikes: elementary units of neuronal signal transmission
- Electrical pulses:
  - 100 mV of amplitude
  - 1-2 ms of duration
- Spike train: chain of spikes emitted by a single neuron
- Absolute refractory period
  - Minimum distance between two spikes

Synapses



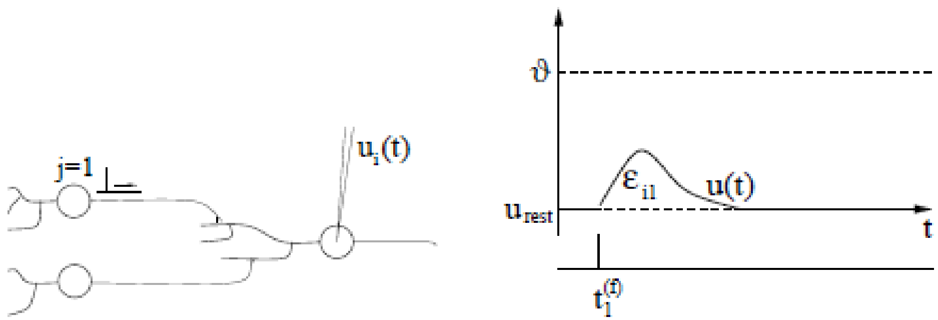
Contact axon – dendrite

Chemical synapse:

- A presynaptic action potential triggers the release of neurotransmitters
- The neurotransmitters are detected by the postsynaptic cell membrane
- The permeability of the postsynaptic membrane to ions changes, leading to a change in membrane potential
- Post Synaptic Potential (PSP): the voltage response of the postsynaptic neuron to a presynaptic spike

Neuronal Dynamics

- Membrane potential $u(t)$
  - Potential difference between the interior and the exterior of the cell
  - Constant value at rest: $u(t) = u_{rest} \approx -65mV$



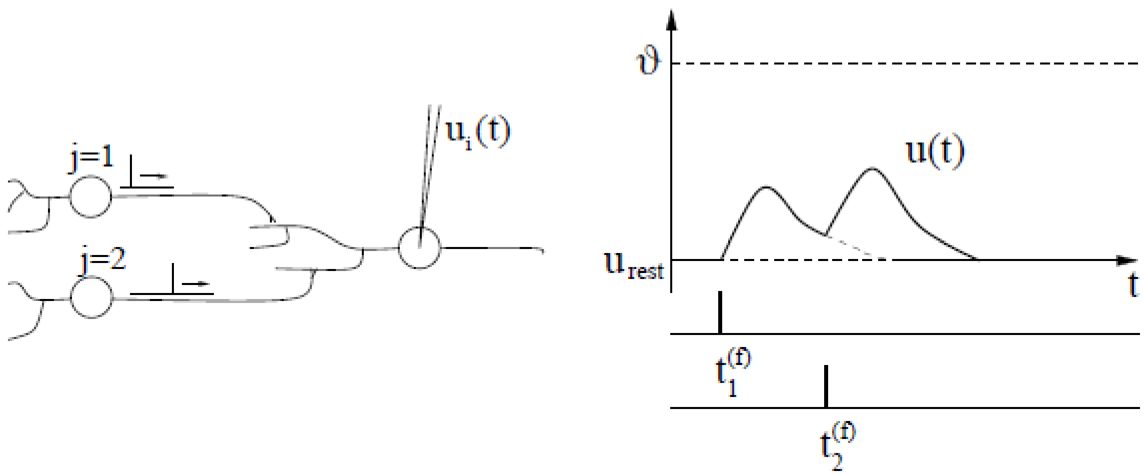
- At t = 0 neuron j fires
- PSP induced in neuron i

$$PSP_{ij} = \epsilon_{ij}(t) = u_i(t) - u_{rest}$$

> 0 Excitatory PSP (EPSP)
depolarization

< 0 Inhibitory PSP (IPSP)
hyperpolarization

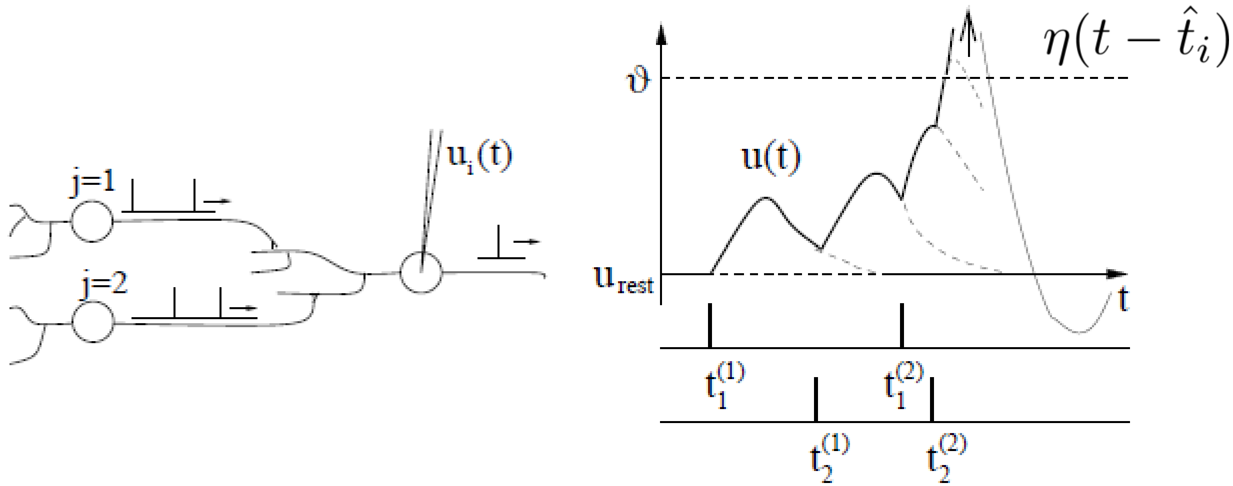
Firing Threshold and Action Potential



$$u_i(t) = \sum_j \sum_f \epsilon_{ij}(t - t_j^{(f)}) + u_{rest}$$

When there are only a few presynaptic spikes the membrane potential can be approximated by a linear combination of the individual PSP

Firing Threshold and Action Potential



When the membrane potential exceeds a threshold the dynamics changes:

- spike or action potential:
  sudden depolarization (100 mV excursion) of the membrane potential
- spike-afterpotential:
  after the spike there is a phase of hyperpolarization below the resting value

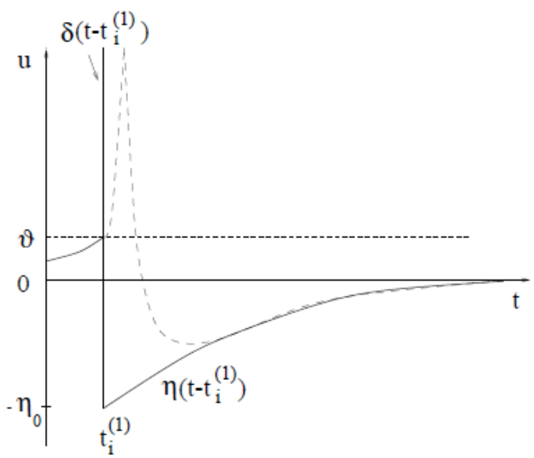
$\hat{t}_i = \max\{t_i^{(f)} | t > t_i^{(f)}\}$ time of last spike of neuron i

Spike Response Model

$$u_i(t) = \underbrace{\eta(t-\hat{t}_i)}_{\text{models the spike and the spike-afterpotential}} + \underbrace{\sum_j \sum_f \epsilon_{ij}(t-t_j^{(f)})}_{\text{PSPs}} + \underbrace{u_{rest}}_{\text{resting potential}}$$

If the membrane potential reaches the threshold from below then fire!

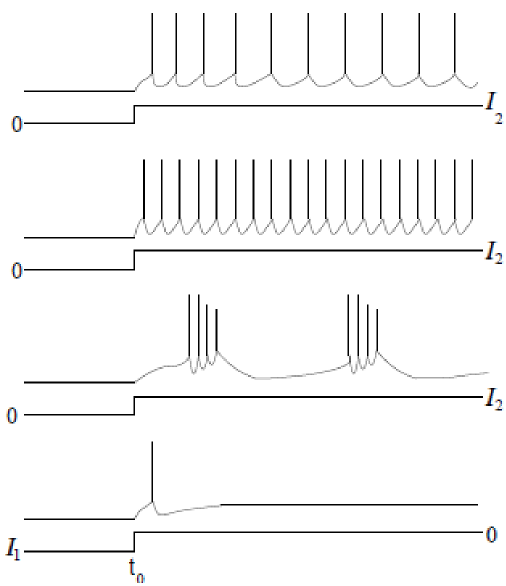
$$u_i(t) = \vartheta \text{ and } \frac{du_i(t)}{dt} > 0 \;\Rightarrow t_i^{(f)} = t$$



$$\eta(t-t_i^{(f)}) = \begin{cases} 1/\Delta t & \text{for } 0 < t - t_i^{(f)} < \Delta t \\ -\eta_0 \exp\left(-\frac{t-t_i^{(f)}}{\tau}\right) & \text{for } \Delta t < t - t_i^{(f)} \end{cases}$$

Limitations of the Spike Response Model

- Highly simplified model
  - PSP have always the same shape
  - Dynamics of the neuron depends only on the last firing time
- Not able to simulate many dynamical behaviors observed in biological neurons



regular spiking with adaptation

fast spiking

bursting

rebound spike
(release of inhibition can trigger a spike)

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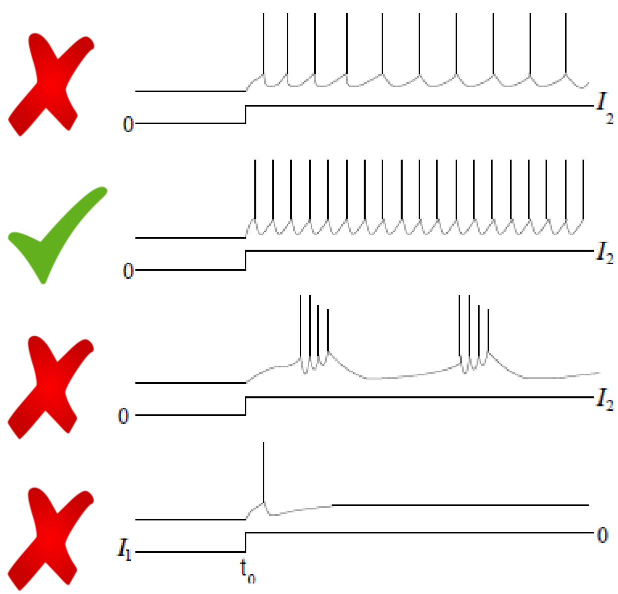

regular spiking with adaptation

fast spiking

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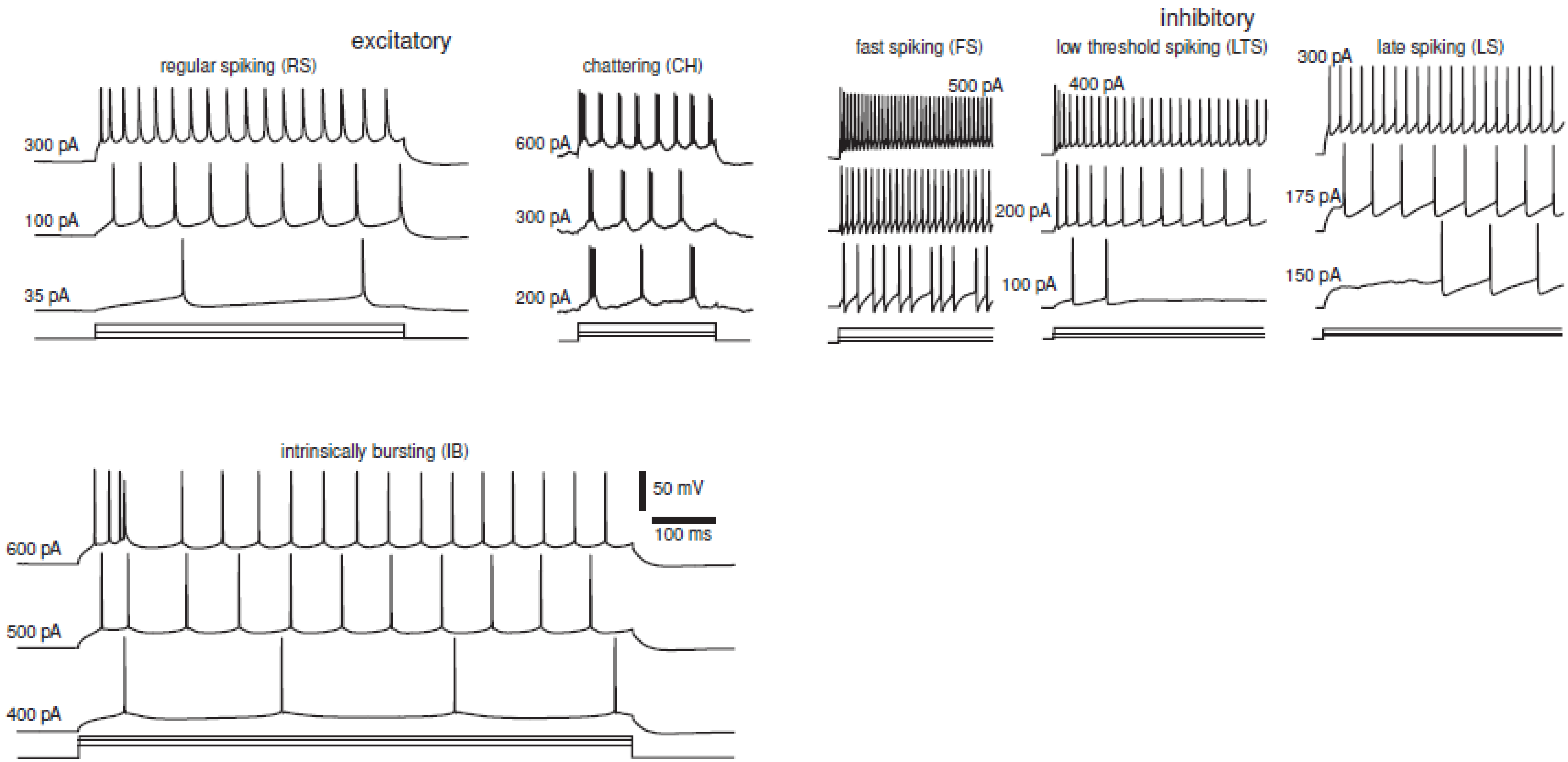
rebound spike
(release of inhibition can trigger a spike)

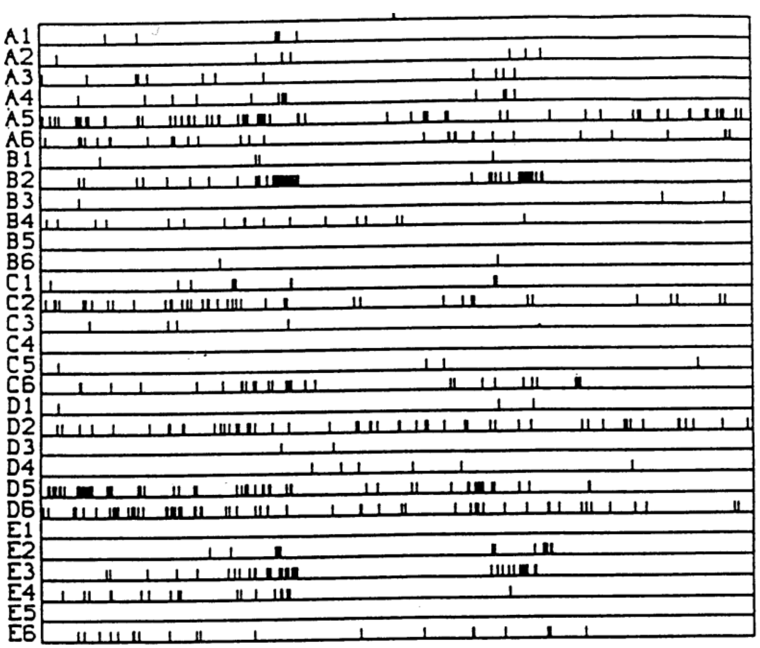
Particular Neural Dynamics in the Neocortex

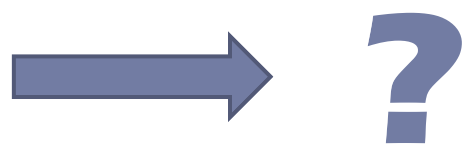
- Only 6 fundamentals classes of firing patterns



Neural Coding

- How do neurons communicate?
- What is the information contained in a spatio-temporal pattern of spikes?





Rate Codes

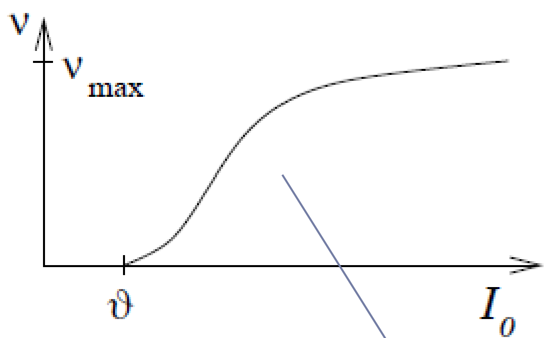
Code expressed by means of firing rate

- Rate as a spike count – average over time

$$\nu = \frac{n_{sp}(T)}{T}$$

Frequency – Current (FC) curve

- Relation between the frequency of firing and the applied (input) current



$$\nu = g(I_0)$$

transfer function of the neuron

Cons:

- Unlikely that neurons can wait to perform a temporal average

Pros:

- Spikes are a convenient way to transmit a real value: just two spikes at 1/ ν interval would suffice to encode the value ν

Rate Codes

- Rate as a spike density – average over K runs

$$\rho(t) = \frac{1}{\Delta t} \frac{n_K(t; t + \Delta t)}{K}$$

- Rate as a population activity – average over N neurons

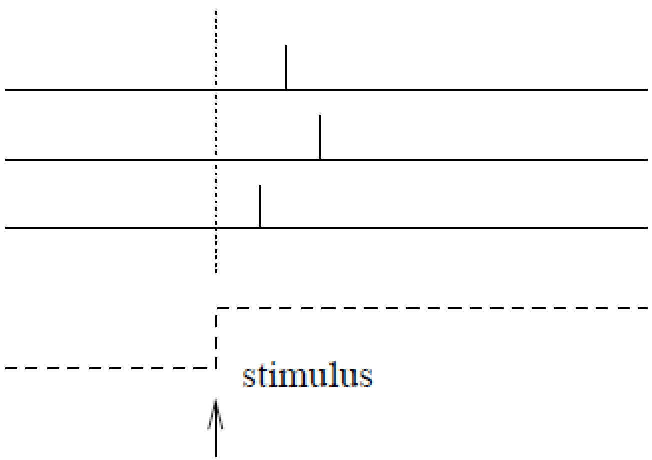
$$A(t) = \frac{1}{\Delta t} \frac{n_{\mathrm{act}}(t; t + \Delta t)}{N}$$

  - Idealized/not realistic (population of N identical neurons)
  - May vary rapidly and reflect sudden changes in the stimulus conditions

Spike Codes

Neurobiological evidences say that spiking time has a role

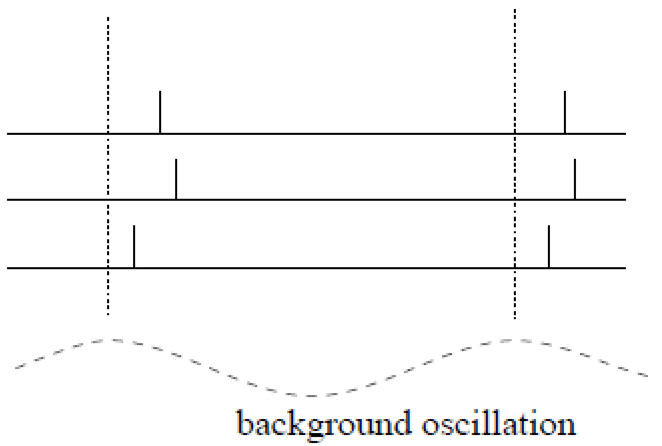
- Time to first spike



The information is encoded in the temporal distance of the neuron's response to the input

Spike Codes

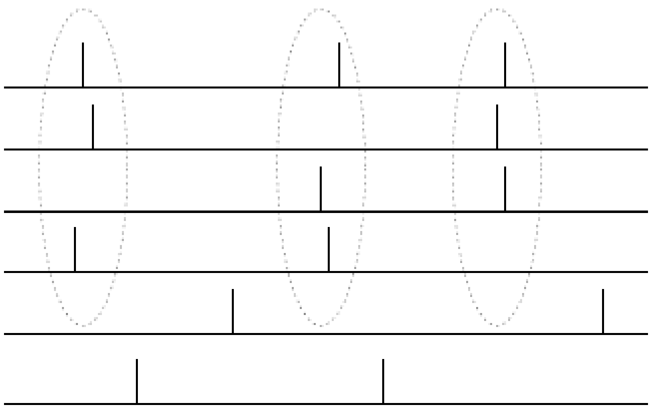
- Phase



The information is encoded in the phase of the spiking time with respect to a background oscillation

Spike Codes

- Synchrony

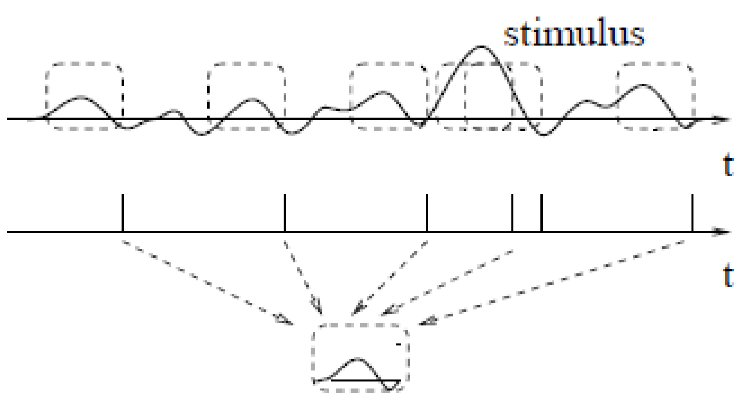


The information is encoded in the pattern of firing synchrony within a population of neurons in response to a stimulus

Spike Codes

- Reverse Correlation
  - Reconstruct the time course of the input stimulus that led to a postsynaptic spike
  - Average the input under condition of an identical response

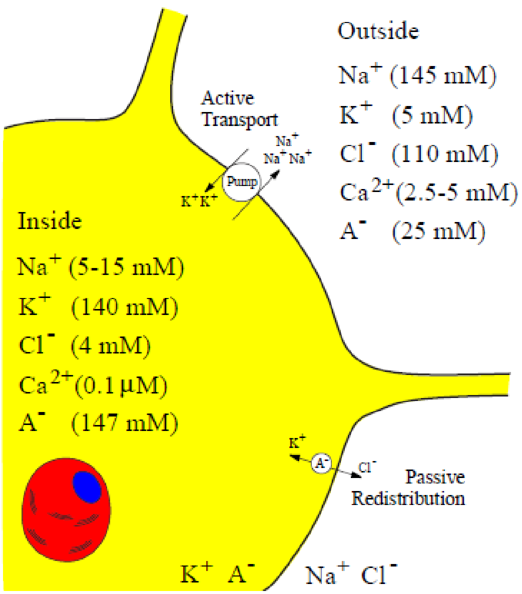
    spike-triggered average



Detailed Neuron Models

Action Potential and Ion currents

- From a biophysical perspective changes in the membrane potential $u(t)$ are due to currents of ions that passes through the membrane
- Main ions that take part into this process
  - Sodium Na^{+}, Potassium K^{+}, Calcium Ca^{2+}, Chloride Cl^{-}



The difference of ions concentration between inside and outside the cell is responsible for the generation of an electrical potential

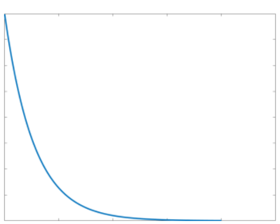
Nernst Potential

- The probability that a molecule takes a state of energy E is proportional to $e^{-\frac{E}{kT}}$
- Given a positive ion with charge q, its energy in position x is

$$E(x) = qu(x)$$

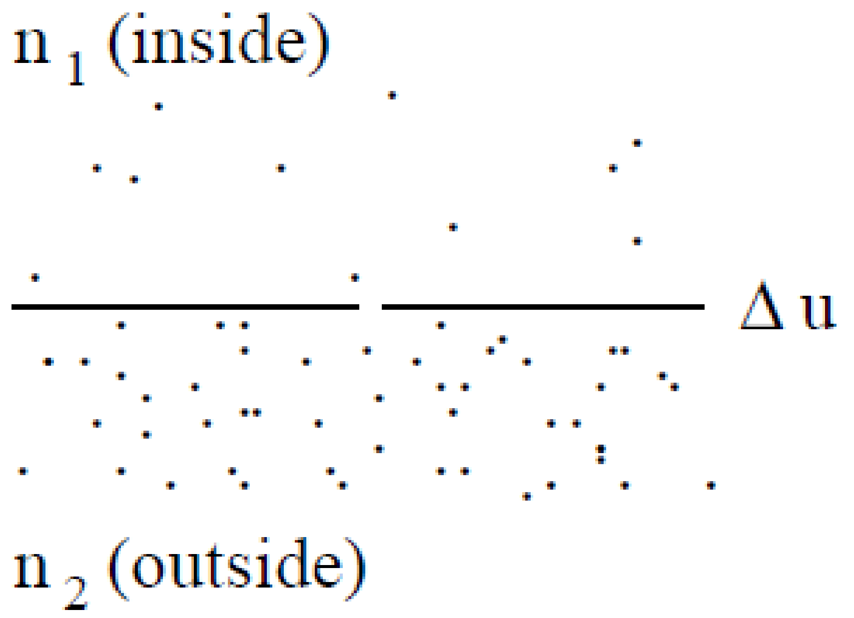
- The ions density in a region with potential $u(x)$, $n(x)$ is then proportional to

$$n(x) \propto e^{-\frac{qu(x)}{kT}}$$

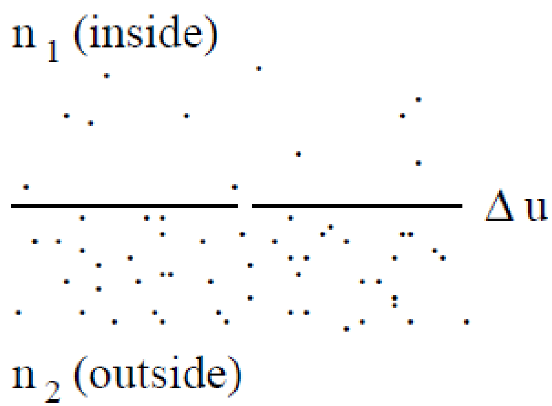


- The lower the potential, the higher is the density of positive ions

Nernst Potential



Nernst Potential



- The ratio between the ions density at two points is

$$\frac{n_1}{n_2} = \frac{n(x_1)}{n(x_2)} = e^{-q\frac{u(x_1)-u(x_2)}{kT}} = e^{-q\frac{\Delta u}{kT}}$$

- Thus, the concentration difference implies a voltage, called Nernst potential

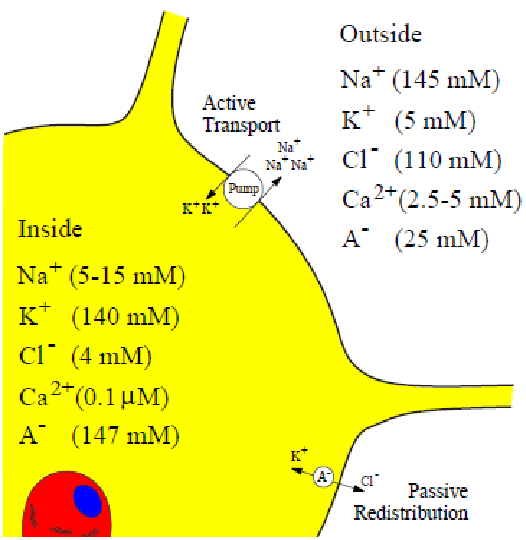
$$\Delta u = \frac{kT}{q} \ln \frac{n_2}{n_1}$$

Reversal Potential

- The reversal potential of an ion is its Nernst potential

$$E_{[ion]} = \frac{kT}{q_{[ion]}} \ln \frac{n_{out}}{n_{in}}$$

- If $\Delta u < E_{[\mathrm{ion}]} \Rightarrow$ ions flow into the cell
- If $\Delta u > E_{[\mathrm{ion}]} \Rightarrow$ ions flow out of the cell



Equilibrium Potentials

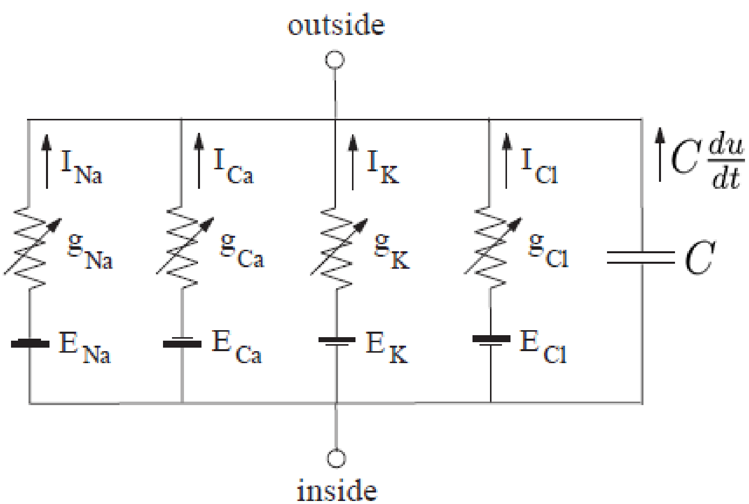
$$\begin{array}{lrcl}
\mathrm{Na}^+ & 62\log\frac{145}{5} & = & 90\ \mathrm{mV} \\
 & 62\log\frac{145}{15} & = & 61\ \mathrm{mV} \\
\mathrm{K}^+ & 62\log\frac{5}{140} & = & -90\ \mathrm{mV} \\
\mathrm{Cl}^- & -62\log\frac{110}{4} & = & -89\ \mathrm{mV} \\
\mathrm{Ca}^{2+} & 31\log\frac{2.5}{10^{-4}} & = & 136\ \mathrm{mV} \\
 & 31\log\frac{5}{10^{-4}} & = & 146\ \mathrm{mV}
\end{array}$$

$$E_K < E_{Cl} < \underset{-65mV}{u_{rest}} < E_{Na} < E_{Ca}$$

- **Ion channels**: try to equilibrate the concentration of ions, i.e. try to meet the reversal potential
- **Ion pumps**: active pumps that balance the flow of ions

Equivalent Circuit

- Electrical properties of neurons' membranes depicted in terms of the electrical circuit



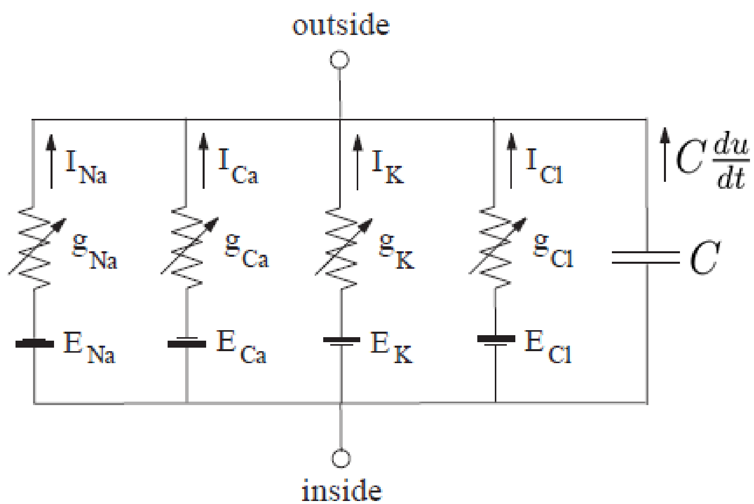
- Membrane: capacitor
- Ions' channels: resistors + battery (reversal potentials)

$$I_{[ion]} = g_{[ion]}(u - E_{[ion]})$$

- What happens if a current I is applied?

Equivalent Circuit

- Electrical properties of neurons' membranes depicted in terms of the electrical circuit



- Membrane: capacitor
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$$I_{[ion]} = g_{[ion]}(u - E_{[ion]})$$

TO BE CONTINUED

...see you on Wednesday