Dynamics of Neural Systems
Introduction

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Overview

- Introduction
- Organizational issues
- Basic facts about neurons

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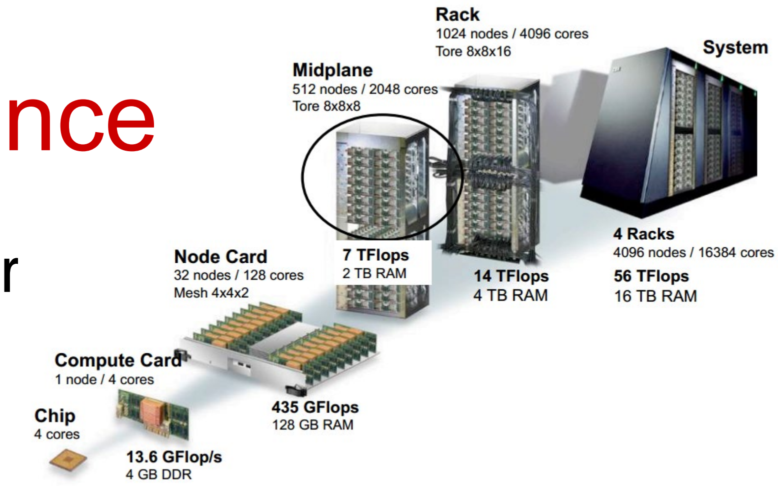
- Basic facts about neurons

Theoretical neuroscience

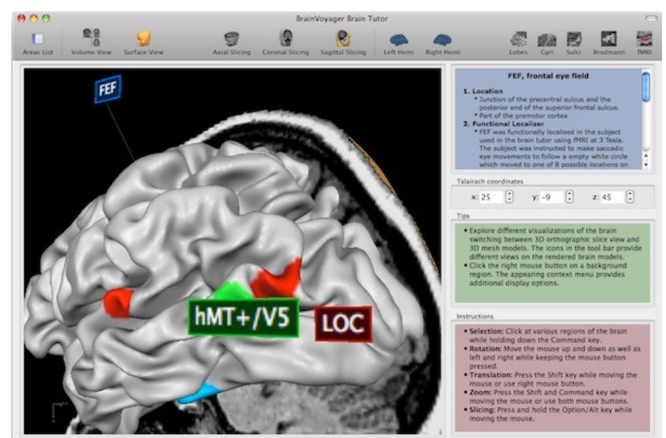


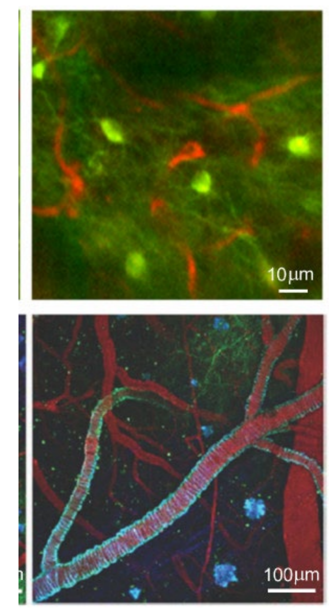
- Studying the brain by computer simulations.

  Human Brain Project

  'Flagship project' of the EU (2012-2023):
  Funding: 1.2 Billion EUR
  > 150 partners

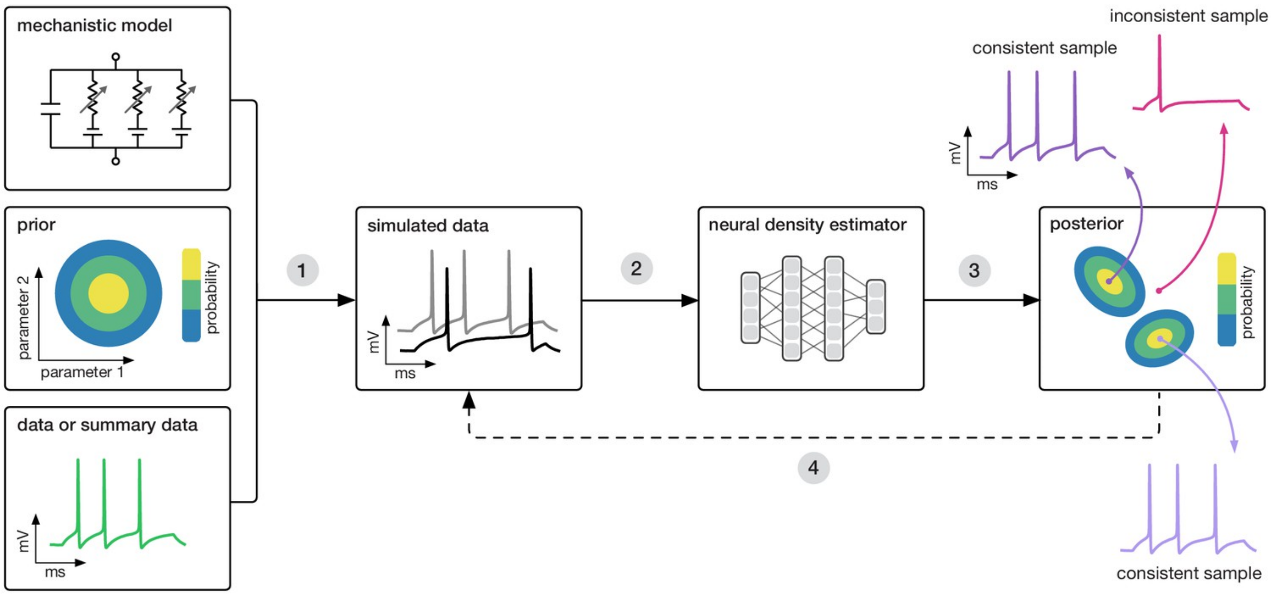
- Analysis of data from the brain using computers (multi-unit recordings, imaging techniques, morpho-logical data, connecto-mics, proteomics, behavior (ADL), …).





Theoretical neuroscience

- Simulation-based inference (parameter optimization through extensive simulation; NN learns mapping from data features to posterior of model parameters); ‘digital twin’.



Goncalves, …, Macke. *Elife* (2020)

Brain-inspired technology

Silver et al. *Nature* (2016)

- Recent boost in performance of artificial intelligent systems reaching human performance (computer vision, computer games, ChatGPT, …).
- **Nobel prices in Physics and Chemistry 2024** going to people working on artificial neural networks.

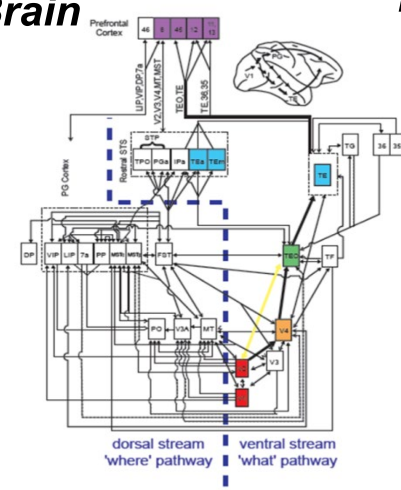
Demis Hassabis

J. Hopfield   G. Hinton

Brain-inspired technology

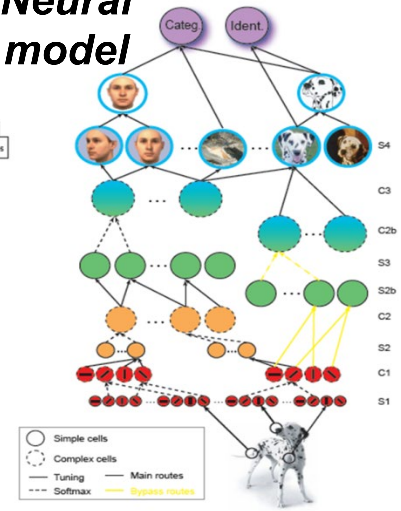
- Huge amounts of training data.
- Limited theoretical understanding.
- Problems of ‘explainabiliy’, ‘transparency’, ‘trustablility’ of learning algorithms.

Brain



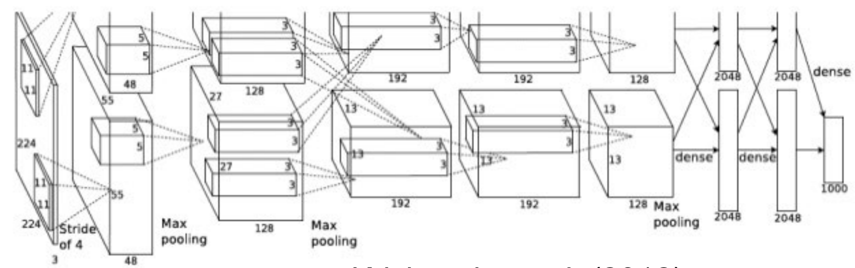
van Essen, ….

Neural model



Serre & Poggio (2005)

CV system



Krizhevsky,et al. (2012)

Silver et al. *Nature* (2016)

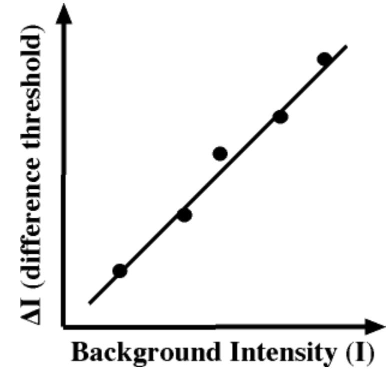
Theories

- **Descriptive models** (summarizing, not explaining data).
- **Mechanistic models** (explaining function based on anatomy and physiology).
- **Interpretative models** (computational theories, information-theoretic or neural network investigations of brain function, abstracting from detailed mechanisms).

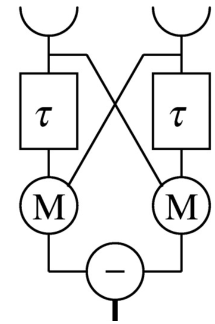
$$\frac{\Delta I}{I} = K$$

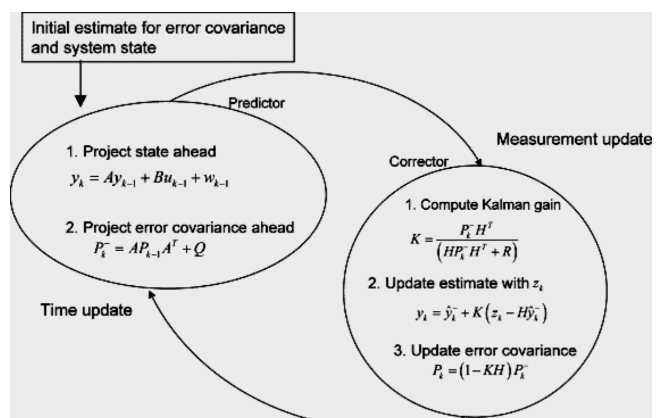
The Weber fraction

Weber's law



Reichardt detector
(Hassenstein & Reichardt, 1956)





Brain as predictive (Kalman) filter

Importance of theories in neuroscience

- Automatic processing of large data sets (Data Science)
- Summary of data
- Linking of different data sets (physiology, fMRI, EEG, …)
- Testing of computational hypotheses
- Testing logical and quantitative consistency of hypotheses
- Making hidden assumptions explicit and precise
- Deriving predictions and interesting parameter regimes and stimulus sets for experimental testing

(Mis-)conceptions about models in theoretical neuroscience

- ‘Only models that beat actual benchmarks in engineering / computer vision are really relevant for the brain’ (now: super-human performance for many problems using architectures that have questionable relationships to the brain).
- ‘Questions going beyond maximizing end-to-end performance measures of machine learning are irrelevant / an old-fashioned way to address the brain.’
- New area in machine learning: transparency / explainability of deep learning algorithms (= what models do internally often not easy to understand even though algorithms have phantastic end-to-end performance with enough tr. data)

My personal view

- Neuroscience needs a multi-level approach (like physics).
- Theoretical neuroscience should go beyond producing nice curve fits or running Python scripts for analysis. (**Theories** must generalize to new data / link different data sets and phenomena / generate understanding.)
- Computer science can provide important input to neuro-science, e.g. by specifying the computational complexity of problems (often ignored in biological models).
- Many popular algorithms in machine learning / engineering might be completely irrelevant as models for the brain, even if they reach (super-)human performance.

Problems of modeling in neuroscience

- Inconsistent data; unclear definitions of concepts in biology.
- Validity of models beyond small set of experiments
- Finding right level of **model complexity** (models never explain all phenomena; one needs to decide about which phenomena to model, and which level of detail is adequate for a model):

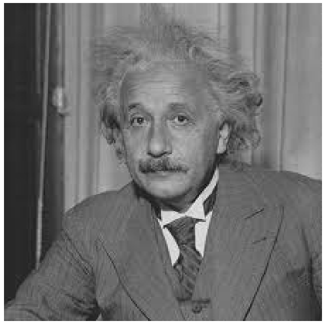
  too complex $\rightarrow$ model does not generalize or intractable

  too simple $\rightarrow$ model does not capture all relevant data

Problems of modeling in neuroscience

- Principles for selecting model complexity: **Occam's razor** (*lex parsimoniae*): 'Entities must not be multiplied beyond necessity.'
- Albert Einstein: 'Make everything as simple as possible but not simpler.'
- Machine learning approaches: optimization of model complexity, Structural Risk Minimization, Bayesian model selection

W. of Occam



A. Einstein

Major topics in theoretical neuroscience

- **Neurodynamics, modeling of neurons and circuits** (this lecture!)
- Neural encoding and decoding (treated in *Neural Coding* by A. Levina)
- Neural Modeling (P. Dayan, Z. Li, W. Ilg)
- Neural data analysis (treated in course *Neural Data Analysis* and several elective courses, e.g. on fMRI/MEG).

Major topics in theoretical neuroscience

- Systems level models (e.g. vision, motor) (treated in lectures about specific system function: *Sensory Systems*, *Computational Cognitive Science, Understanding Vision*, etc.)
- Special topics (neuron simulators, deep learning, …) treated in summer schools, block courses, courses in computer science department

Recommended auxiliary course: *Advanced Computational Methods in Theoretical Neuroscience* (Elective)

- Fridays 10:15-11:45; Hertie Institute (Otfried-Müller-Str. 27, level 2).
- Content will be adapted to progress in this lecture and cover advanced topics; examples:
  electrical circuit theory, frequency analysis of neural structures, advanced concepts from nonlinear dynamics, nonlinear oscillators and related neuron models, variational calculus and optimal control
- Small in-class exercises; not graded, but presented by students
- Specifically recommended for students interested in theory
- Basic calculus and math is absolutely mandatory for this course.

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Lecture times and credits

- Lecture: Mondays 8:15-10:00
- Exercises: Tuesdays 10:15-11:45, Crona or the Lehr-/Lerngebäude (please see schedule on ILIAS)
  (TAs: Ahmed Abdelrazik, Albert Mukovskiy:
  ahmed.abdelrazik@student.uni-tuebingen.de;
  albert.mukovskiy@medizin.uni-tuebingen.de)
- Exercises will have to be handed in at a fixed date and will be corrected individually; correct solutions will be posted after that.
- No code will be run or debugged by the TAs!!!
- Credit: Exam: 100 %; 50 % of Exercises' credits needed to obtain admission for the final exam.

Overview (Lectures)

Weeks	Monday	Topic	Lecturer
1	21.10.	*Introduction (no exercise this week)*	Giese
2	28.11.	*Single Compartment Models*	Giese
3	4.11.	*Cable Theory and Multi-compartment Models*	Giese
4	11.11.	*Membrane Channels / Hodgkin-Huxley Equation*	Giese
5	18.11.	*Extensions of the HH Model and Simplified Neuron Models*	Giese
6	25.11.	Tutorial	Giese
7	2.12.	*Linear Dynamical Systems*	Giese
8	9.12.	*Local analysis of nonlinear systems I*	Giese
9	16.12.	*Local analysis of nonlinear systems II and Lyapunov functions*	Giese
10	13.11.	Tutorial / Dynamic neural fields: Excitatory and inhibitory networks I	Giese
11	20.01.	Dynamic neural fields: Excitatory and inhibitory networks I	Giese
12	27.01.	*Dynamic neural fields: Excitatory and inhibitory networks II*	Giese
13	3.02.	Tutorial / *Oscillations: Mathematics*	Giese
	tba.	**Exam** (time to be announced)	

Books

Dayan P. & Abbott, L.F. (2001 / 2005) *Theoretical Neuroscience: Computational and Mathematical Modeling of Neural Systems.* MIT Press, Cambridge MA, USA.

Perko, L. (1998) Differential Equations and Dynamical Systems. Springer-Verlag, Berlin.

Sterratt, D., Graham, B, Gillies, A., Willshaw, D. (2011) *Principles of Computational Modelling in Neuroscience.* Cambridge University Press, UK.

Gerstner, W., Kistler, W., Naud, R., & Paninski, L. (2014) *Neuronal Dynamics.* Cambridge University Press, UK.

Izhikevich E. (2004) *Dynamical Systems in Neuroscience*. MIT Press, Cambridge MA, USA.

Koch, C. (1999) *Biophysics of Computation*. Oxford University Press, UK.

Trappenberg, T.P. (2010) *Fundamentals of Computational Neuroscience* (Paperback). Oxford University Press, UK.

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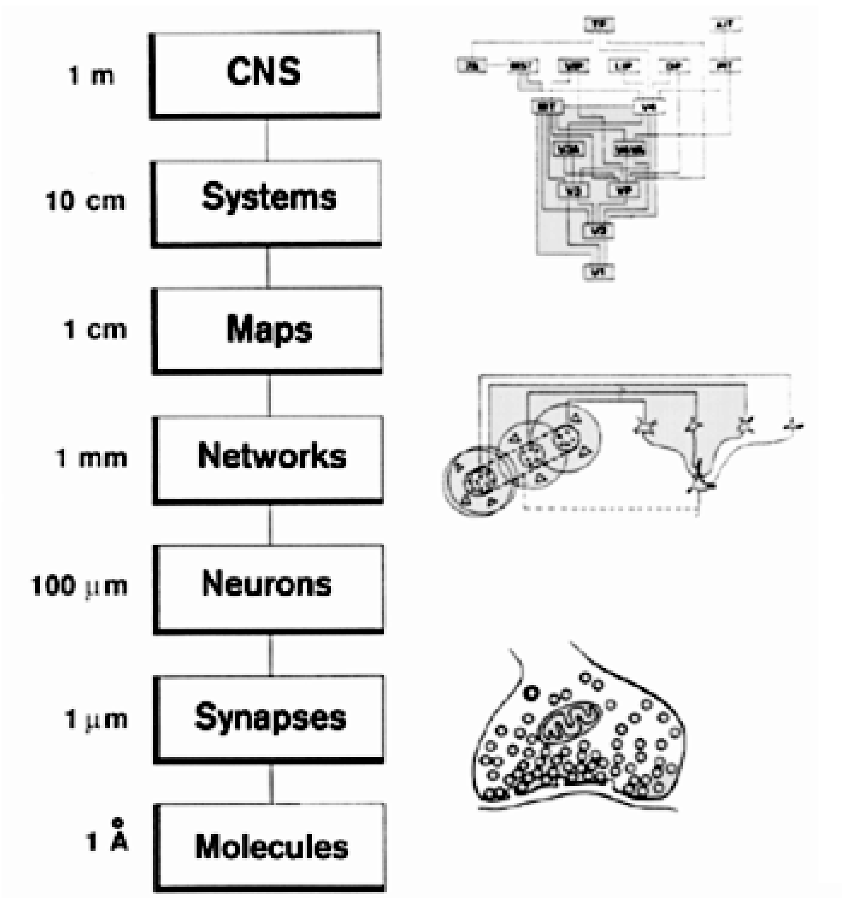
The brain as computer

- Brain processes information, but quite different from computer.
- ~10^{11} neurons, parallel processing.
- Individual neurons noisy and slow.
- On average 10^4 connections per neurons; very high connectivity.
- Learning and adaptation on many different time scales.
- No clear separation of processing stages (functional modules).

Organization levels of the brain

Spatial scales

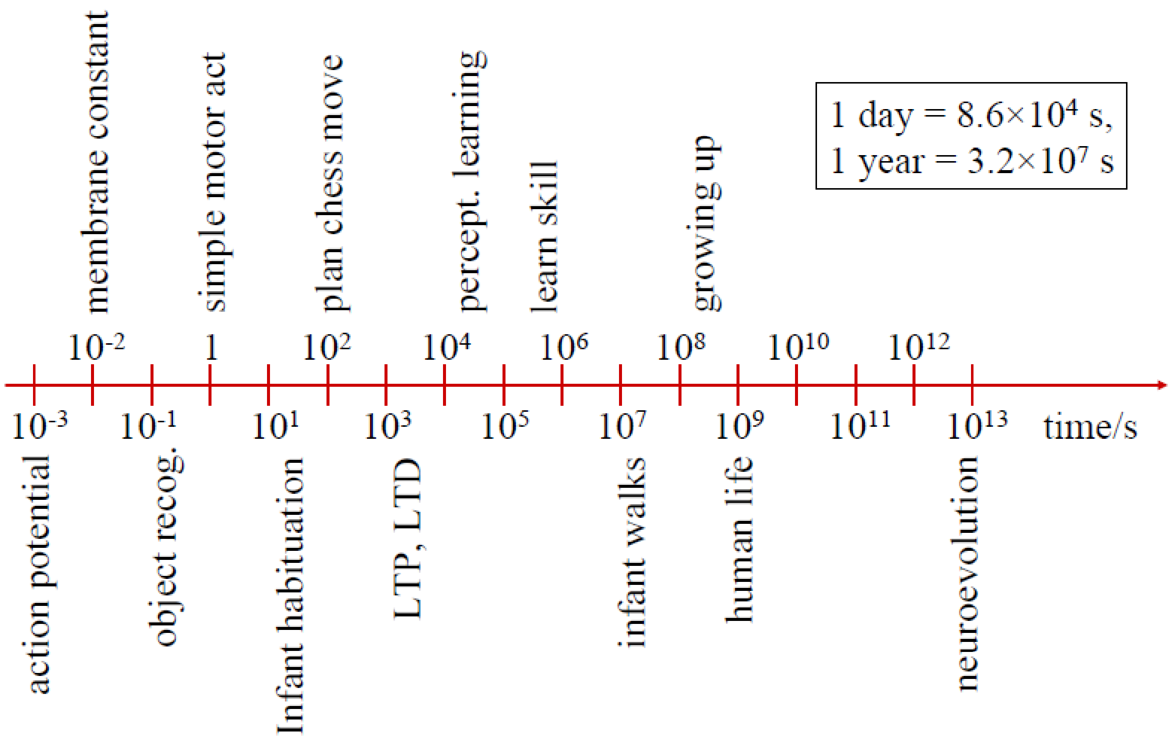


(Churchland & Sejnowski, 2002)

- Processes underlying brain function can be described on variety of different scales.
- Individual functions are best described at specific levels of resolution (e.g. it does not make sense to study higher cognitive functions at the level of channel dynamics).

Organization levels of the brain

Temporal scales



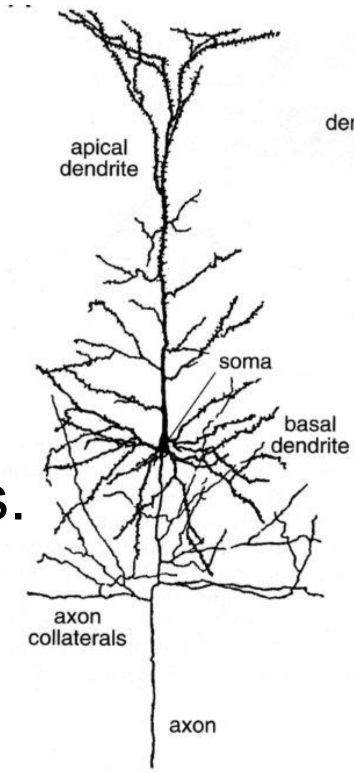
(Todorov & Triesch, 2004)

- Neural dynamics and learning happens on many different time scales.

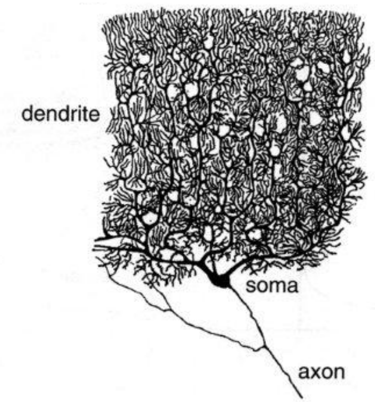
Anatomy of neurons I

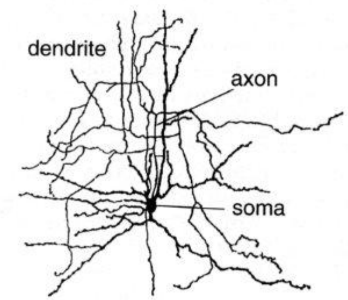
- Neurons propagate electrical activity.
- Action potential / ‘spike’ (‘binary’ signal).
- Many different anatomical forms.
- **Soma:** cell body, contains nucleus and cell organs (organelles).
- **Neurites** (carry signals):
  Dendrites: receive input from other neurons.
  Axons: carry output to other neurons.

Pyramidal cell



Purkinje cell
(cerebellum)

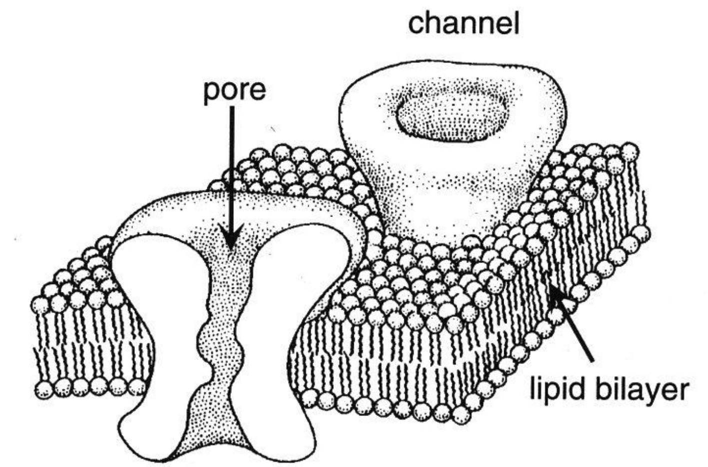


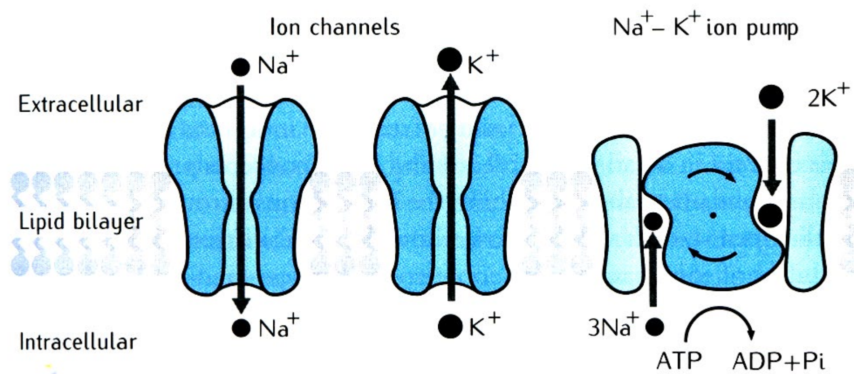


Stellate cell
(inter-neuron)

Anatomy of neurons II

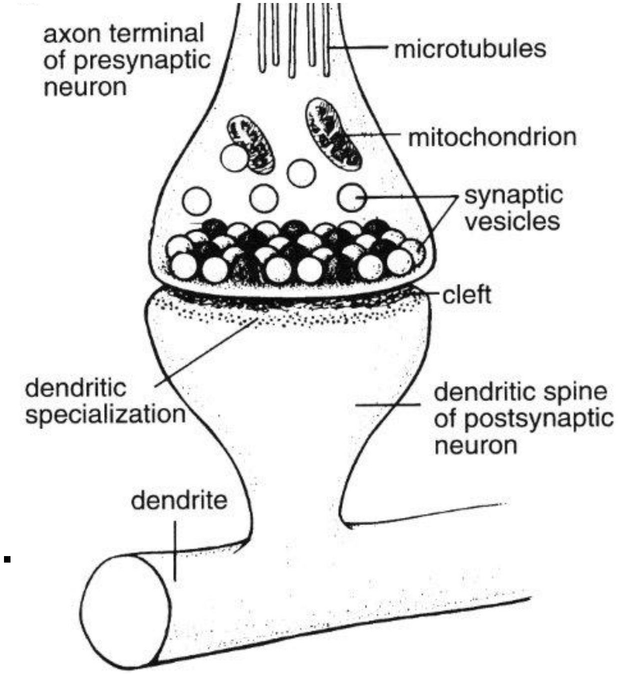
- Neurons enclosed by **membrane** (lipid double layer, insulator, 3-4 nm thick).
- **Ion channels** embedded in membrane
- Active (gated) vs. passive (always open) channels.
- Many different anatomical forms.
- **Ion pumps** (e.g. Na-K pump) to maintain concen-tration differences.
- **Synapses** link different neurons.

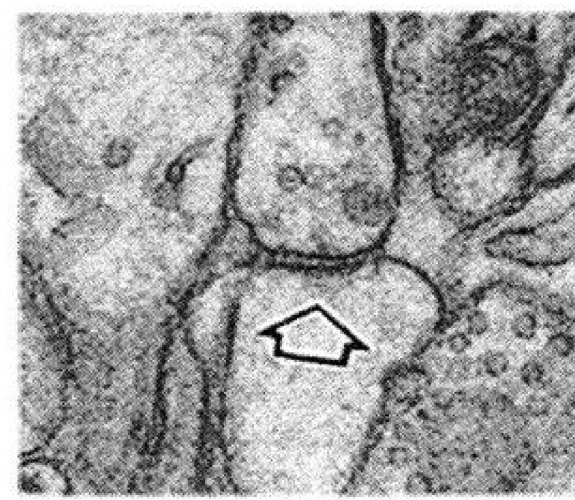




Synapses

- Link axons to dendrites and soma of other cells; 10^{15} in human brain.
- Electrical vs. chemical synapses.
- Voltage transients open ion channels.
- Ca^{2+} influx triggers release of **neurotransmitters** from synaptic vesicles.
- Important neurotransmitters:
  Acetylcholine (ACh) $\Rightarrow$ Excitatory Postsynaptic Potential (EPSP)
  Gamma Aminobutyric Acid (GABA) $\Rightarrow$ Inhibitory Postsynaptic Potential (IPSP)





Membrane polarization I

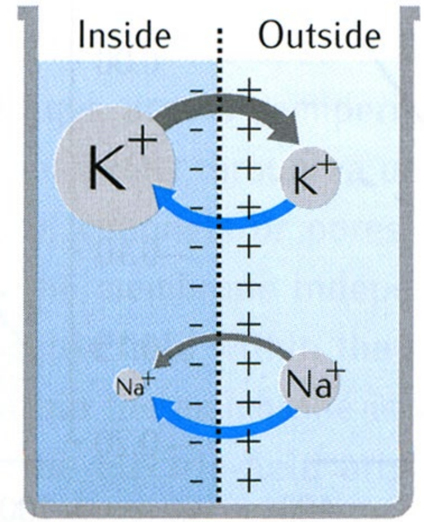
- If cell is at rest very unequal concen-trations of ions inside and outside:

  $[K^+]_{in} \gg [K^+]_{out}$

  $[Na^+]_{in} \ll [Na^+]_{out}$

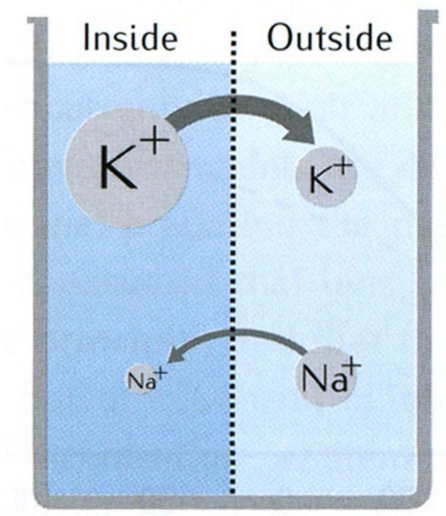
- Membrane partially permeable for these ions; this causes potential difference from the inside to the outside (see later).
- Typical difference: **Resting potential**:

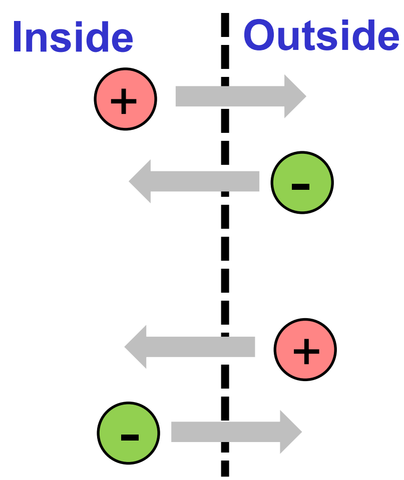
$$\Delta E := E_{in} - E_{out} \approx -70 \text{ mV}$$



Membrane polarization II

- Due to pre-synaptic stimulation membrane channels can be opened.
- Concentration differences balance out due to diffusion; this induces currents through the membrane.
- Membrane currents induce potential changes (relative to the outside):





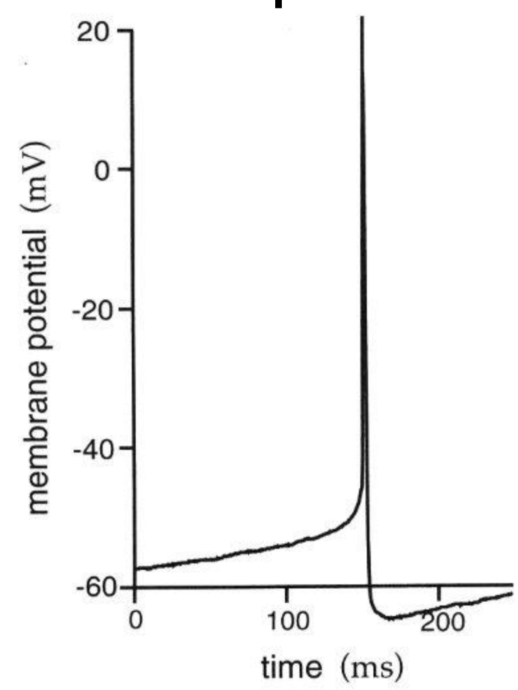
Hyperpolarization: $\Delta E < 0$

Depolarization: $\Delta E > 0$

Action potential

- If membrane potential exceeds certain threshold spikes are generated.
- Based on instability due to positive feedback process (details later).
- Amplitude ca. 100 mV; duration ca. 1 ms.

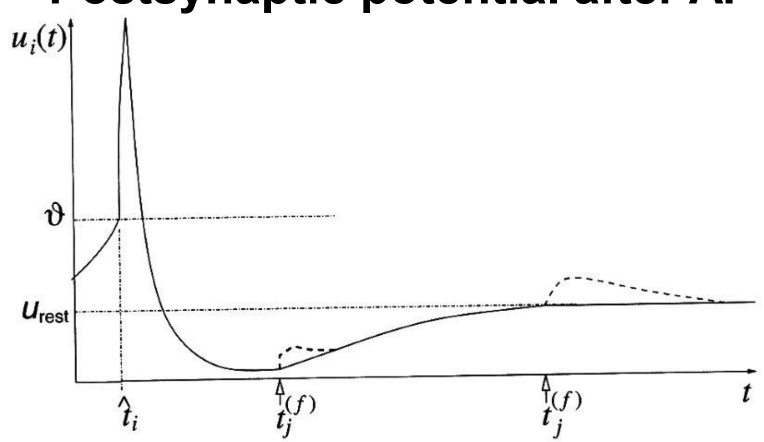
Action potential



- **Refractory period:** reduced excitability after action potential; duration typically > 10 ms

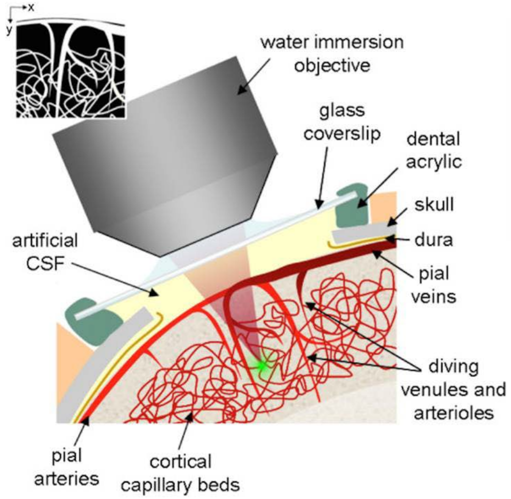
  absolute RP: no initiation possible
  relative RP: initiation more difficult

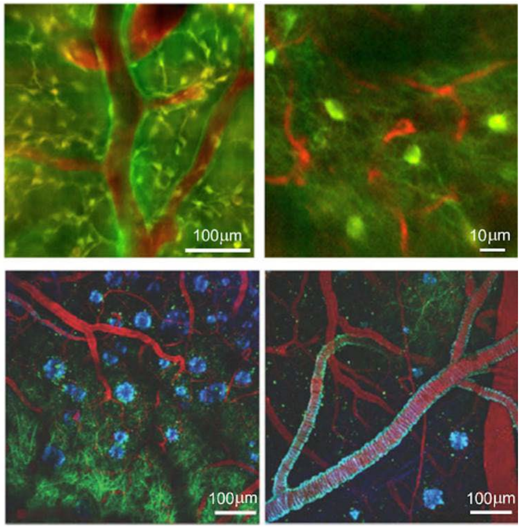
Postsynaptic potential after AP



Recording of neural responses

- Classical method: recording with glass or metal electrodes.
- More recently: imaging methods (fMRI, calcium imaging, intrinsic imaging, voltage-sensitive dyes).

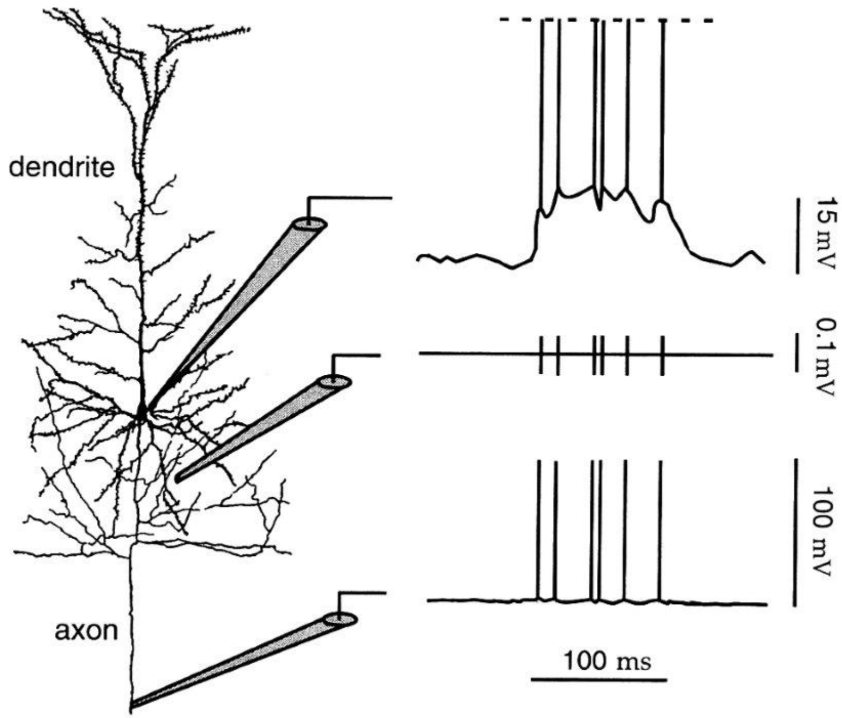




Recording of neural responses

- Recording sites:
  intracellular: electrode in contact with cytoplasm (e.g. in soma or axon)
  extracellular: electrode in extra-cellular space near neuron

Recording sites

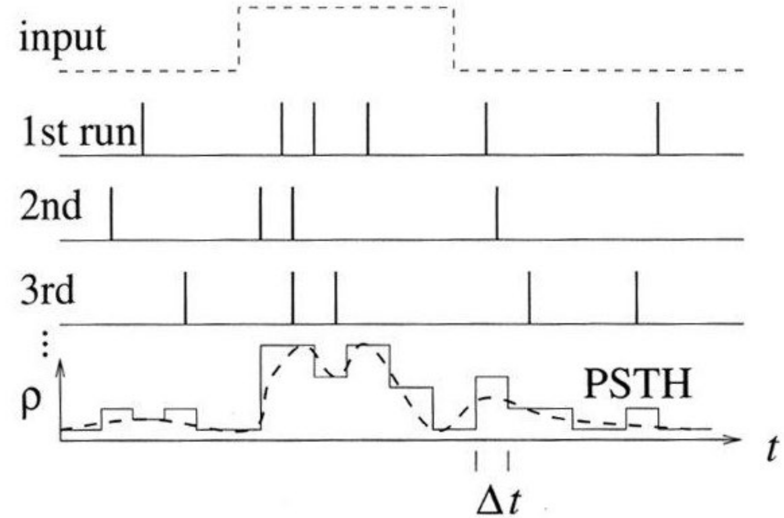


Quantification of spike activity

- Many possible measures (see Lecture: Neural Coding).
- Idealized model of a spike train:

$$u(t) = \sum_{n=-\infty}^{\infty} \delta(t - t_n)$$

spike time



‘Peristimulus time histogram (PSTH)’

- **Firing rate:** (average over time)

$$r(t) = \frac{1}{T} \int_t^{t+T} u(t')\,\mathrm{d}t' = \frac{K_{[t,t+T)}}{T}$$

No. of spikes in interval [t, $t+T$)

- Average over M trials: $\langle r(t) \rangle = \frac{1}{M} \sum_{m=1}^{M} r^m(t)$

trial no.

- Ideal estimate for spike probability for $M \to \infty;\ T \to 0.$

Things to remember

- Importance and role of modeling in neuroscience
- Levels and general problems of modeling
- Multiple scales in the CNS $\rightarrow$ 2)
- Basic properties of neurons $\rightarrow$ 1)
- Anatomy of the membrane $\rightarrow$ 1,2)
- Action potential $\rightarrow$ 1)
- Firing rate $\rightarrow$ 1)

(Numbers relate to literature on next page.)

Literature (for this lecture)

1) Dayan P. & Abbott, L.F. (2001 / 2005) *Theoretical Neuroscience: Computational and Mathematical Modeling of Neural Systems.* MIT Press, Cambridge MA, USA. Chapters 1 and 5.

2) Sterratt, D., Graham, B, Gillies, A., Willshaw, D. (2011) *Principles of Computational Modelling in Neuroscience.* Cambridge University Press, UK. Chapter 1.