Neuromorphic Engineering I

Information Coding in Biology

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Slides adapted from M. Ziegler, U Kiel

2.3 Information Coding in Biology

Learning objectives:

In the chapter approaches are presented how information can be encoded within neuronal systems. On the one hand, current methods of information coding are shown and their limits in terms of reality and performance are shown.

In this chapter we want to explain **3 of the most fundamental questions in neuroscience**:

- What is the information contained in such a spatiotemporal pattern of pulses?
- What is the code used by the neurons to transmit that information?
- How might other neurons decode the signal? As external observers, can we read the code and understand the message of the neuronal activity pattern?

Remark: unfortunately, a real answer to this question cannot be given.

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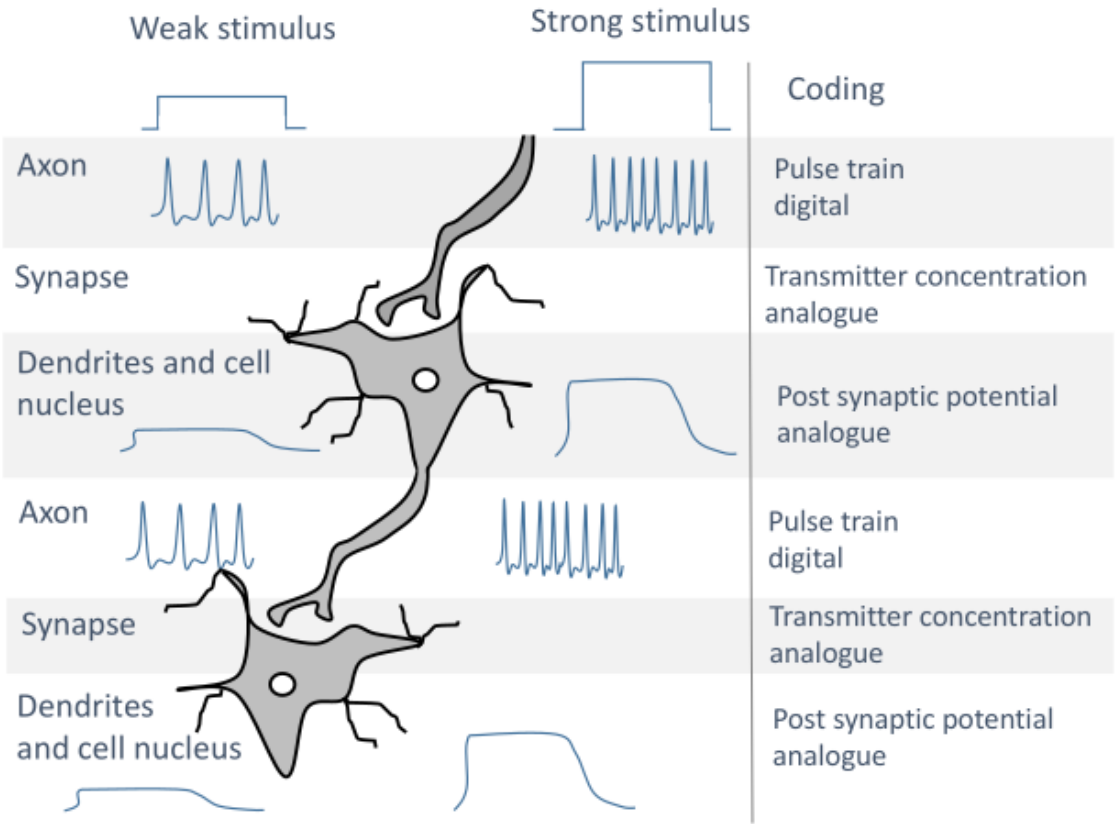
- In principle, it is important for every type of information transmission to encrypt the information so that it can be decrypted later.

  - In neurons, information is translated into changes in membrane potential, as we discussed in detail in section 2.1.
  - The content always refers to the duration and intensity of the excitement or stimulus.
  - In different areas of the neuron, the information is coded different.
  - The information is digitally encoded in the axon.
  - In the dendrites and the cell nucleus, as well as at the synapses, the information is coded by passive potential changes. That means analogue.



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- This means that in the axon the information is coded in the frequency of the action potential (spikes).
  - With a weak stimulus, few impulses are generated per time, while with strong stimuli, many impulses are generated.
  - Recoding takes place from one nerve cell to the other (at the synapses). This means that biology always changes from digital and analogue.

- At first glance, this may seem a bit complicated and some of you might as, why this make sense? But, it has a number of advantages. Let's see:
  - On the one hand, the neurons are decoupled over the synapses, so that the postsynaptic cell has no effect on the presynaptic neuron. That's what we know from electronics ... Galvanic isolation, Decoupling the output of a circuit, operational amplifiers,…
  - The digital coding in frequency is also more fault-tolerant. Just think on the case all information would be encoded into potential levels: even the smallest potential fluctuations would lead to the loss of information. Now with the spike frequency this is much more robust: here it is not the exact amplitude and pulse shape that matters, but only the number of spikes.

- Now one might think that everything is clear and understood. Stimulus strength is converted into a number of action potentials and their pulse sequence encodes my information. Nothing which really scares us…. We already know such kind of encoding of signals already very well from electrical engineering. Unfortunately it is not as easy as we will see in a moment ...

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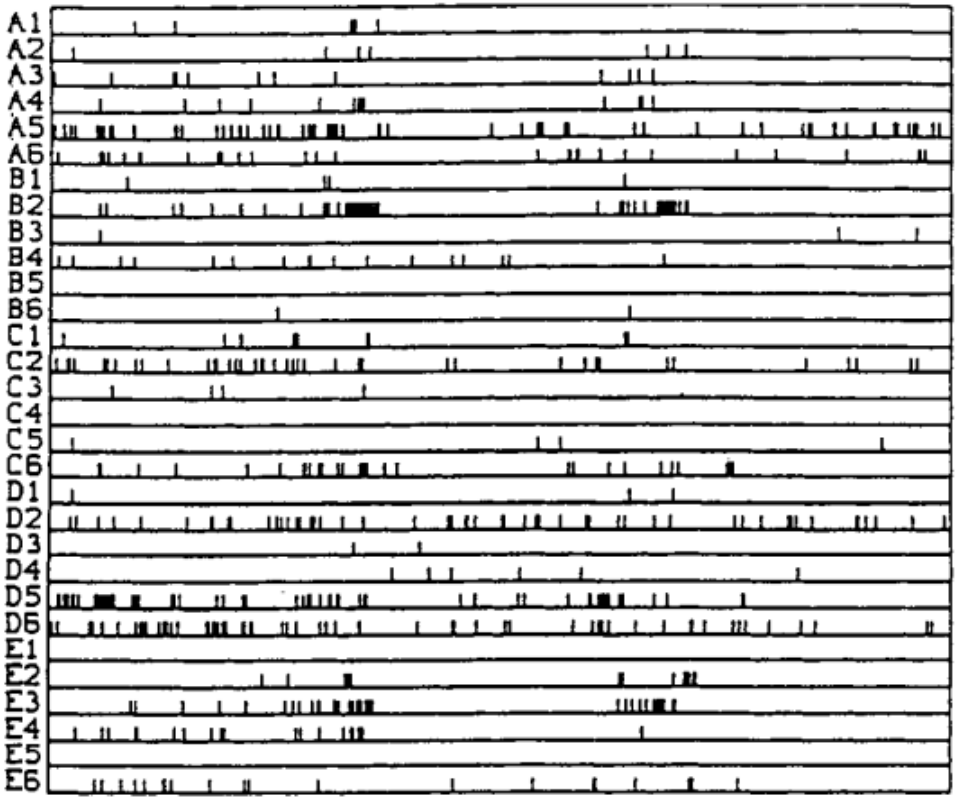
- As we already know, our brain does not consist of one neuron, but rather an extremely large number: to be exact 10^{11} neurons, which have an average of 1000 synaptic connections with other neurons. So we're talking about a network consists of up to 10^{14} interconnections.

  - Unfortunately, there is also no clock frequency like the computer have with operation at specific times: our brain works asynchronously.
  - An example of spike pattern of 30 neurons of different areas in the brain is shown in the figure, which is named **Spatio-temporal pulse pattern** *(A1–E6, plotted along the vertical axes are shown as a function of time; horizontal axis, total time is 4000 ms).*
  - Now we understand the action potential per neuron itself, but that doesn't help us much, since information is shown between areas in the brain, as we discussed in the last section.



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- So the following fundamental questions in neurosience arise regarding information coding in the brain:

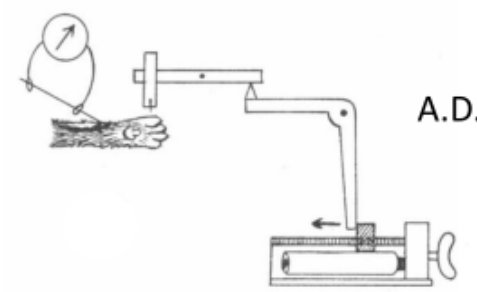
  a. What is the information contained in such a spatiotemporal pattern of pulses?
  b. What is the code used by the neurons to transmit that information?
  c. How might other neurons decode the signal? As external observers, can we read the code and understand the message of the neuronal activity pattern?

- The answer to these questions is referred to as the **brain code**. Unfortunately, there is a bad answer at the beginning: nobody knows the brain code….
  - It has not yet been understood how information is decoded in the brain. There are some ways to measure this. But, mostly you can only say quite simply area *xy* or area *xy* in the brain is important for the task *1* or task *2*.
  - In addition, unfortunately, you do not measure the same activation pattern from person to person.
  - There are possibilities to measure brain states for certain tasks. This is done to control e.g. protests. But this is very difficult to train and cannot be transferred from one person to another.
  - Maybe you can think of this as a shelf. Almost everyone (or a lot of us) has the Ikea shelf billy at home, but if I know how a shelf I set up my shelf, I can not conclude that all billy shelves in this world are set up exactly the same way…

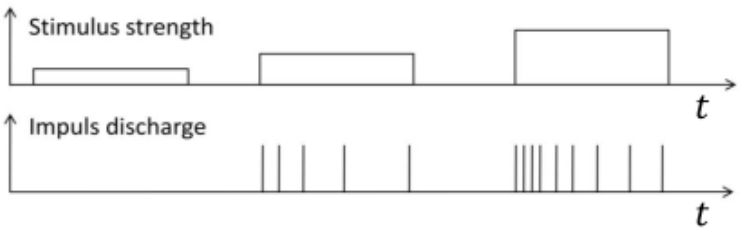
- In spite of this, there are of course models of how our brains could code information. Even if they do not describe the complete complexity, they help to understand different facts and to model parts of the brain.

2.3 Information Coding in Biology

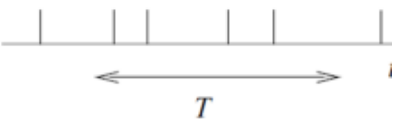
- A.D. Adrian was one of the pioneers in research into neural information coding. Adrian, who dealt with this question as early as 1926.
  - In an experiment, he stuck a needle into a frog's leg and measured the neural response regarding to that stimulus. Its measurement setup is shown in the figure.
  - What he could determine was that the force he exerted on the frog leg is transferred proportionally to the number of spikes of the sensor neuron, as shown schematically in the figure.



A.D. Adrian (1926)



- Now this allows a first modelling of the information coding in the neuron:
  - The resulting model is called the **rate code** because it averages over time the neural activity.



  - Neural activity ν is defined as number of spikes n_{sp} per time interval T : $\nu = \frac{n_{sp}}{T}$
  - The time averaging of the impulse sequence $x_i(t)$ (spike pattern) of neuron i gives the rate: $\langle x_i(t) \rangle = \frac{1}{T} \int_0^T x_i(t)\, dt$
  - The activity or spike frequency is a function of the input intensity I_0, i.e. the strength of the stimulus: $\nu = g(I_0)$

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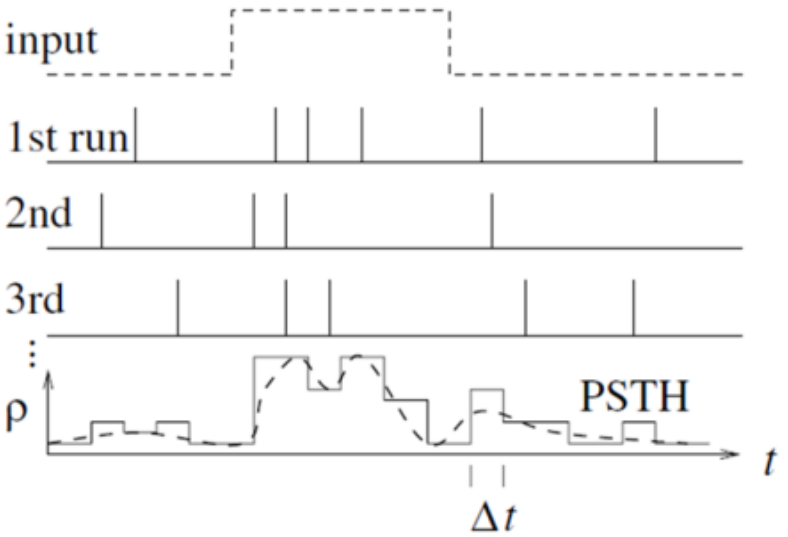
- A rate coding model which takes into account the difference in the number of spikes over time is the spike density rate.

  - In this model, the information is not extracted from one single run, rather it averages over different runs K. See therefore the figure, which is called a Peri-Stimulus-Time Histogram (PSTH).
  - Dashed line is the input stimulus, where *K = 3* spike trains n_k are shown representing the neural answer of the same stimulus. The bottom graph is the resulting spike density ρ over the *K* runs:

$$\rho = \frac{1}{\Delta t}\frac{1}{K} n_k(t, t + \Delta t)$$

  - The advantage is that you no longer look at the individual spikes, but rather their temporal density: is e.g. for an event the number of spikes is quite high, so the state is represented in the brain.



- As an experimental procedure, the PSTH measure is a useful method to evaluate neuronal activity, in particular in the case of time-dependent stimuli: we call it the time-dependent firing rate.

From Gerstner, W., Kistler, W. M., Naud, R., & Paninski, L. (2014). Neuronal dynamics: From single neurons to networks and models of cognition. Cambridge University Press.

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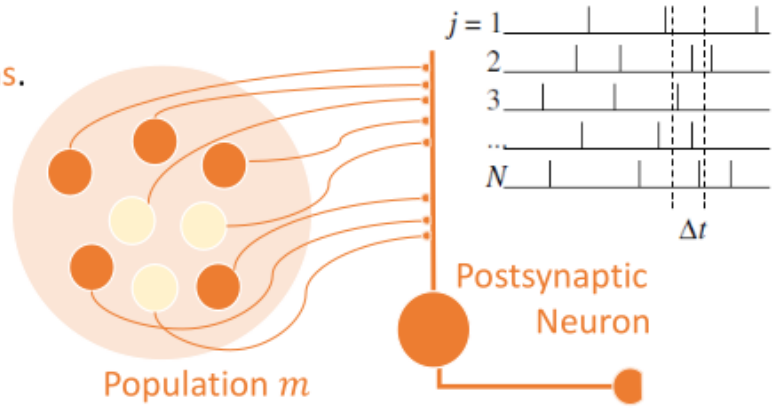
- We had seen several times that it is not a single neuron that processes information but many neurons. Often many neurons have similar properties and respond to the same stimuli.
  - Therefore, it may not make so much sense or it is not possible to really describe all processes in detail of the individual neuron, but instead to see what an entire ensemble of neurons does.
  - As an example, think of the different areas of the cerebral cortex that communicate with each other.
- That's why we want next describe the rate as a population activity (average over several neurons)
  - Let us idealize the situation and consider a population of neurons with identical properties.
  - Population *m* of neurons with identical properties.
  - All neurons have the same pattern of input and output connections.
  - If we now consider a postsynaptic neuron as shown in the figure, which receives information about his dendrite from the neurons of the population, the population activity can be determined as:

$$A_m(t) = \frac{1}{\Delta t} \cdot \frac{n_{act}(t, t+\Delta t)}{N}$$



  - where *N* is the size of the population, $n_{act}(t, t+\Delta t)$ is the number of spikes (summed over all neurons in the population) that occur between t and $t+\Delta t$ where T is a small time interval defines a variable with units inverse time – in other words, a rate.

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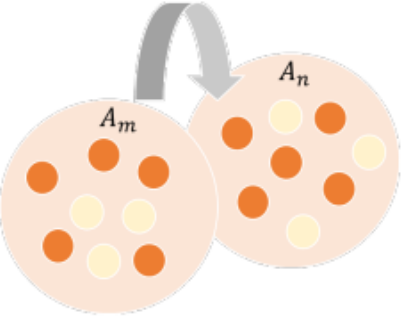
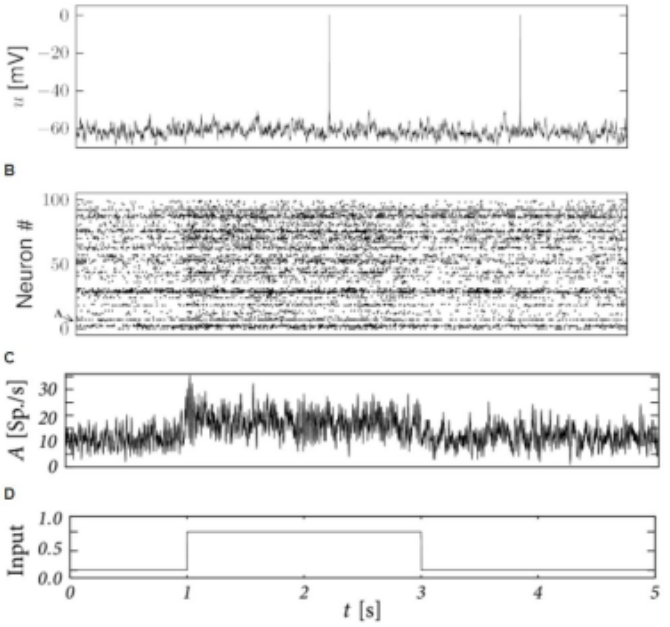
- Of course, this does not only apply to one neuron in the post-synaptic population and can easily be expanded:
  - Spikes of the neurons in a population m are sent off to population n.
  - Each neuron in population n receives input from all neurons in population m.
  - Formally, we can define the population activity in the same way (see figure).



- This makes it possible to describe large ensembles of neurons and also to describe processes that are very fast in time:
  - Population activity may vary rapidly and can reflect changes in the stimulus conditions nearly instantaneously as shown in the figure as an example.
  - Network of 8000 excitatory and 2000 inhibitory neurons:
    - A. Voltage trace as a function of time for a single model neuron. Spikes (vertical lines) are generated whenever the membrane potential (solid line) hits the firing threshold.
    - B. Spike raster of 100 neurons in the network. Spike times (dots) of a single neuron appear along a horizontal line.
    - C. Population activity A(t) as a function of time, measured by averaging across the spikes of the subpopulation of 100 neurons shown in B. From time t=1s to t=3s, all neurons in this population receive a nonzero input.
    - D. Input to the subpopulation of 100 neurons.



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- Many simulation models and neurobiological models are based on this right simple coding models of a rate code.
  - Even if it is quite simple, many functional relationships can already be described, as we will see later in the lecture.
- Nevertheless, the question arises how biologically realistic is the model of time-averaged spike rates?
  - Unfortunately, reaction times in behavioural experiments are often too short to allow long temporal averages. Humans can recognize and respond to visual scenes in less than 400 ms
  - Recognition and reaction involve several processing steps from the retinal input to the finger movement at the output.
  - If, at each processing step, neurons had to wait and perform a temporal average in order to read the message of the presynaptic neurons, the reaction time would be much longer.
  - Furthermore, there is a certain fluctuation between the individual spikes in the pattern, which affects the coding as noise and can only be suppressed by averaging over several runs.
- Furthermore, rate coding is stationary, while real-world inputs are often changing on a fast time scale.
  - Here we could see that PSTH helps that can also take into account changes in time, since it averages the density and not the spikes themselves. As an example, you can imagine a moving object where there is always new image information, but you can still see that it is the same object.
  - But PSTH is of course too slow too, since it also has to average over several passes.
- The coding within a population rates can react quickly enough to input changes and also describe large ensembles of neurons. However, we assumed that these ensembles are homogeneous, which does not seem very realistic. An expansion here is possible, but poses further problems.

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- An extension, or to say it better, precision is not only to use the rate of neuronal activity when coding information, but also to take into account the timing of the neural activity (spike time).
  - This makes particular sense if you consider that time is an important factor for us in learning and memory processes.
  - Think e.g. to the memory structure discussed in the last chapter, which goes from ultra-short-term memory to long-term memory.
  - Or to the temporal correlation of events that is so important for recognizing and learning patterns: a child who puts a hand on a hot stove plate will not do it again, if she also feels the painful hand. If the hand only hurt a day later, this would hardly be attributable.

- Thus, it make sense to discuss coding strategies based on spike timing of neurons.
  - Let's start with the following scenario: We run towards a traffic light that suddenly changes from green to red. That means within a few seconds the information in our field of vision has changed to stop moving.
  - For this we can consider the following strategy in which, after an external stimulus (traffic light), exactly the first neuron that spiked contains the relevant information (red traffic light). All other information is subordinate to this.
  - Now, to put it more precisely, you can say a neuron which fires shortly after the reference signal is interpreted as a strong stimulation of this neuron, whereas firing somewhat later would signal a weaker stimulation.

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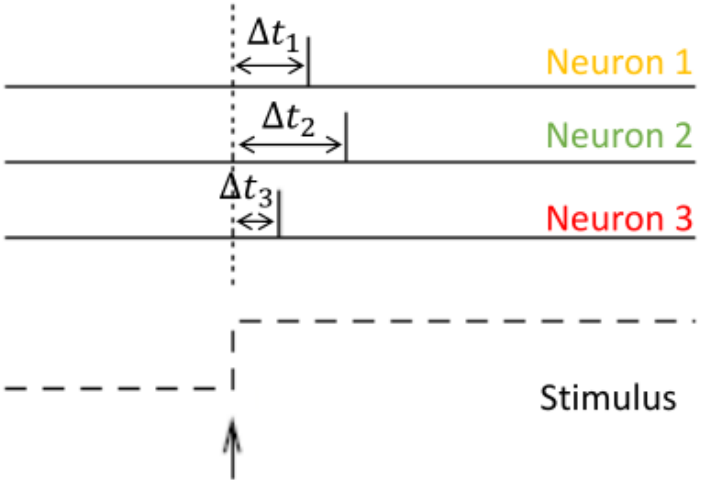
- This is exactly what is shown in the figure and is called **time-to-first-spike**: the neuron which first spikes after the reference signal contains all information.
- Thus, the neuron which fires shortly after the reference signal (neuron 3 in the figure) could signal a strong stimulation; firing somewhat later would signal a weaker stimulation:

$$\Delta t_3 < \Delta t_1 < \Delta t_2$$

- Since each neuron in such a scenario transmits exactly one spike per stimulus, it is clear that only the timing conveys information and not the number of spikes.

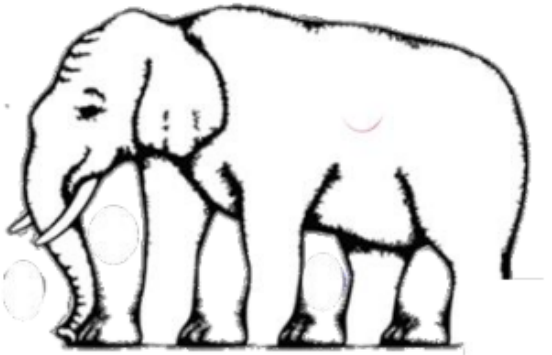


- Now the question remains is this biologically plausible?
  - The answer is yes, there is really experimental evidence that biology does this.
  - An example are touch sensors in the finger tip encode the strength and direction of the touch in the timing of the first spike emitted by each neuron.
  - The big advantage here is of course the speed. This is the main reason why some scientists claim that the information is in the first spike, others have only secondary information.

2.3 Information Coding in Biology

- An essential question in modern neuroscience is how local and mostly stochastic activity patterns of individual neurons generate global activity patterns that extend across the central nervous system?
  - This question is closely related to the question of how our brain constructs uniform perceptions from a multitude of sensory impressions (sensory integration).

- The latter is also known as the binding problem and is the question behind the already discussed optical illusion of the elephant.
  - Depending on whether we focus on the background or on the body of the elephant, the picture appears to us correctly or not. To reinforce this impression, the background is coloured blue in the lower picture.
  - What some may also observe when looking at the picture is that it is bistable, i.e. it switches back and forth between right and wrong.
  - This may be an indication that the neuron ensemble flexible fires for one as well as another perception.
  - But, how does this work? Unfortunately there is no exact answer to this. But there is strong evidence in which direction to look for the answer.



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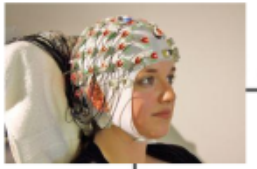
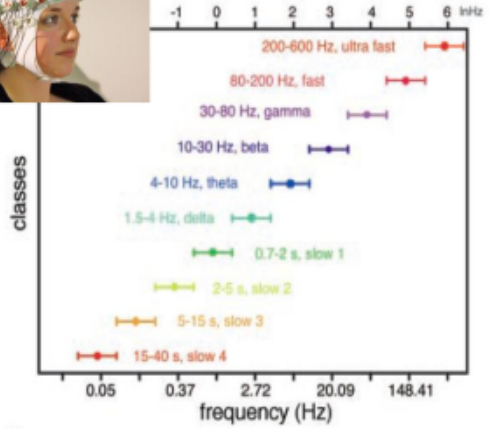
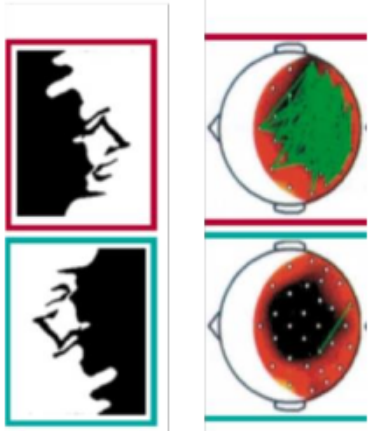
- When brain activity was recorded by Electroencephalography measurements, one could observe that there are several frequency bands in which our brain works (see figure).
  - These rhythms are crucial for various functions in the brain, such as memory formation in the hippocampus and in interaction with areas of the cortex.
  - Furthermore, it could be shown that when a pattern is recognized, a higher correlation is visible in the activity pattern of the firing neurons.
  - An example is shown in the figure below, where Electroencephalography measurements which gives an hint between correlated firing of neural ensembles and pattern recogniton:



G. Buzsàki and A. Draguhn
Science 2004





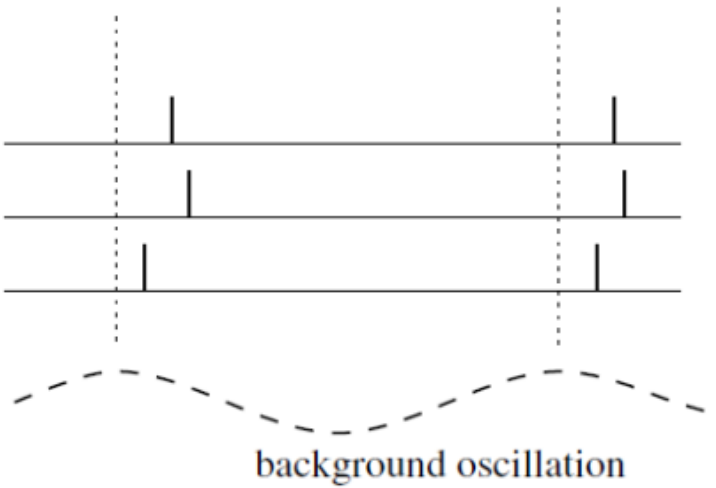
F. Varela et al., Nat. Rev.

- Here, a clearly higher synchronicity of neural activity is recognizable in the case of a recognizable pattern than in the case that no pattern can be recognized.
- This suggests the these oscillations could serve as an internal reference signal and gives an answer to the binding problem, as already proposed in 1981 by von der Malsburg:

Neurons which represent the same object
could be "labeled" by the fact that they fire synchronously

2.3 Information Coding in Biology

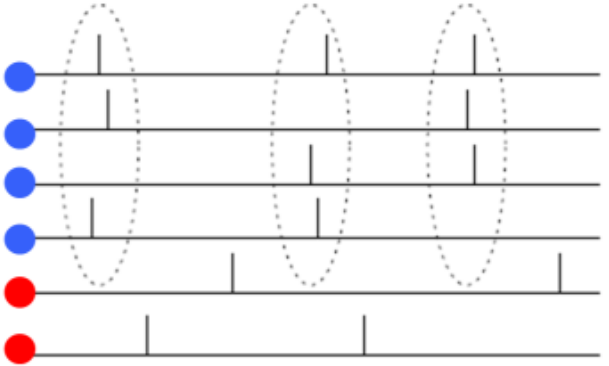
- Brain oscillation as a collective rhythm of neuron ensembles can also be combined with spike-time coding schemes.
  - The rhythm can be understood as background oscillations, which phase position stimulates or suppresses individual spike events from specific neurons (see figure).
  - Here, three neurons are shown which fire at different phases with respect to the background oscillation (dashed).
  - The phase could code relevant information in a way that the neuronal spike trains could encode information in the phase of a pulse with respect to the background oscillation.
  - If you think of the image of the elephant again, the observable bistability can be explained by the fact that we perceive the image as incorrect or correctly drawn, depending on the phase.



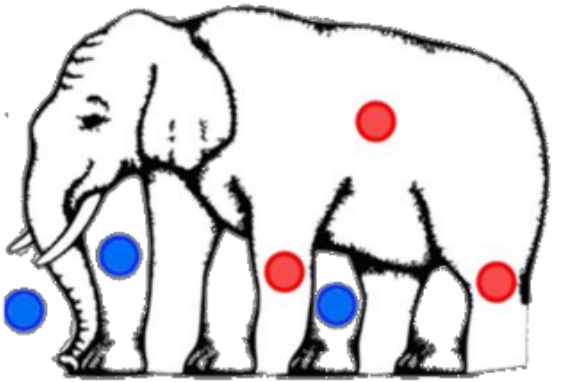
- In addition, such a mechanimus would allow experienced events (information) to be saved or " remembered ".
  - if the input does not change between one cycle and the next, then the same pattern of phases repeats periodically.
  - Such mechanisms play an important role in the transfer of information into long-term memory. What mainly happens during sleep and areas of the hippocampus and cortex are involved.

2.3 Information Coding in Biology

- Now the connection must not only be made in relation to a background oscillation, but it can also happen directly between neurons ensembles.
  - Let us again consider again the example of the elephant:
  - some neurons (marked in red) could represent the body of the elephant and other neurons (marked in blue) the background of the image.
  - Depending on the temporal correlation - synchronicity of spikes - the neurons could then be assigned in different representations of the image.



- Correlation or, in other words, binding of information through synchrony of neural activity is an elegant solution to the binding problem.
  - this would also explain in a simple way how even distant areas of the brain could be correlated for different tasks.
  - Even if there is a lot to be said for this solution, doubts have been raised again recently.
    - It takes time to develop synchronous states, too much time for many tasks ...However, research into brain oscillation is one of the currently big and heavily worked-out topics in neuroscience.



2.4 Modeling and Emulation Methods in Neuroscience

Learning objectives:

In the chapter I would like to show you how to transfer biological observation into mathematical models. We will discuss many of the models shown in detail later. The goal is to give you an overview and a feeling for the procedure.

In this chapter I would like to answer the following questions:

- How can biological paradigms of information processing and storage be converted into mathematical models?
- What are the approaches?
- What are the limits of the approaches and what do you have to consider?
- Why do we still want to build all this in hardware?

2.4 Modeling and Emulation Methods in Neuroscience

- In the previous chapters we got to know the basic building blocks of neural systems and their functions.
  - We have gone from the level of individual cells to global networks and discuss their functionality in terms of information processing. Even we striving the question about perception, awareness and consciousness.
  - However, a large number of the concepts presented are at the descriptive level: just as biology does. Describe the living nature.
  - However, in order to make these concepts usable for an technical emulation, it is necessary to move from the descriptive level to an abstract mathematical level.
  - This is what we know from engineering and what is well known to all of them: for example before the first electronic circuits were designed, Maxwell formulate the basics about electrodynamics in its famous set of equation.
- Of course, one would also like to use a similar process chain for neuromorphic electronics, i.e. exploring the biological effect, formulate a mathematical model for description, transfer this model into an electronic circuit…
  - Here we are faced with a huge problem: How can I reconstruct biological processes in such a way that I can grasp them within a mathematic theory?
  - The answer to the question is difficult again. **Biology is not based on laws like physics, but on rules.** This poses enormous problems for our logic-based mathematics.
  - However, there are some approaches on how to and should proceed here. I will briefly introduce modelling approaches used in neuroscience in the following.

2.4 Modeling and Emulation Methods in Neuroscience

- Let's start with the basic view of how to approach the problem and what the common methods in neuroscience are:
  - Modeling work in neuroscience can be classified using two different criteria:

    - Complexity of the model: this is an important point that relates generally to theoretical description and model building. It will hardly be possible to model the nature in all its complexity. It is important to have a model that takes the essential aspects into account to answer the question asked.

    - Direction of workflow: from microscopic to macroscopic scales (bottom-up) or from behavioural target functions to properties of components (top-down)

- We want to take a closer look at both points below and explain them using examples. The main part of this chapter is taken from a very well written paper by Wulfram Gerstner (see *).

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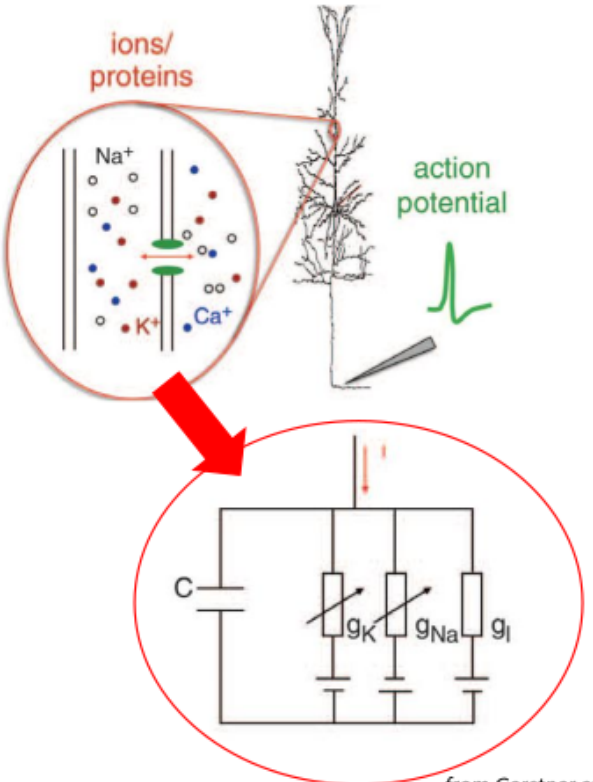
*from Gerstner et al., From Detailed to Abstract Models of Neural, *Science 338 (6103), 60-65.*

2.4 Modeling and Emulation Methods in Neuroscience

- Let's start with the bottom-up path, i.e. from detailed models that describe very precisely the processes that take place at the cellular level to abstract models:

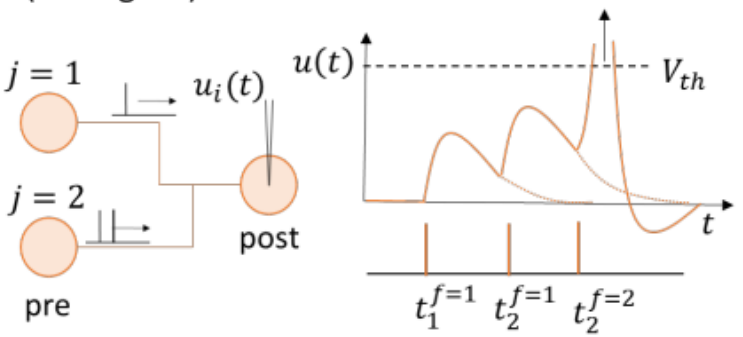
  - As we have already seen, the ion current through the cell membrane can be modelled using an RC circuit.
  - If you extend this to the different types of ions and take into account the voltage dependency of the ion channels, you can construct an equivalent circuit as shown in the adjacent figure:
    - The ion currents flowing through channels in the cell membrane (left) are characterized by an equivalent electrical circuit comprising a capacity C and a set of time-dependent conductances *g*, one for each channel type (right).
    - These currents can generate action potentials (green).
  - This is the most famous model for simulating neurons. It was developed in 1952 by Alan Lloyd Hodgkin and Andrew Fielding Huxley, originally to describe the development of action potential in the giant axon of the octopus.
  - A model of this kind describes the ion processes in the cell in great detail and can be used to explore the electrochemistry of the cell (we will discuss more about such a model later in the lecture).



from Gerstner et al.

2.4 Modeling and Emulation Methods in Neuroscience

- Well, the problem with the detailed description of cellular activity is that it takes a lot of computing resources. This makes it difficult to simulate entire networks.
  - Thus, a transition to more abstract models is requested, which are not as detailed in the cellular description of the biological processes, but take into account the essential mechanisms of neural activity.
- We have already discussed the next level of abstraction, which allows you to leave the cellular level and open a transition to the network. These are so-called spiking-neuron models (see figure):
  - Action potentials are treated as formal events ("spikes") generated whenever the membrane potential *u(t)* (solid orange line) crosses a threshold V_{th} (dashed line). After each spike the voltage is reset.
  - Arrivals of spikes from presynaptic neurons (j= 1,2) generate postsynaptic potentials.

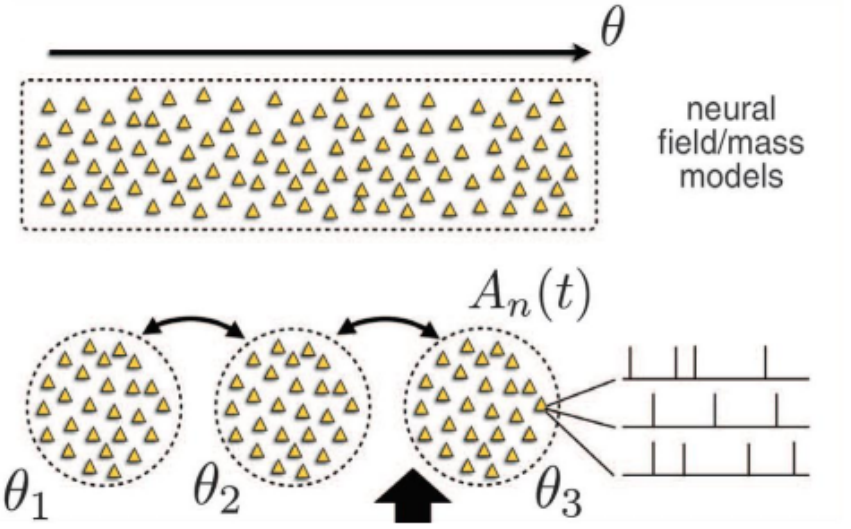


- In this more formal model, the dynamics of the ion channels is no longer preserved, but rather focuses on the synaptic integration of incoming signals and the firing of the neuron.
  - However, it still contains important cellular aspects that determine the shape of the postsynaptic potential.

2.4 Modeling and Emulation Methods in Neuroscience

- Now we have seen that we have the number of neurons in our brain like stars in a galaxy. Of course, this can hardly be solved in full complexity, even if there are approaches to this, such as the Human Brain Project. Thus, this will hardly be possible if we have to solve a differential equation for each neuron.

  - Therefore, it makes sense to be a little more abstract in the description of neurons and synapses in neuronal networks.
  - We have already discussed this and include the description of neuron ensembles, as shown schematically in the figure:
    - Groups of neurons interact by their population activity $A_n(t)$ derived mathematically from neuronal parameters.
    - In a continuum description (neural field model), different neuronal populations are characterized by their input characteristics such as the preferred orientation *Θ of a visual stimulus.*



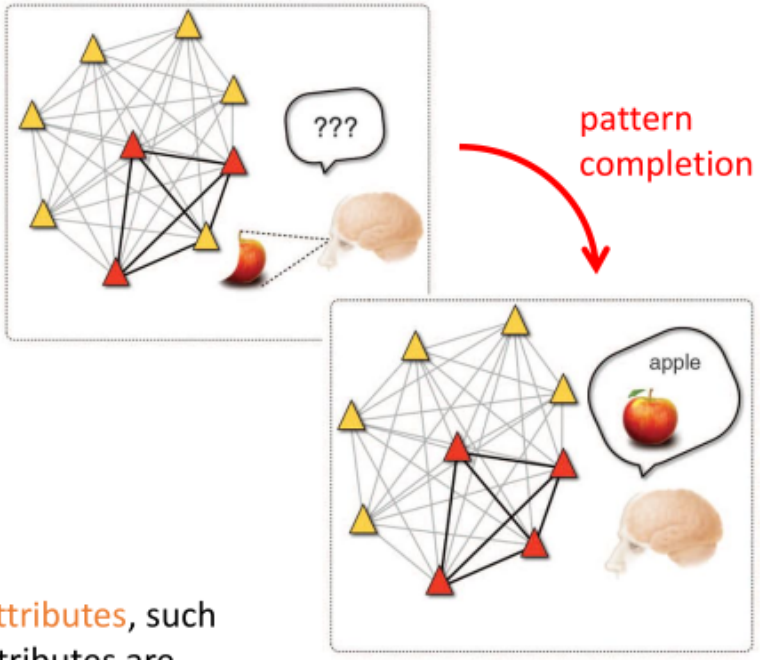
from Gerstner et al.

- This model, designated as Neural mass model, thus allows entire brain areas to be described on a macroscopic scale. The scale that is accessible to us essentially through the large number of examination methods of neuroscience.

2.4 Modeling and Emulation Methods in Neuroscience

- Now we have reached a very abstract level in which cellular properties of the individual neurons are only taken into account via activity patterns. This immediately leads to the question: how can learning processes be simulated?
- We are on the top-down path: global events, such as certain behaviour patterns, are reconstructed in such a way that local structures form within the neural networks. We talk about connectivity.

  - An example of this is Hebbian Assemblies and Associative Memories, which is shown schematically in the figure:
  - Hebb was a Canadian psychologist who started thinking about synaptic connections and the cellular correlation of learning and memory processes at a very early stage.
  - According to Hebb, neurons that are active together (red triangles) during a concept such as “apple” form a cell assembly with stronger excitatory connections with each other (thick lines) relative to connections to and from inactive neurons (yellow).
  - Therewith: Partial information is sufficient to excite the inactive neuron of the assembly and retrieve the full concept, which is called pattern completion.

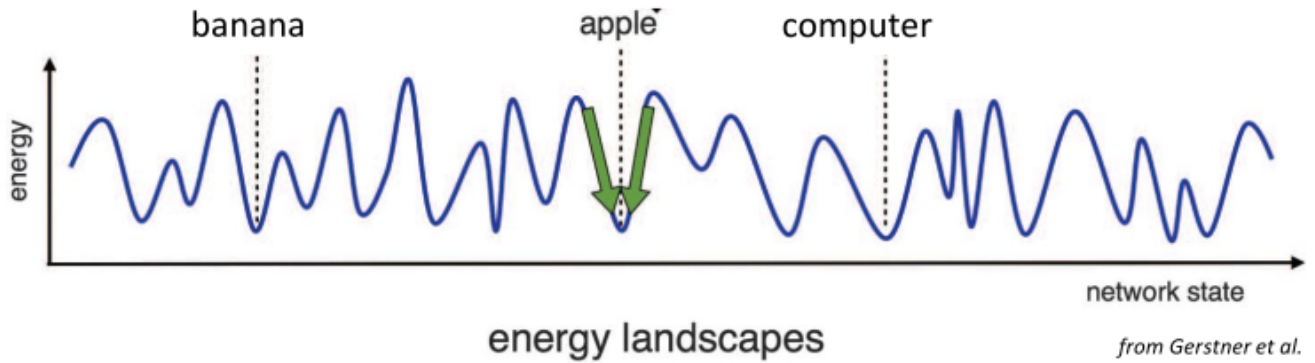


from Gerstner et al.

- This allows an object, such as the apple, to be described using important attributes, such as round, red, sweet, fruit, ... Of course, we also recognize an apple if its attributes are missing, such as the bitten apple that is no longer round .

2.4 Modeling and Emulation Methods in Neuroscience

- The dynamics of the pattern recognition process can be described with the help of attractors:
  - Attractor describes a subset of a phase space (i.e. a certain number of states) to which a dynamic system moves over time and which is no longer left under the dynamics of this system.
  - That is exactly what happens in the recognition process. You look at an object and classify its various aspects to classify whether it is more of an “apple” or a “banana”, or a “computer”, … .
  - This means that a set of variables approaches (over time) (asymptotically) a certain value, a curve, or more complex (i.e. a region in n-dimensional space) and then stays close to this attractor over time.
- The dynamics can be visualized in an energy landscape (energy as a function of network state) as a downward flow into the well corresponding to “apple”; other concepts (car, grandmother) correspond to other minima of the energy.

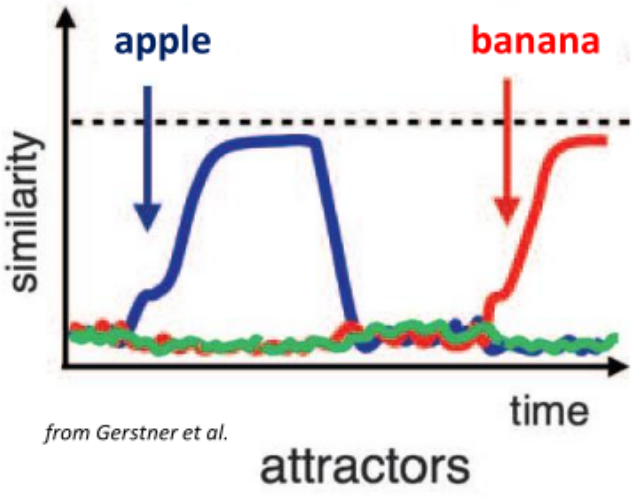


energy landscapes

from Gerstner et al.

2.4 Modeling and Emulation Methods in Neuroscience

- Now, as shown in the figure, this concept is relatively easy to apply to the pattern recognition process:
  - Thus, after a short presentation of partial information resembling the concept “apple,” the network moves toward an attractor state with high similarity (blue line in figure) to the corresponding assembly.
  - After a reset, the network is ready to respond to a second stimulus (“banana,” red line in figure). Similarity with other learned patterns (green line in the figure) remains nearly unchanged during retrieval of one of the memories.
  - The dashed horizontal line indicates maximal similarity, and therefore identity, with a stored assembly.

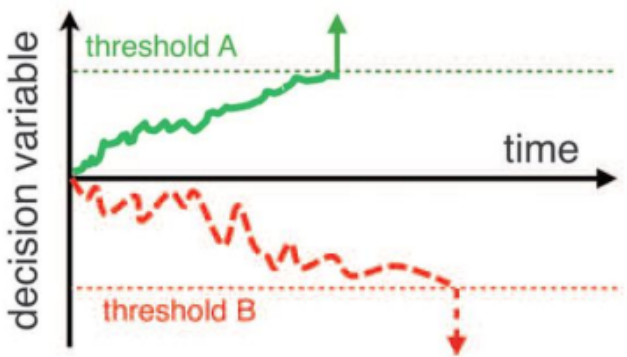


from Gerstner et al.

- This type of description of learning and memory processes is very common and is widely used in the field of neuroscience.
- We will therefore return to the Hebbian learning theory and its applications in networks in more detail later.
- Let us leave it at this point and in the following turn to the question: how you can combine both paths top-down and bottom?

2.4 Modeling and Emulation Methods in Neuroscience

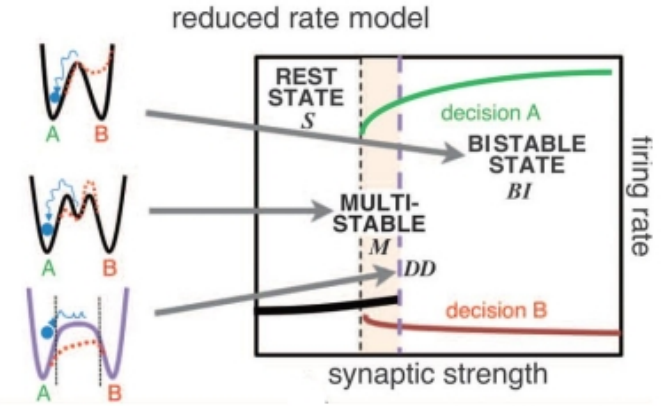
- What we used here was a simulation model that uses both top-down and bottom-up: On the one hand, it was important to see what a local weakening of individual neural connections does in relation to global performance in the area of global behavioural tasks, the pattern recognition.
- Well, let's go back to the systematic description of model building and consider a simpler process that we all often do every day, the process of decision making.
  - Let's look at the decision-making process as to whether you go to the cafeteria for lunch or not.
  - After getting up at breakfast, where you can fortify yourself well, you might say - no, I am not going to the cafeteria today. However, this opinion can change over the day due to various influences. The hunger comes back or all your friends are there or for whatever reason.
- Drift-diffusion models can be used to simulate the decision-making process on a very abstract global level, as shown in the figure:
  - Decision is descripted by a single variable and a threshold.
  - A decision is taken (arrow) when the decision variable hits a threshold (first trial, green, choice A; second trial, red, choice B).
- The question remains what is behind the variable or how you can represent it in a more detailed model?



from Gerstner et al.

2.4 Modeling and Emulation Methods in Neuroscience

- At the mesoscopic level, this can be understood as the competing two states of two neuron ensembles:
  - One can again consider the rates of the neuron ensembles that are mutually concordant. Depending on which rate is higher, the decision to use one or the other option can be used.
  - Thus, we end up with a mathematical model of interacting populations:
  - A decision can be visualized (left) as a ball moving down the energy landscape into one of the minima corresponding to A or B.



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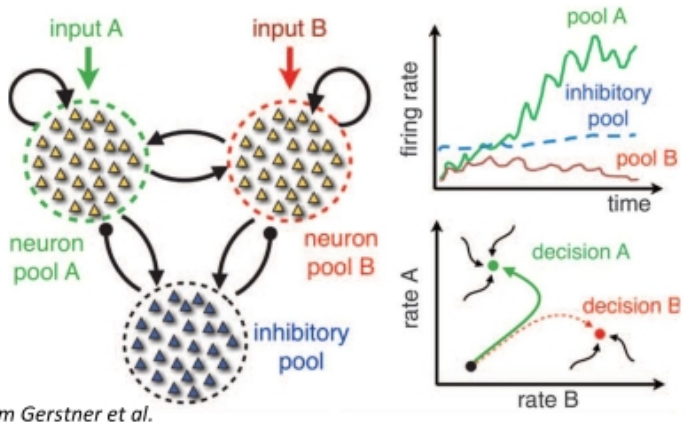


from Gerstner et al.

- This can be described in more detail on a biophysical model, as shown in the figure.
  - To be more precise, a multineuron spiking model is shown in the figure opposite:
  - Two pools of neurons (left) receive input representing evidence for choice option A or B, respectively, while shared inhibition leads to a competition between the pools

2.4 Modeling and Emulation Methods in Neuroscience

- Now the final question remains to be answered, why do we still want to build all this in hardware?
  - The answer to this, of course, is complex and has many aspects.
  - In the first week we talked about energy efficiency and parallel computing, which is particularly promising from a technical point of view

- The point may not seem particularly important for the neurobiology itself, since one is interested in understanding the processes and not in smart technical solutions.
  - Here, however, an argument can be made which I already made at the beginning of this chapter. As complex as our mathematical models are, they only describe reality to a certain extent.
  - We saw this in the chapter. The more abstract the model becomes, the more undetailed it becomes with regard to cellular properties.

- Here you have an advantage in hardware **- you basically use nature to describe nature -** in particular solid state physics / electronics.

2.5 Outlook and Prospects for Technology

Learning objectives:
This chapter goes beyond the textbooks in the field and is intended to give you a feeling for the topic and to show in which direction neuromorphic engineering is developing. So a lot of exciting questions (for me at least) and a few approaches that we are currently researching. So I would be happy if one or the other does not skip this chapter ;-)

In this chapter we want to give answer to the following questions:

- Why we need a paradigm shift in information processing?
- How dynamic is our brain? Or how fast can neural networks grow?
- What is meant by heterogeneity, randomness, and modularity?
- What is a small-world-network?
- What tells us evolution theory?

2.5 Outlook and Prospects for Technology

- In this chapter, I would like to go into two important properties of biological systems that we have not discussed up to now and which are of little interest in technology.

1. On the one hand, there is the theory of evolution, which describes an essential aspect of the complexity, functionality and structure of our brain: our brain is the result of millions of years and not of a day.

2. On the other hand, it is about growing and the dynamics of neural networks. In contrast to an electronic circuit, our brain is highly dynamic and constantly forms new neurons and synaptic connections.

➢ This variability offers a multitude of possibilities, but also presents enormous challenges in its replication.

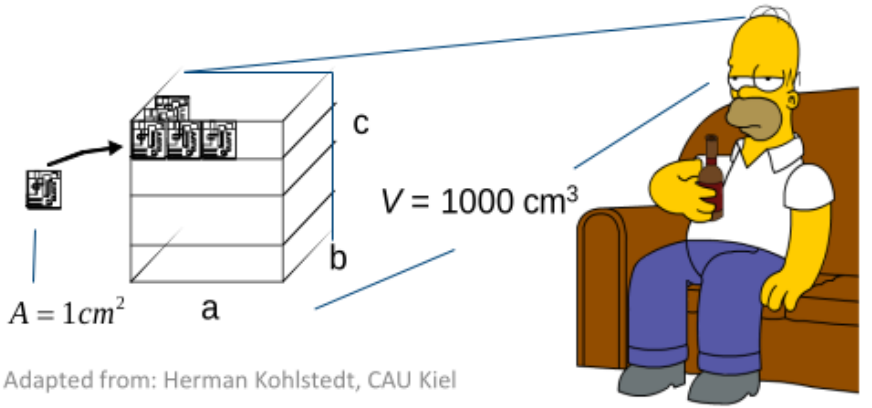
➢ In the following, I would like to discuss those points in a little more detail and show where are the problems we are facing, but also the opportunities for the technology.

2.5 Outlook and Prospects for Technology

- I like to start with a simple estimate of whether you can recreate a human brain using today's technology for electrical circuits.

  ➢ First of all, we assume that we would know how to do it and that circuits, structure and their functionalities are known (a really strong assumption - but that's not the point now):

  - For this we imagine the brain, as shown in the figure, as a cube with a volume of V = 1000 cm^3. We assume that the individual circuits (chips) with an area A = 1 cm^2 could be arranged in rows like the components in a computer. Thus, we can fill the cube with N_{chips} = 2 10^4 chips.



Adapted from: Herman Kohlstedt, CAU Kiel

  - Furthermore, in today's Si technology we can pack around $N_{Transitors/chip}$ = 10^{10} transistors on one chip, which gives us a number of $N_{Transitors}$ = 2 10^4 10^{10} = 2 10^{14} transistors in the whole brain.
  - This number roughly corresponds to the synapses that we have in the brain: $N_{synapse}$ = 10^{14} .
  - Now let's look at the power consumption: for this we assume that a single transitors consumes $P_{transistor}$ = 5 nW, which leads to P_{total} = 1 MW for the system. This value choc us not too much, since it is the range of today's supercomputers.
  - In comparison, our brain consumes approximately only $P_{total, brain}$ = 25 W.
  - If we calculated this value down for each synapse we end up at $P_{synapse}$ = 250 fW. Means by 1V signal amplitude a current of 1fA per switch. This is smaller than every leakage current…

Thus, a difference of 4-5 orders of magnitude in the power consumption!

2.5 Outlook and Prospects for Technology

- With this simple estimate, one conclusion can be drawn: it probably takes a little more than simply replicating the brain circuits and simulating our brains.
  - More than that, we need a paradigm shift in information processing that takes essential aspects of biology into account.
  - But what are these? Well, one approach may not be to understand the brain as a separate wiring of components, but rather as a dynamic object.

- This motivates a holistic view of our brain, which takes into account the different scales on information processing.
  - The connectome is an attempt to develop a kind of wiring diagram of our brain, which would include the mapping of all neural connections within an organism's nervous system.
  - It ranges from a detailed map of the full set of neurons and synapses within part or all of the nervous system of an organism to a macro scale description of the functional and structural connectivity between all cortical areas and subcortical structures.

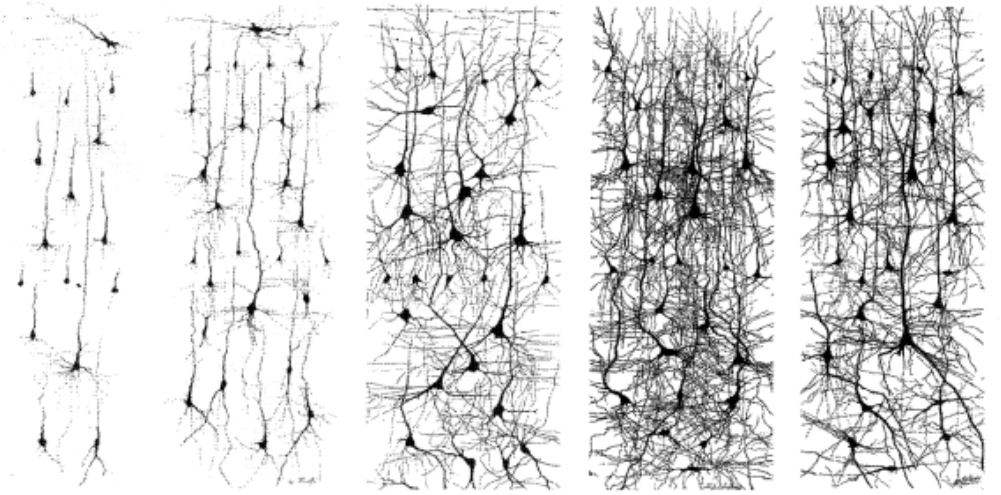
- However, in the case of fairly simple organism with only a few thousand neurons, in which such a connectome was constructed, it could not reach the functional level.
  - That means knowing the structure alone is not enough, you have to understand more about the dynamics of the networks.

2.5 Outlook and Prospects for Technology

- The dynamics of the brain network can be seen particularly impressively if you look at what happens in the brain of a child in the first two years of life.
  - The figure shows a section of the neuron network within the first 4 years of a child.
  - What you can easily see is that there is a strong growth of neurons within the first 2 years and after 2 years the number of neurons decreases again.
  - In numbers, this means for two year old baby:

    Average growth rates:

    2300 neurons/s; 2.3 million synapses/s; 6 m/s axon formation

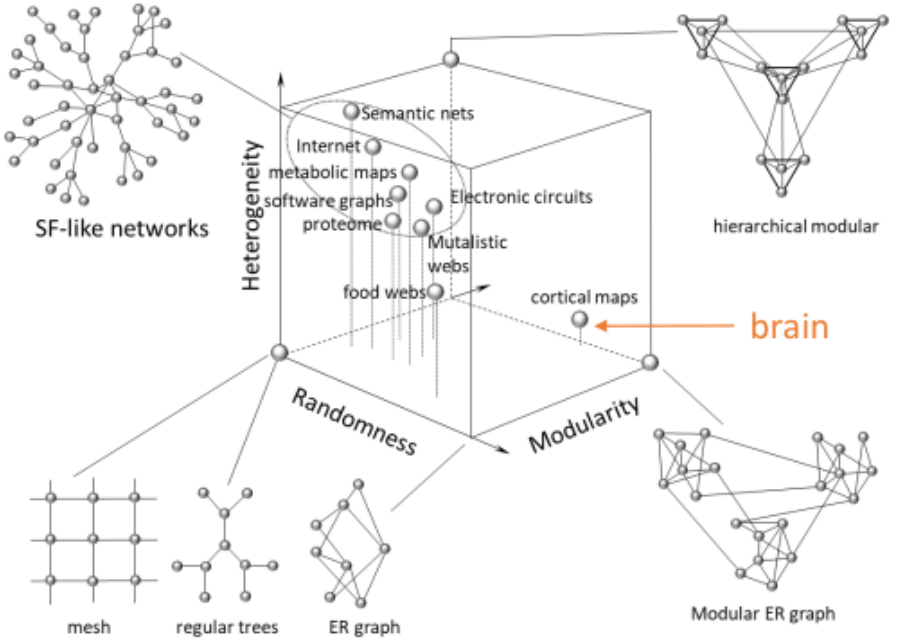


S. Seung: "Connectome: How the brain`s wiring makes us who we are?" MIT Cambridge, 2012

- If this is related to the signal transmission speed on an axon (100m/s), then the growth reaches 6% of the signal speed. In relation to our technical systems, this would mean that our cables in the circuits would grow at 14 400 000 m/s.
  - It only shows how flexible our network actually is in the brain and how important it must be to take this dynamic into account and not to leave it out.
- Of course, this process, called blooming & pruning, does not happen independently, but under the influence of external stimuli: for example, children are still relatively flexible in learning new languages and can learn them without an accent, while in adulthood only a few people have the ability to learn a foreign language without an accent.

2.5 Outlook and Prospects for Technology

- Well, how can this be put mathematically? one approach is graph theory, which describes networks at a very abstract level, but with which one can discover certain structures and principles in what appear to be chaotic networks:
- Network networks can be generally classified along 3 axes:
  - Heterogeneity: how indistinguishable are local structural units, such as the individual devices (cell phones, tablets,..) with different operating systems in computer networks.
  - Randomness: describes the structural order. A crystal lattice has a low randomness because the atoms are arranged inside the lattice.
  - Modularity: it measures the strength of division of a network into modules. Networks with high modularity have dense connections between the nodes within modules but sparse connections between nodes in different modules. Think on the formation of learning groups from a total number of students.



Adapted from: Olaf Sporns, Networks of the Brair
The MIT Press, Cambridge, 2011, p. 23, Original: Solé and Valverde, 200

- We see how our brain arranges in that map - medium randomness and high modularity with a low heterogeneity.

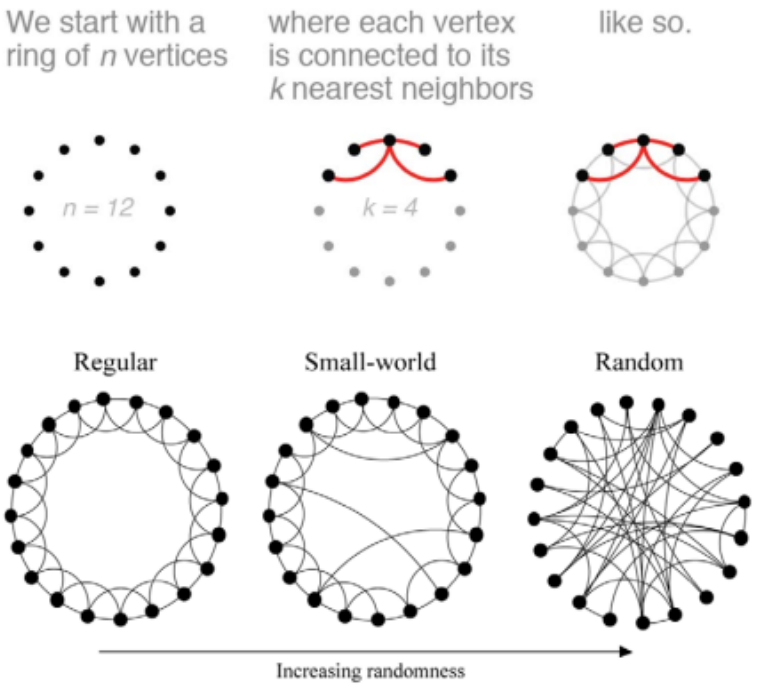
2.5 Outlook and Prospects for Technology

- This means our brain is modular:
  - We have a large number of closely linked subnetworks and few but far-reaching connections between them.
  - One thinks of our cerebral cortex in which there is a strong local connection between the neurons, which in turn are also integrated into other areas of the nervous system.
- The low heterogeneity is based on the fact that the central components (neurons and synapses) have an identical structure in almost all areas.
- The randomness of our brain's network worries us the most in its description.
  - If you only think of the crystal lattice, it is enough to look at an elementary cell with sometimes only 2 atoms in order to understand the complete macroscopic crystal.
  - A network of 2-3 neurons does not help here. It does not help us to understand the brain.

- Networks or mathematically formulated graphs of this kind are referred to as small-world networks:
  - Small-world properties are found in many real-world phenomena, including websites with navigation menus, food webs, electric power grids, metabolite processing networks, voter networks, telephone call graphs, airport networks, and social influence networks and some more.
  - In a small-world network most nodes are not neighbours of one another, but the neighbours of any given node are likely to be neighbours of each other and most nodes can be reached from every other node by a small number of hops or steps.

2.5 Outlook and Prospects for Technology

- To understand this a little better, let's consider a mechanism for constructing a small-world network –named also as Watts–Strogatz model:
  - Regular graph with degree k connected to nearest neighbours.
  - As next step rewire each edge in the network to a random node with probability p.
  - With p=1 we have a random graph the so called Erdos-Renyi network. Thus, there is a range of p values where the network exhibits properties of both, i.e. random and regular graphs.
  - Small-world networks are somewhere between, as shown in the figure on the right. They exhibits an high clusterisation and short path length.
  - In contrast, regular networks have an high clusterisation and high path length, while random networks have low path length and low clusterisation.



- Thus, each brain network is unique microscopically, but in large scale networks one can observe macroscopic common properties, which provide a path to the understand the connectome of our brain.

2.5 Outlook and Prospects for Technology

- In summary, our brain can be understood as a small-world network with high dynamics in terms of variability that take growth into account.
  - However, there is still a high time dependency to be taken into account, which allows cellular processes to generate action potential to be related to long-term memory, in which we store memories of our earliest childhood.
  - At this point I would like to stop my explanations and move on to the important evolution theory mentioned in the beginning of this chapter.

- Evolution is the change in the inheritable traits of a population of living beings from generation to generation.
  - These traits are encoded in the form of genes that are copied during reproduction and passed on to the offspring.
  - Mutations result in different variants (alleles) of these genes, which can cause changed or new characteristics.
  - These variants as well as recombinations lead to hereditary differences (genetic variability) between individuals.
  - Evolution takes place when the frequency of these alleles in a population (the allele frequency in the gene pool) changes, i.e. these characteristics become less or more frequent in a population. This happens either through natural selection (different survival and reproductive rate due to these characteristics) or by chance through gene drift.

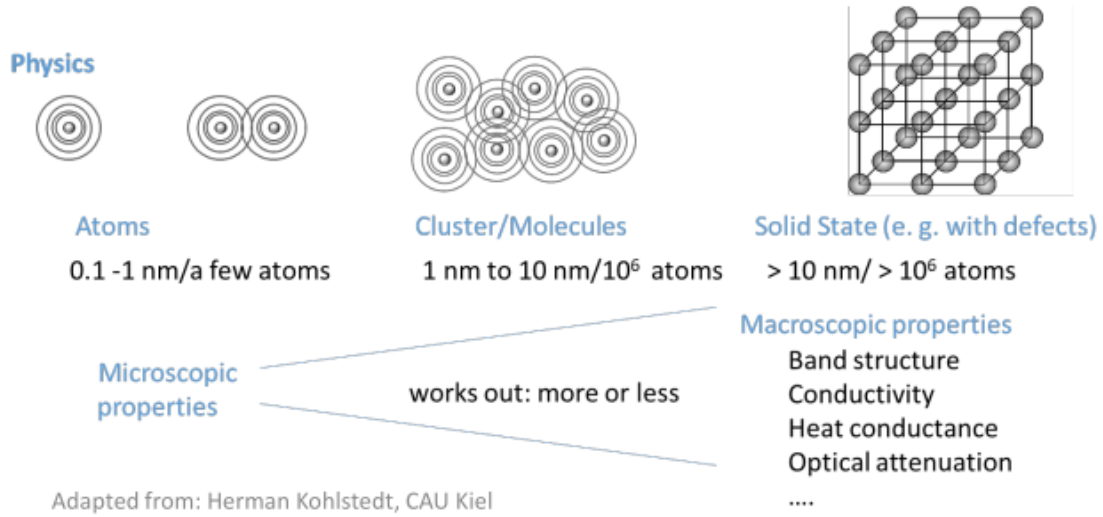
2.5 Outlook and Prospects for Technology

- That means evolution determines everything in nature and evolution influences biological principles on different levels:
  - Structure and function: All structures of living beings and other functions are the results of evolution. Even if they seem perfect to us after millions of years of selection, they are always compromises between a wide variety of environmental factors.
  - Information and communication: in the course of evolution, a huge store of biological information has emerged that encompasses the gene pool of all living things today. All organizational levels of the living have developed an exchange of information, from molecular communication between the cells to the development of language in humans.
  - Reproduction: Through reproduction, living beings are connected with their ancestors. But this is not perfect, i.e. descendants are not the same as their ancestors. It is only due to the inaccuracies that mutations and recombinations arise This generates a variety, which some of them are more likely to cope with changing environmental conditions.
  - Compartmentalization (spatial separation): On all organizational levels of the living, evolutionary processes rely on the division of spaces. For example, the separation of poulations is a prerequisite for the emergence of new species.
  - Variability and adaptability: variability is both an important product and a prerequisite for evolution. All living creatures are considerable variants and those with the largest number of offspring are called adapted. Thus, adaptation can only arise through variability.

2.5 Outlook and Prospects for Technology

- This means that evolutionary theory can state at least one big thing for neuromorphic engineering:
  - Basic principles have not changed over millions of years and although our brain is much more complex than a jellyfish, the basic principles (the building block of nature) are the same.
- Now, that gives hope and motivates us to take action that we have successfully carried out over decades in solid state physics and electronics and to which we owe our technological developments today.
  - This is shown schematically in the figure:

  - The understanding of the individual atom and its structure was used to transfer models from the microscopic scale to the macroscopic scale to describe entire crystals and macroscopic phenomena.
  - These models are the key to our technology today and the basis of our progress.

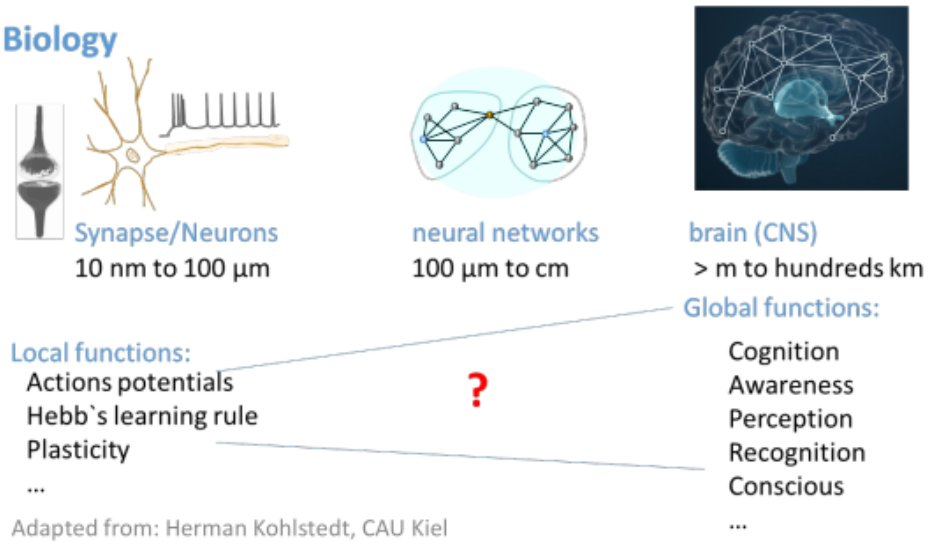


Adapted from: Herman Kohlstedt, CAU Kiel

2.5 Outlook and Prospects for Technology

- The idea of modern neuromorphic engineers is to apply this approach to neural systems, even if these form complex structures as crystals. This is shown in the figure and will concern us in the coming chapters:

  - The simulation of neuronal function blocks within mathematic models and or electronic components and circuits.
  - Relevant cellular paradigms of learning and memory processes are transferred into multi-dimensional network structures to simulate cognitive functionalities.
  - However, which cellular properties are relevant to lift them to a multi-dimensional level remains a mystery.



- Well you can say we are still at the very beginning of the path, maybe like Rutherford more than a hundred years ago with his atomic model, only with the difference not knowing whether we have the real atomic model to take the next step ...