Computational Neuroscience

Lecture 10: networks in brain

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Agenda

Neuronal wiring

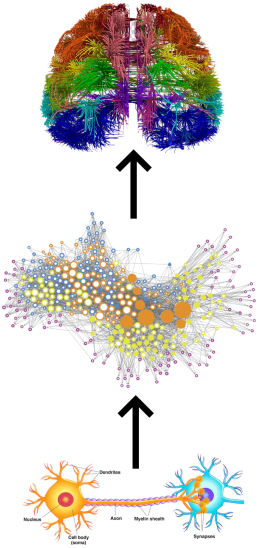
Network models

Neuronal wiring

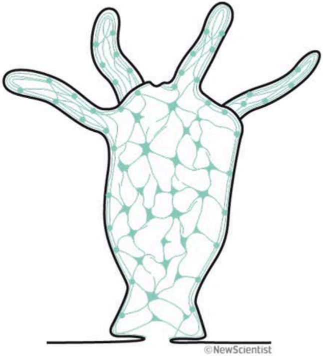
System level

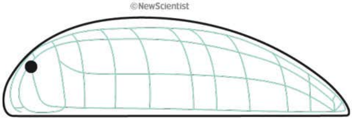
Brain is organized in multiple levels, from up to bottom:

- Whole-brain
- Small neural networks (hundreds/thousands of neurons)
- Single-several neurons



Origins

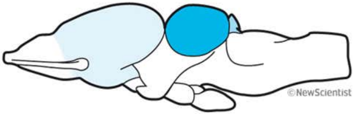


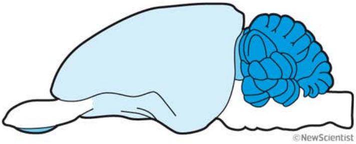


- First nerve-cells
- Could carry electrical signals
- Sense & react

- Process information
- Beginning of specialization
- Visual & taste systems

The evolution continues

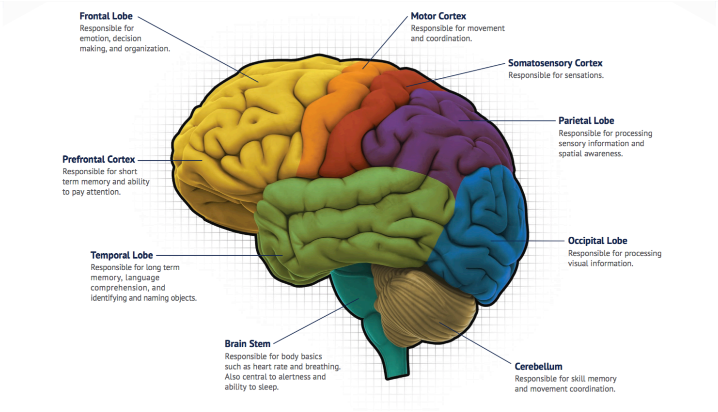




- Complex behaviour: avoiding predators, finding food, e.t.c
- Neocortex!
- Reward system

- Olfactory bulb (smell)
- Growth of visual subsystem
- Social interactions

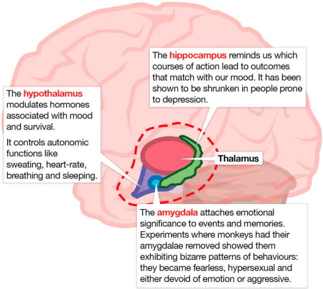
Functional map



Ancient brain

The limbic system

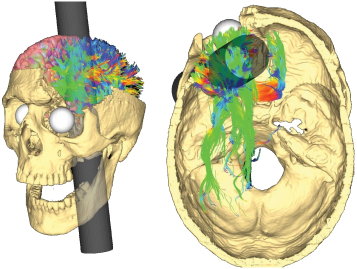
- Controls mood e.g. fear
- Heart rate, sweating
- Shown to be shrunken during chronic depression



Can survive damage

Phineas Gage case

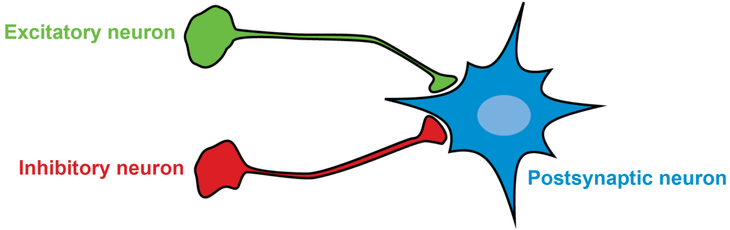
- Mood instability
- Aggression
- Lack of forethough



Member neurons?

Neurons are connected with synapses of two major types:

- Excitatory (increases potential)
- Inhibitory (decreases potential)



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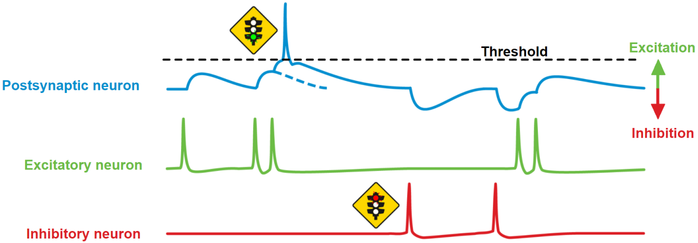
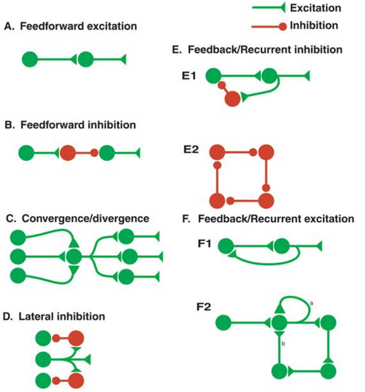


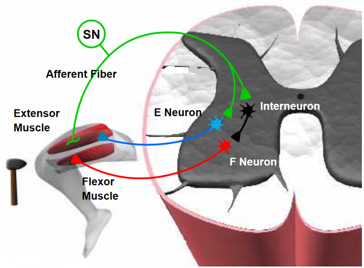
Microscale motifs

A single neuron may have up to thousands of connections $\rightarrow$ combinatorial explosion!
But we may find several **motifs** - small network patterns repeated everywhere.

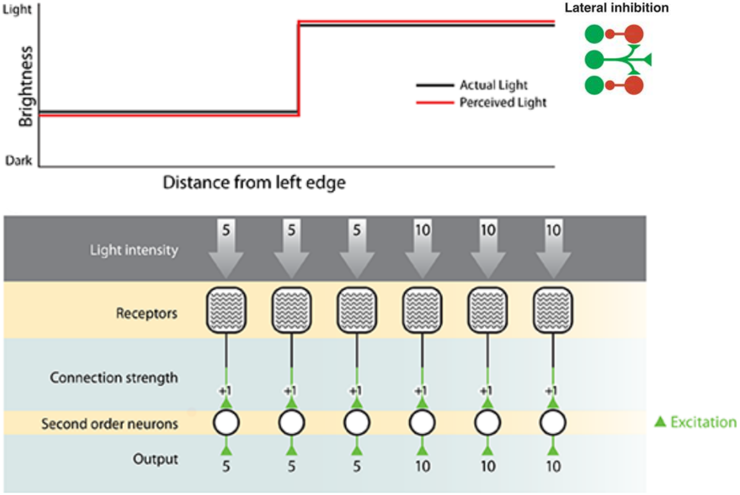


Example 1: knee jerk

- Stimulus cause an action potential in sensory neurons
- This AP stimulates an extensor neuron to stretch a muscle
- After a delay an inhibitory neuron stops the activity of extensor



Example 2: edge sharpening



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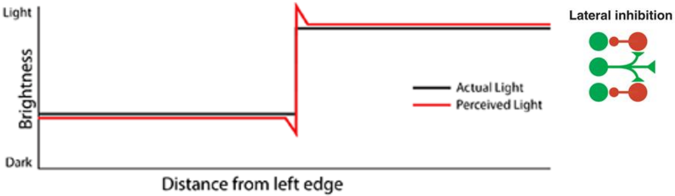
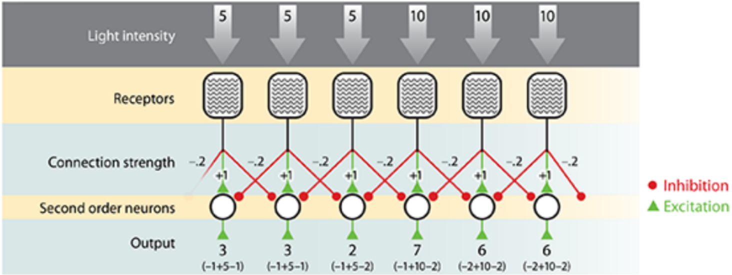
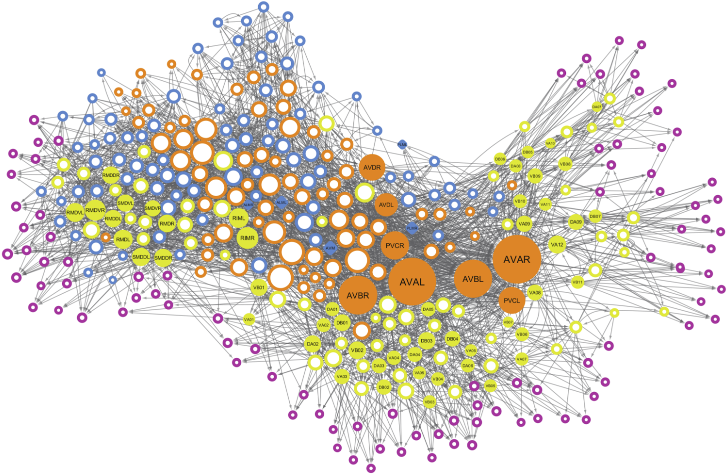


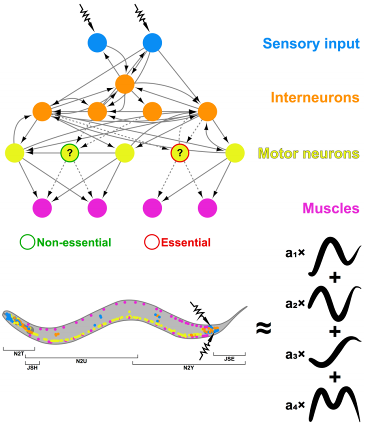


Whole-species scale networks



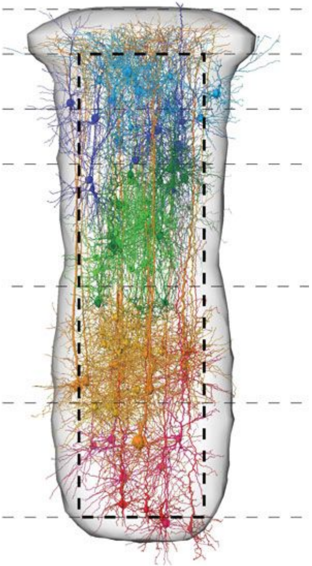
c.elegans connectome

- Always consists of **302** neurons
- Has several neuronal types.
- Has input (sensory neurons) and output (motor neurons).



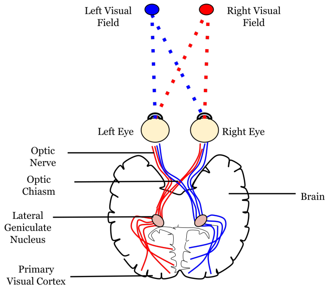
Cortical columns

- A neuron reacts on simple feature e.g. gradient
- Minicolumns reacts on higher-order features e.g. bimodal gradient
- A column reacts on complex shapes or objects



Evolution could be weird

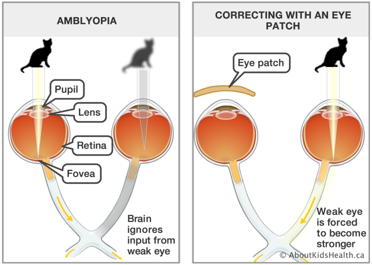
- Visual cortex is located on the ”backyard”
- Left and right sides are interchanged
- Possible reason: a lot of preprocessing!



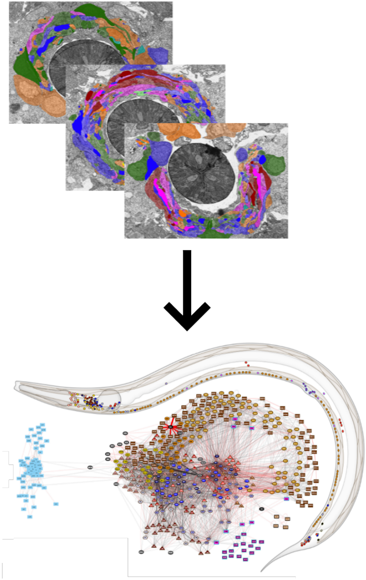
Axon growth

Neurons that fire together wire together

- If there are spikes - a connection is useful
- A connection naturally decays with time
- Has limits



Imaging: microscopy



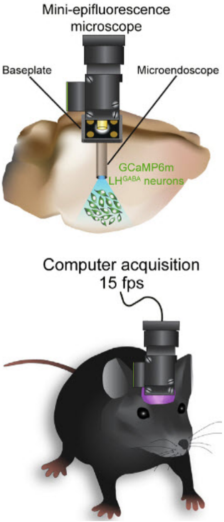
Microscopy is one of the major methods to gather data.

- Segment a collection of microscope images.
- Reconstruct connectome

Imaging: activity in action

We want to record real-time in-vivo activity of individual cells.

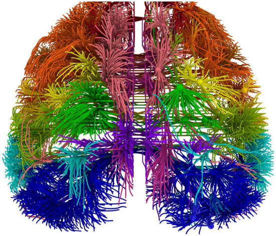
- A surgery is required.
- High-quality microscopy images
- Can record activity!



Imaging: DTI

We cant get cell images without implanting or dissecting a subject.

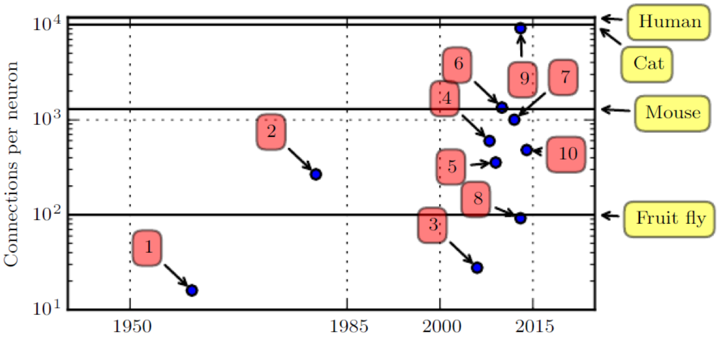
- Indirect measure of connectome (white matter fibers)
- Static in time (no activity!)



Functional implication

Neural structure is important for:

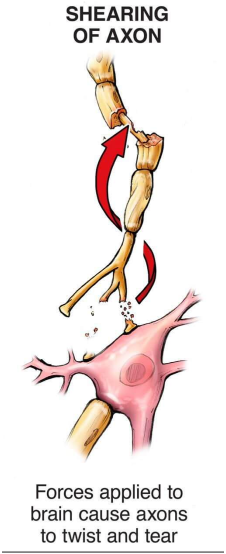
- Information transfer
- Learning



Example: brain injury

TBI-induced axon loss may cause:

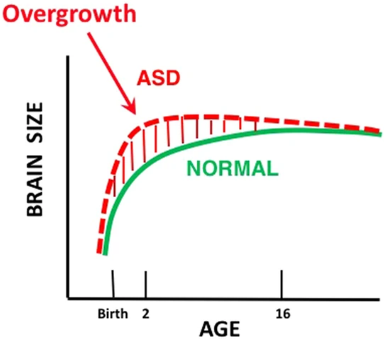
- Cognitive impairment (memory problems)
- Broken inhibition/excitation balance (epilepsy)
- Migraines

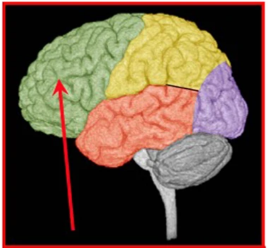


Example: ASD

Too many is bad either:

- May be caused by cell cycle dysregulation
- Disrupts a neural network development
- Lack of feedback regulation



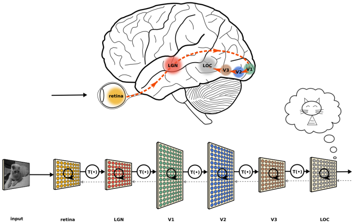


67% More Prefrontal Neurons in ASD Children

Network models

Why do we need network models?

- To explore computational potential of neural circuit
- Many diseases are related to structure pathology
- Cortical columns are a major focus of interest

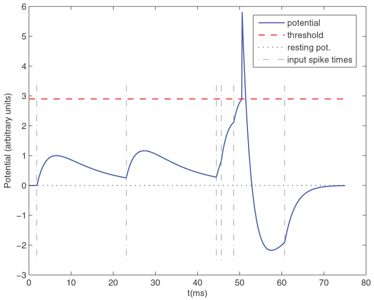


Member single neuron model?

General solution of a single-neuron model:

$$\frac{du}{dt} = Internal(t) + External(t)$$

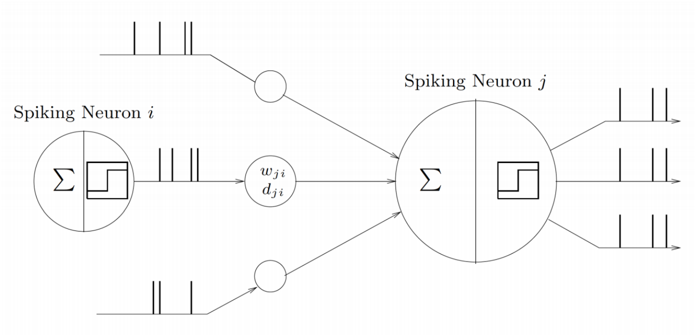
- Leaky Integrate-and-Fire
- Izhikevich's model
- Wilson–Cowan model



Abstraction

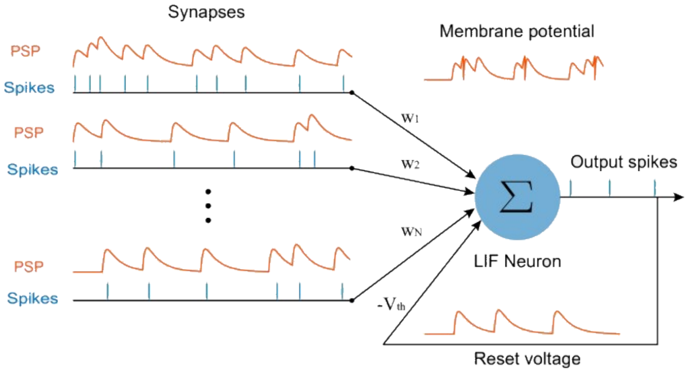
A neuron may act as a single computional unit:

- State of a neuron defined with potential (u)
- When potential > spiking threshold $\rightarrow$ neuron spikes
- Output of neuron is characterized by the array of spike-times



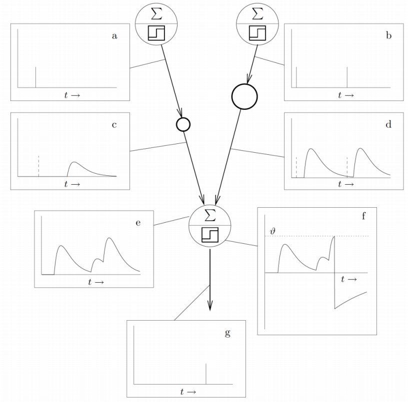
LIF network

Neurons have the same *interface* $\rightarrow$ lets connect it to a network!



LIF network

1. Two neurons fire spikes
2. Synapses transform input into spike responses
3. Incoming spike responses are summed to increase a neuron potential
4. The potential crosses the threshold, fire a spike and drops due to the refractorines



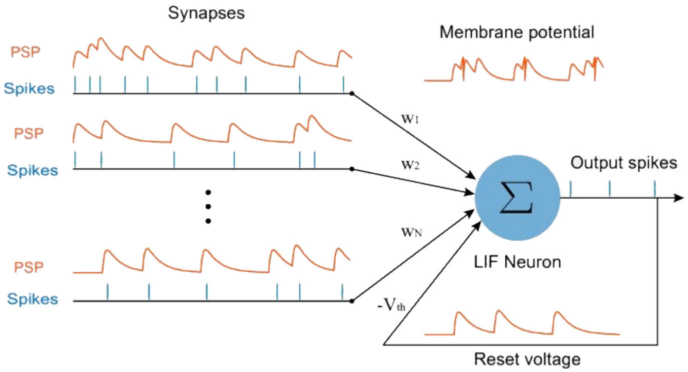
Pros and cons

Pros:

- Physiology!
- We can ”zoom in”

Cons:

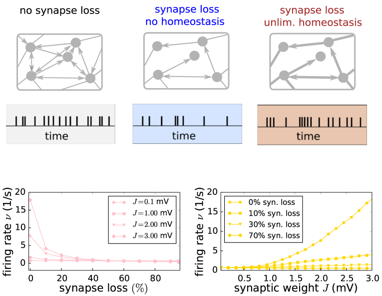
- Hard to train (no naive backprop)
- Could be slow to compute



Example: alzheimer's model

Alzheimer's disease cause severe cognitive impairment.

- Synapse loss is one of the reasons
- How lack of connections affect a network dynamics?
- No synapses $\rightarrow$ information cannot be transfered



Training

Training allows us:

- Use SNNs in Machine learning tasks
- Explore neural circuits ability to learn
- Model pathologies and find possible treatments

Unsupervised training

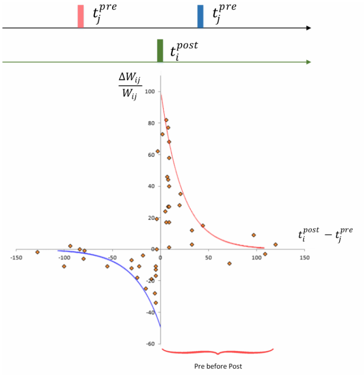
Hebb's rule:

$$t_w \frac{dw_{ji}}{dt} = \alpha_j * \alpha_i$$

STDP rule:

$$\Delta w_j = \sum \sum W(t_j^l - t_i^k)$$

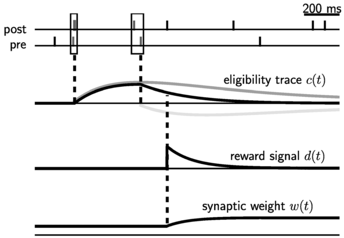
$$w_{\text{new}} = \begin{cases} w_{\text{old}} + \sigma \Delta w (w_{\max} - w_{\text{old}}), & \text{if } \Delta w > 0 \\ w_{\text{old}} + \sigma \Delta w (w_{\text{old}} - w_{\min}), & \text{if } \Delta w \leq 0 \end{cases}$$



Reinforcement learning

$\frac{d}{dt}w_{ji}(t) = c_{ij}(t) * r(t)$

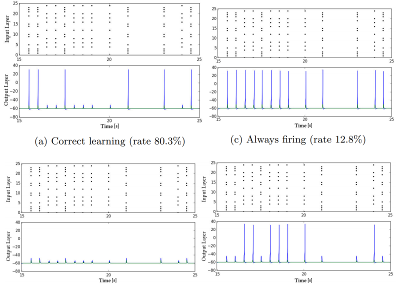
Where $c_{ij}(t)$ is an eligibility trace and $r(t)$ is reward at moment t.



Examples of trained spike-trains

SNNs may suffer from the same problems as other ML methods:

- Underfitting
- Overfitting
- Instability



(a) Correct learning (rate 80.3%)

(c) Always firing (rate 12.8%)

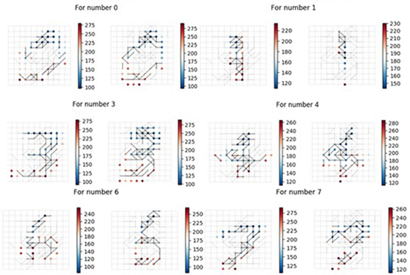
(d) No learning (rate 1.1%)

(e) Wrong learning (rate 0.1%)

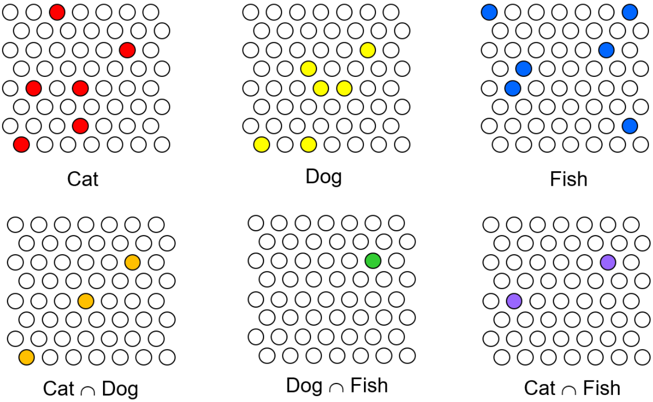
Examples: associative memory

Using SNNs one may model memory networks in a brain

- Memory is a key concept of cognition
- Network structure play a role in memory formation
- Can we create artificial memories?



Sparsity



SNN vs DNN

SNN's share the same concept with DNN's: multiple interconnected neurons; but architecture is different.

DNN

- float input & output
- No time dimension
- Differentiable blocks
- Immediate reward

SNN

- Spikes as input & output
- Time-dependant
- Sparse in time & activation
- **Delayed reward**

How can it serve us?

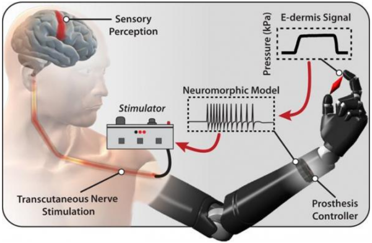
Electrophysiology
SNNs are used as building blocks to simulate electrical activity of a network.

Network topology
Because SNN's are sparse it can be used to prune existing synapses or grow new ones.

Learning
Learning algorithms used in SNN's are fundamental and can be used in other models (from Hebbian rule to Temporal difference)

Brain-inspired neuromorphic chips can be used as low-energy integrated data processing unit or in medicine.

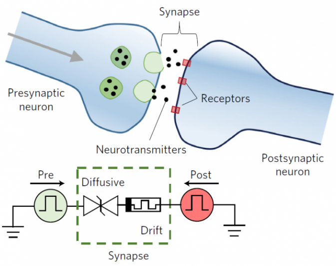
- Mobile devices
- ANN's
- Autonomic devices
- Prosthetic



Hardware

Implementations are based on the use of memristor (a kind of resistance with memory).

- SpiNNaker (ARM processors)
- TrueNorth (contains 5.4 billion transistors that consumes only 70 milliwatts)
- BrainScaleS (plasticity)



Conclusions

- Neurons have two types of connections: inhibitory and excitatory
- Neurons are organized in complex networks but we can find motifs
- We can model neural networks using SNNs
- SNNs can show comparable training performance

Homework

You will need to implement & train a spiking neural network

- Implement SNN
- Train a network in unsupervised manner
- Train a network in supervised manner
- Check model parameters vs accuracy

Additional reading:

- Neuronal dynamics: 13.4 Networks of leaky integrate-and-fire neurons
- Neurostimulation stabilizes spiking neural networks by disrupting seizure-like oscillatory transitions
- Generalized leaky integrate-and-fire models classify multiple neuron types
- Training Deep Spiking Convolutional Neural Networks With STDP-Based Unsupervised Pre-training Followed by Supervised Fine-Tuning
- Simplified spiking neural network architecture and STDP learning algorithm applied to image classification
- Constructing an Associative Memory System Using Spiking Neural Network
- Training Deep Spiking Neural Networks Using Backpropagation
- https://nba.uth.tmc.edu/neuroscience/m/s1/introduction.html
- https://www.newscientist.com/gallery/brain-evolution/
- Development and Evolution of Cerebral and Cerebellar Cortex