Neural Networks

Overview:
- Anatomy of Neuronal Networks
- Formal Neural Networks
- Are they realistic?
- Oscillations and Phase locking
- Mapping problem: Kohonen Networks

Nice books to start reading:
e.g. Manfred Spitzer: Geist im Netz

Brick-like text-books:
From Neuron to Brain by John G. Nicholls, John G. Nicholls, Bruce G. Wallace, Paul A. Fuchs, A. Robert Martin
Principles of Neural Science by Eric R. Kandel, James H. Schwartz, Thomas M. Jessell
Neuroanatomy

The brain mostly consists NOT of neurons, there are about **10-50 times more glia** (greek: “glue”) cells in the central nervous tissue of vertebrates.

The function of **glia** is not understood in full detail, but their active role in signal transduction in the brain is probably small.

**Electrical** and **chemical synapses** allow for **excitatory** or **inhibitory** stimulation. They most often sit at the dendritic tree, but some also at the surface of a neuron.

In many neuron types, these inputs are can trigger an **action potential** in the **axon** which makes connections with other dendrites.

However, only recently, it was found, that action potentials also travel **back into the dendritic tree**, a crucial prerequisite for learning.

From: Principles of Neural Science
Kandel, Schwartz, Jessel, 1991
Neuroanatomy

The brain consists of about $10^{11}$ neurons, divided into approx. 10,000 cell types with highly diverse functions.

The cortex, the outer "skin" of the brain, appears to be very similar all over the brain, only more detailed analysis also shows here specialization in different regions of the cortex.

Most of the brain volume are "wires" in the white matter of the brain.

From: Principles of Neural Science
Kandel, Schwartz, Jessel, 1991
The Cortex is organized into layers which are numbered from I to VI.

Different types of cells are found in the layers.

The layer structure differs for different parts of the brain.

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Figure 12: Basic cell types in the monkey cerebral cortex. Left: spiny neurons that include pyramidal cells and stellate cells (A). Spiny neurons utilize the neurotransmitter glutamate (Glu). Right: smooth cells that use the neurotransmitter GABA. B, cell with local axon arcades; C, double bouquet cell; D, H, basket cells; E, chandelier cells; F, bitufted, usually peptide-containing cell; G, neurogliaform cell.
Cortex Layers

I. Molecular layer: few scattered neurons, extensions of apical dendrites and horizontally oriented axons.

II. External granular layer: small pyramidal neurons and numerous stellate neurons.

III. External pyramidal layer: predominantly small and medium sized pyramidal neurons and non-pyramidal neurons.

I-III are main target and Layer III the principal source of intercortical connections.

IV. Internal granular layer: stellate and pyramidal neurons. Main target from thalamus.

V. Internal pyramidal layer: large pyramidal neurons and interneurons. Source of motor-related signals.

VI. Multiform layer contains few large pyramidal neurons and many small spindle-like pyramidal and multiform neurons. Source of thalamus connections.
A typical synapse delivers about **10 - 30 pA** into the neuron. In many cases, this means that it increases the membrane voltage at the cell body by about **0.2-1 mV**. Therefore, many synaptic inputs have to happen **synchronously** to trigger an action potential.

From: Principles of Neural Science
Kandel, Schwartz, Jessel, 1991
Dendritic Spines: Inputs for Synapses

Excitatory synapses form often at spines which are bulges of dendritic membrane.

Although much is unknown, they probably act as local diffusion reservoir for Calcium signals and change their shape upon learning.
Dendritic Logics

The interplay of currents along the dendritic tree can be intricate and allows the neuronal network to implement various logical operations (left):

A: Inhibitory synapses can veto more distal excitatory synapses: output = [e3 and not (i3 or i2 or i1)] or [e2 and not (i2 or i1)] or [e1 and not i1].

B: Branches can overcome the inhibitory effects. For example [e5 and not i5] and not i7.

So the assumption that a dendritic tree is a simple addition is very simplistic.

From: The Synaptic Organization of the Brain, Gordon M. Shepherd 1998
Sparse Firing

Fast spiking is not the normal mode of operation for most neurons in the brain. Typically, neurons fire **sparsely** where each action potential counts (below).

Experimentally, one can excite large **trains of action potential** (top).

Thus, for long, the **average firing rates** were taken as main parameter of neural networks.

From: Principles of Neural Science
Kandel, Schwartz, Jessel, 1991
McCulloch and Pitts simplified neuronal signalling to \textbf{two states}: 
- Neurons $i=1..N$ are either in state $S_i=-1$ or $S_i=+1$, i.e they are silent or fire an action potential

In the simplest model of an associative memory, the neurons are connected to themselves with a \textbf{coupling strength matrix} $J_{ij}$. It contains the “strength” or synaptic weight of the connections between the neurons.

Assume that the dendrites of neuron $i$ only add the signals. The internal signal of the neuron $h_i$ is then the matrix product of incoming neuronal states $S_j$ according to $h_i=J_{ij}S_j$ (sum over common indexes).

In the simplest form, neuron $i$ fires if $h_i$ is positive: $S_i=\text{sign}[h_i]$.

This update can be performed with time lags, sequentially or in parallel and defines a dynamic of the neuronal net.
The dynamics has a number of defined fix points. By setting \( J_{ij} \), activity patterns can be memorized and dynamically retrieved.

You want to memorize the patterns \( \xi^\mu \) into the network. The recipe to do this is reminiscent of an old postulate in neuroscience.

Hebb postulated in 1949: "When an axon of cell A is near enough to excite a cell B and repeatedly or persistently takes part in firing it, some growth process or metabolic change takes place in one or both cells such that A’s efficiency, as one of the cells firing B, is increased."

Both proportionalities are still present in the learning rule for \( J_{ij} \) on the left.
Images of the size IxI are often used to show the memorizing capability of neural networks. Thus, the image is the pattern vector with length I^2 and the coupling strength matrix J has a size of I^2 x I^2.

For example we store 8 letters with I=10 using N=100 neurons and a coupling matrix of 100x100 weights. The retrieval from highly noisy input is possible, but shows some artefacts (F,G).

Retrieval is performed by starting at the noisy pattern, following the neuronal update dynamics to its fixpoint.

The capacity of a fully connected formal neural network scales with N. The number of patterns which can be stored is about 0.14xN. Thus in above network we can store about 9 letters.

An associative memory with the same number of synapses (10^{15}) than the brain could save 0.14*10^{7.5}=5*10^6 different patterns.

But the connections in the brain are much more complex.
J.J. Hopfield showed 1982 that formal neural networks are analogous to spin glasses.

A spin glass is an amorphous material which fixes spins in a 3D matrix. The spins can be oriented up or down.

The magnetic field from each spin influences the other spins. This “crosstalk” between spins is described by a coupling strength matrix $J$.

Such a spin glass is described by the Hamilton operator $H$ to the left. The fixpoints are now simply the ground states of the system to which the dynamics converge.

The analogy made neuronal networks more accessible to theoretical physicists.
Towards realistic neurons

Synapses of real neural networks show intrinsic noise. For example, chemical synapses either release a synaptic vesicle, or they don’t (“quantal” noise).

It is implemented into neuronal networks with a probabilistic function of \( t(h) \) with \( t \) being the probability to find the output neuron in the state \( S_i = +1 \).

As expected, noise does not change the property of neural networks dramatically.

As everywhere in biophysics, the inclusion of noise in a model is a good test for its robustness.

Until now, we have assumed **instantaneous propagation of signals** in neural networks. This is not the case and typical delays are on the 5-20ms time scale.

Delays leads to new dynamics of the network and can trigger **oscillations** (left).

We will discuss a compelling model which uses these delays in the following.

From: Models of Neural Networks I, Domany, van Hemmen, Schulten, Springer 1995
Phase Locking and Pattern Recognition

A. Recognition by “grandmother cell”

One old theory of pattern recognition is the so called “grandmother cell” proposal. It assumes that partial patterns converge to one cell and if that cell fires, the grandmother is seen. However this approach has severe problems:
- What happens if this cell dies?
- Not much experimental evidence
- “Combinatorical Explosion”: any combination of patterns would require a novel grandmother cell, much more than even the brain can have.

B. Recognition by Cell Groups

The detection of patterns by cell groups as associated memory does not have that problem. Noisy signals can still be detected and the model is robust against death of single cells.

However there are two major problems:
- How should the pattern be read out?
- “Superposition catastrophe”: a superposition of patterns is not recognized since it acts as novel pattern.
Phase Locking and Pattern Recognition

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A biologically motivated and analytically soluble model of collective oscillations in the cortex.
Inhibition

- Delayed
- Fires a few pulses followed by a pause
Phase Locking and Pattern Recognition

Phase Locking and Pattern Recognition

A biologically motivated and analytically soluble model of collective oscillations in the cortex.
Explanation

- Behaviour depends on the relative timing of inhibition and excitation.
- Low delay:
  - Quick feedback, immediate growth.
- Medium delay:
  - Excitation while neuron is inhibited.
- Long delay:
  - Excitation from previous oscillation stimulates the following excitation.
Phase Locking and Pattern Recognition

A biologically motivated and analytically soluble model of collective oscillations in the cortex.
How does the Hebbian learning paradigm keep up with experiments?

Single neurons before and after a synaptic transmission are excited externally with different time delays. The efficiency of the synapse is recorded before and after the learning protocol.

This allows to infer the time resolution and direction of learning increment $\Delta J_{ij}$ for a synapse (left).

These results would for sure have pleased Hebb. Indeed, the precise timing of neuron modulates the learning of a synapse with a very high time resolution on the ms time scale.

Temporal Patterns

If we start from a distribution of axonal lengths, different synapses transport the information of both time delay and strength.

This can actually be used to extend the associative memory of networks onto the temporal domain: a sequence of patterns can be stored. If triggered, movie of patterns is generated (left).

from:
**Finding:** sensory maps are found in the brain with a high large scale organization.

**Problem:** how does the brain map and wire similar outputs next to each other although there is no master to order the things?

**Approach:** Kohonen assumed a “winner takes all” approach where direct neighbors profit from a mapping and more distant ones are punished. With this, a simple algorithm (next page) generates beautiful sensory maps.

**Disadvantage:** We can only guess the real microscopic algorithm behind the approach since it appears that we need a master to determine the winner.
Kohonen Network Algorithm

Step 0: **Initialization.**
Synaptic weights $J_{vl} =$ random.

Step 1: **Stimulus**
Choice of Stimulus Vector $v$.

Step 2: **Find Winner**
Find Stimulation-Winner location $a$ with minimal weight vector - distance from stimulus $v$.

$$
\left\| v - J_{a}^{\text{old}} \right\| \leq \left\| v - J_{a} \right\|
$$

Step 3: **Adaptation**
Move the weights of winner (and its surrounding $h$) towards the stimulus $v$

$$
J_{a}^{(\text{new})} = J_{a}^{(\text{old})} + \varepsilon h_{a, \text{w}} [v - J_{a}^{(\text{old})}]
$$

and **go to Step 1**. This will converge towards a mapping given by:

$$
v \rightarrow a \quad \text{with} \quad \left\| v - J_{a} \right\| \text{ minimal.}
$$
Kohonen Example: 2D to 2D mapping

Example.

Input vector \( v \) is the logarithmic amplitude of two microphones which record a sound in a 2D space.

We start with random weights \( J \).

The Kohonen algorithm results in a map that reflects the setting of the sound location in 2D space.

The Kohonen-map has memorized neighborhood information into their synaptic weights.
Kohonen Example: 2D to 1D mapping

Quite impressive is the Kohonen mapping *between different dimensions* - in this case between the locations in 2D to a 1D receptive Kohonen map.

The mapping problem in this case is similar to the **traveling salesman-problem**.