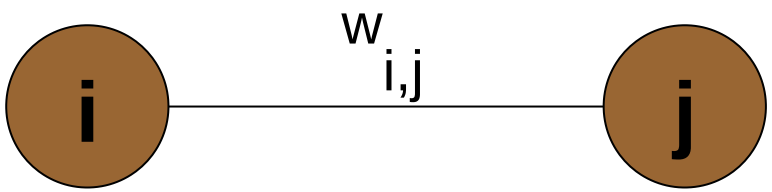
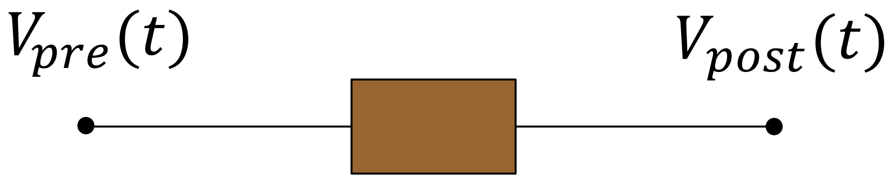
LUND UNIVERSITY

EITP25 2020

Lecture 7 – Spiking Neural Networks Part 2

Last lecture





Synaptic device

But what about the neurons? Spike generation? Spike handling?

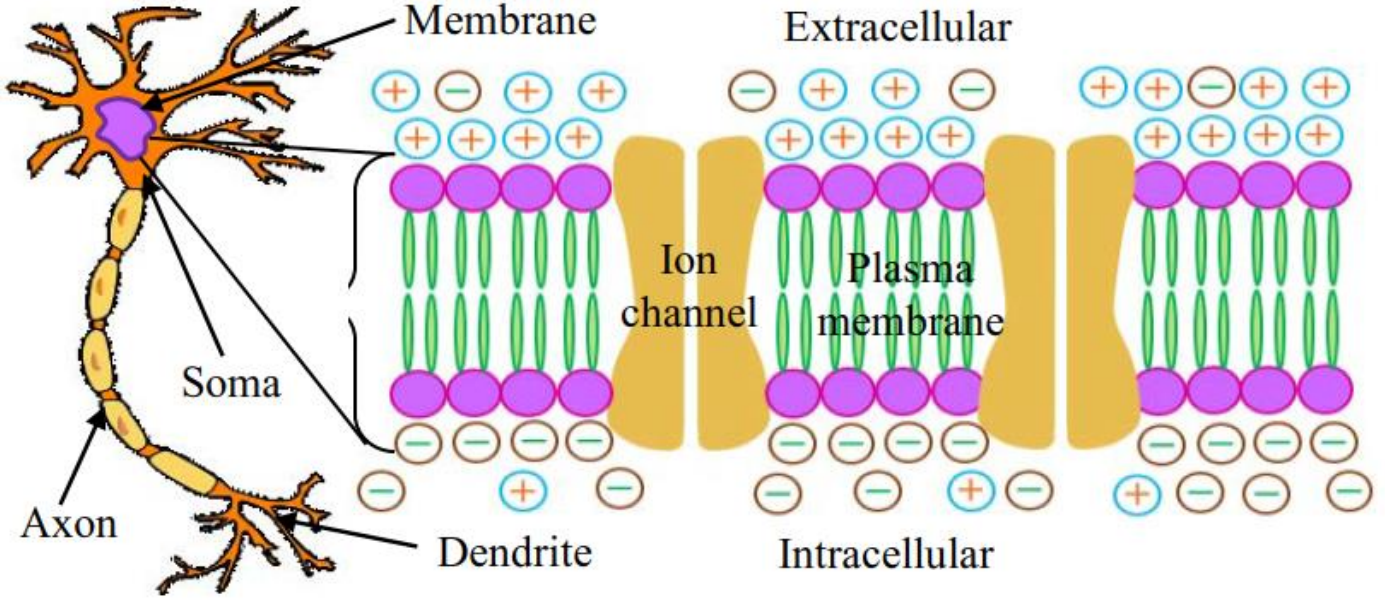
Outline – Lecture 7

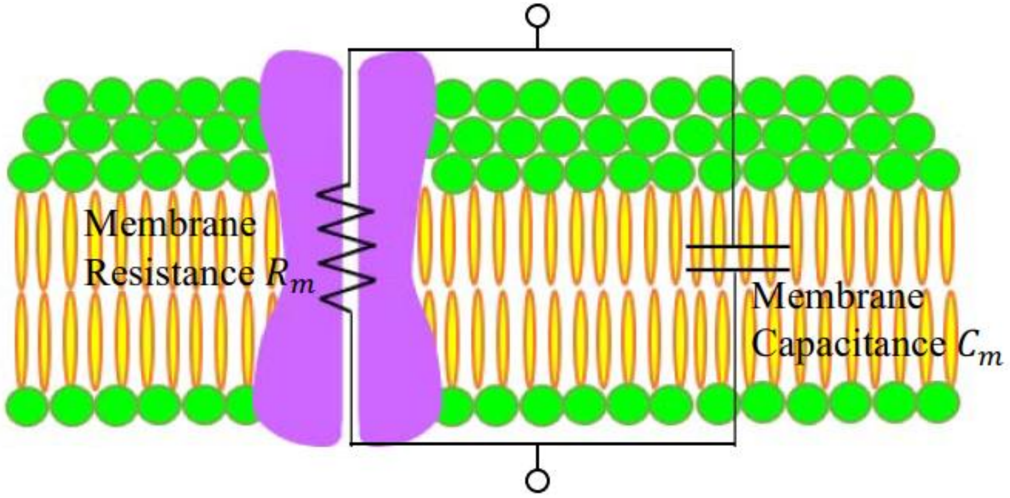
- The biological neuron and it’s functionality
- Mathematical neuron models
- SNN features important for learning
- Examples of SNN implementations (software)

- Make your own quiz question!

The biological neuron

- Electrochemical system
  - A cell membrane separating two ionic liquids
  - Na^+, K^+, Ca^{2+}, and others…
- Neuronal membrane
  - Lipid bilayer with protein ion channels
  - Ion concentration gradient → Electric field across membrane → membrane capacitance C_m.
  - Ionic channels "leak" ions through → R_m



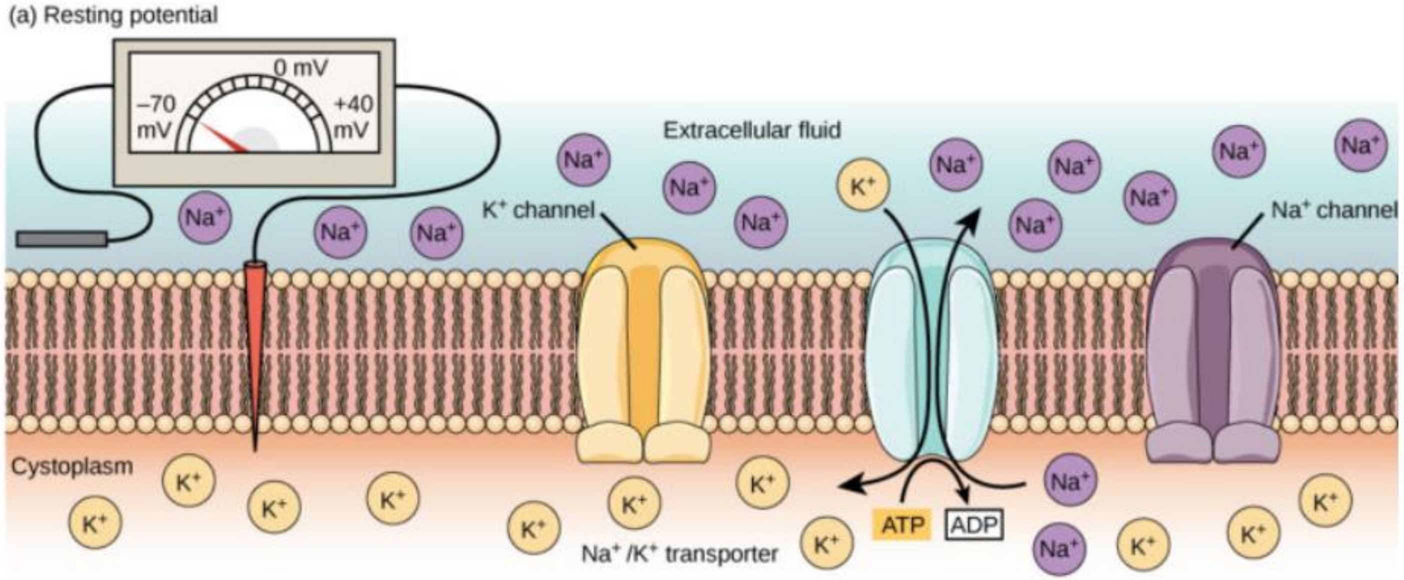


Ehsan et al. IEEE EMCSI 2017

Dynamics of the membrane potential

- Extracellular medium (outside the cell)
  - Rich on Na^+, Cl^-
- Intracellular medium (inside the cell)
  - Rich on K^+, negative proteins
- Ion transport through protein channels
  - K passive channels always open
  - Voltage controlled:
    Open/close depending on V_{mem}
  - Na channel open for $V_{mem} > -55mV$
  - K active channel open for $V_{mem} > 40\ mV$
- Drift-Diffusion →
  Each ion have its own equilibrium state…
  - Na+ → $\mathrm{V_{Na}} = 58\ mV$
  - K+ → $\mathrm{V_K} = -93\ mV$
- Stable resting state at -70 mV maintained by active K/Na pump using ATP→ADP
  - 3 Na^+ out, 2 K^+ in per ATP

$$J = -\frac{D\partial c_i}{\partial x} + q c_i \mathcal{E}$$ *Drift-Diffusion equation*



At the resting potential, all voltage-gated Na^+ channels and most voltage-gated K^+ channels are closed. The Na^+/K^+ transporter pumps K^+ ions into the cell and Na^+ ions out.

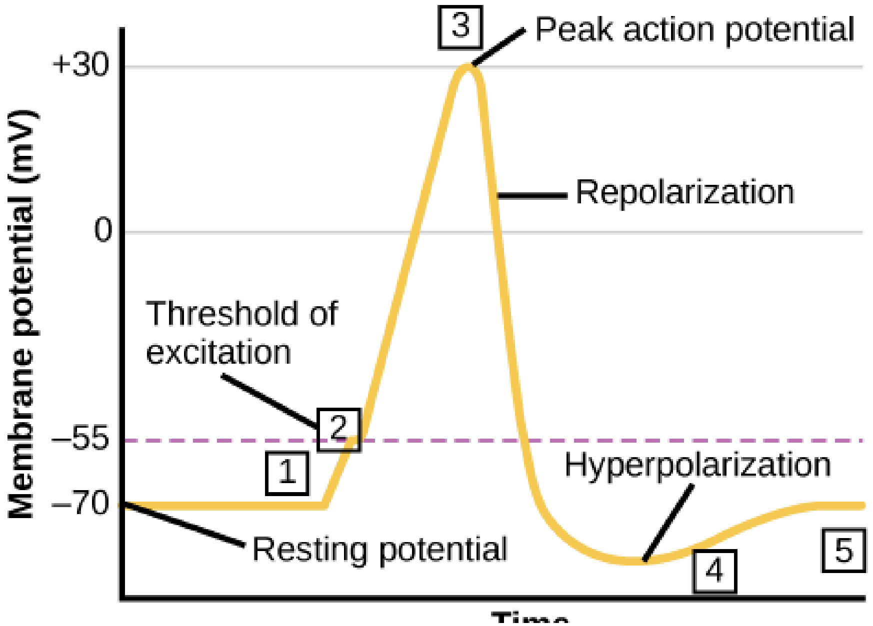
Creating an action potential

1. Incoming signal
   → neurotransmitters binds to receptors
   → Some Na^+ channels open
   → depolarization

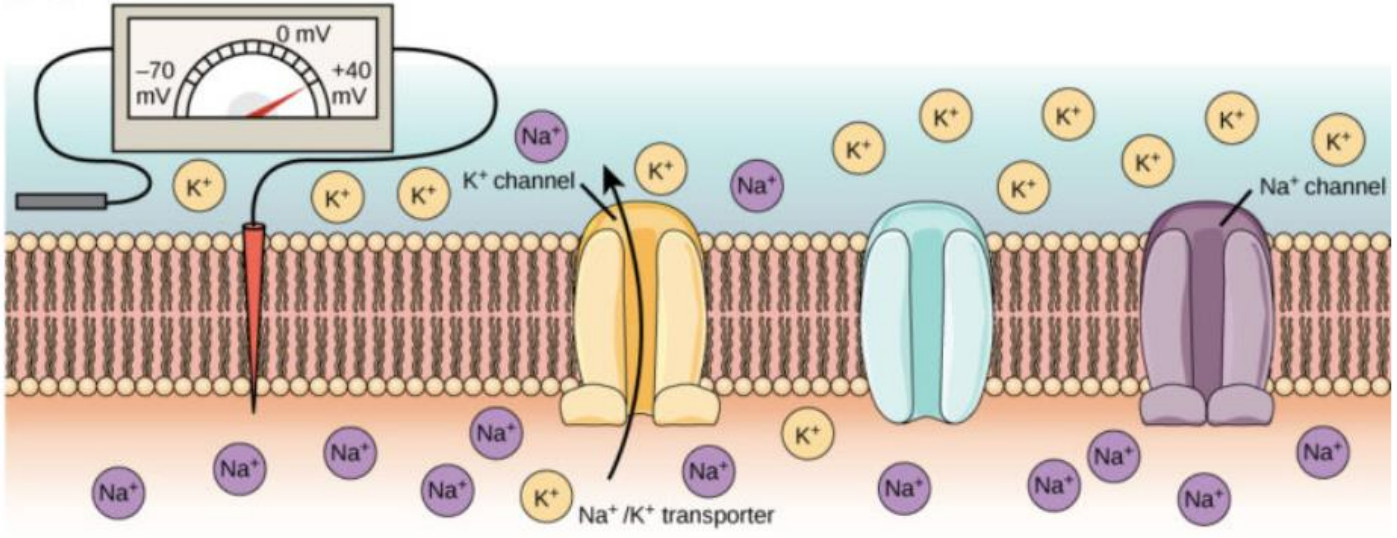
2. When $V_{mem} > -55mV$:
   Majority Na channels open (THRESHOLD!)
   → Na rushes into cell
   → V_{mem} towards Na^+ equil. (58 mV)

3. When $V_{mem} > 30 - 40\ mV$:
   Majority K channels opens
   → K+ rushes out!
   → V_{mem} again towards K^+ equi. (-93 mV)

4. Inverted concentrations restored
   by Na/K pump

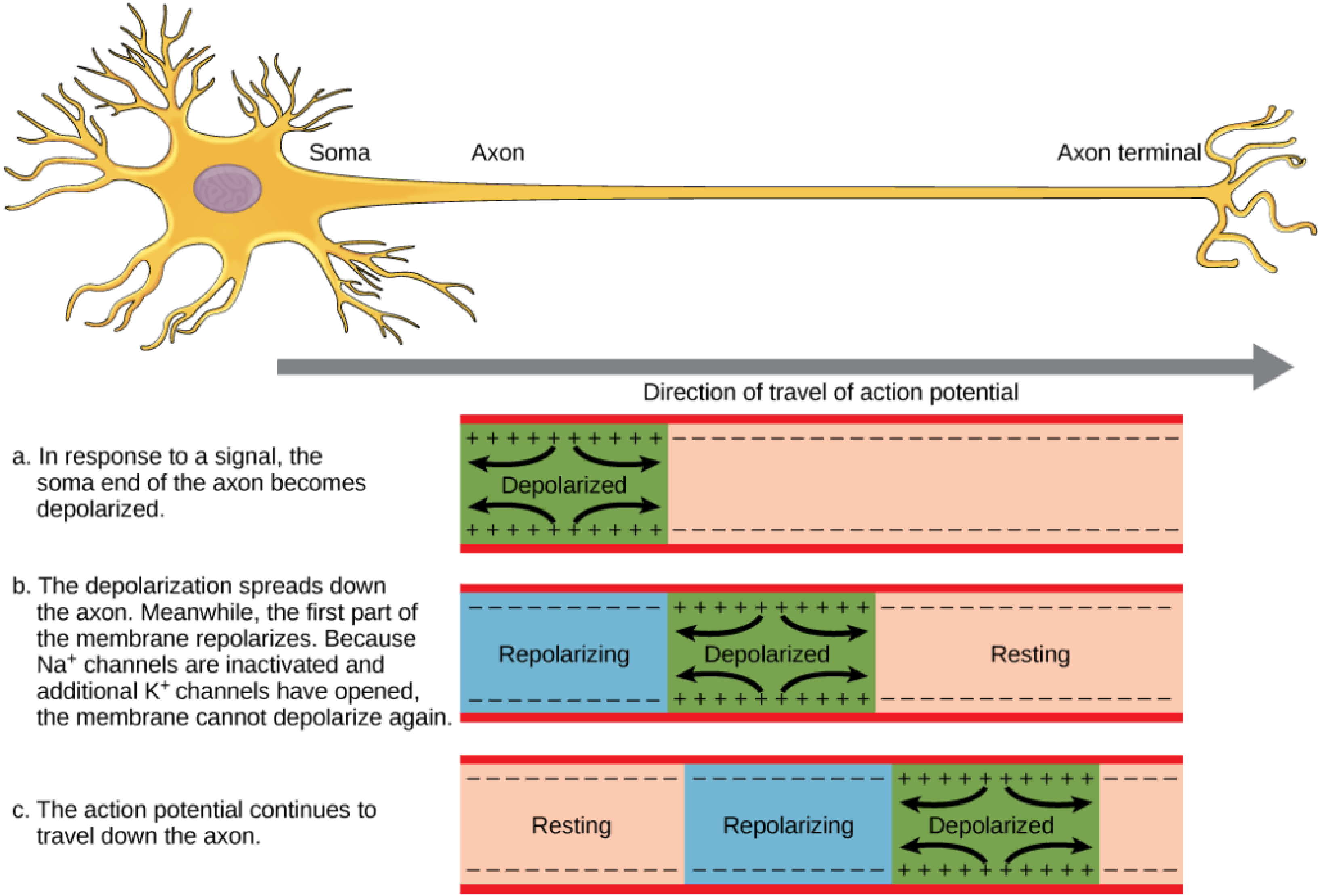


(c) Hyperpolarization



At the peak action potential, Na^+ channels close while K^+ channels open. K^+ leaves the cell, and the membrane eventually becomes hyperpolarized.

Transmitting the action potential



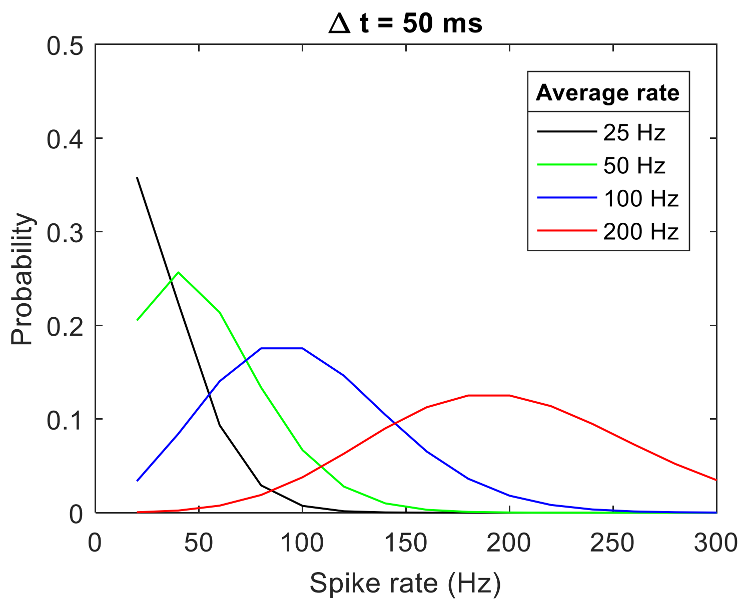
https://courses.lumenlearning.com/wm-biology2/chapter/action-potential/

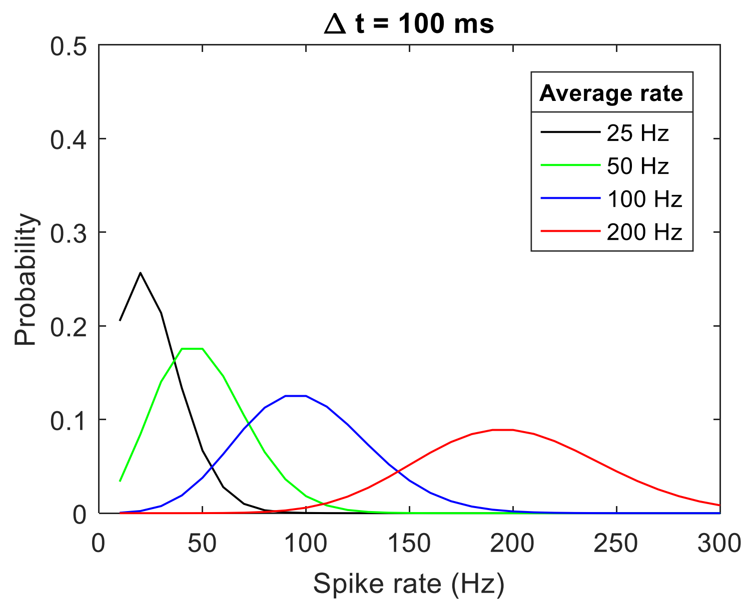
Neurons as Poisson process

- Neuron average activity can be known
  - Depends on input to neuron
- Exact spike timing stochiometric
  - Interactions → noise

- Neurons → Poisson spike sources

- Some randomness may help with learning
  - Avoids resonances, local minima, …





Key attributes of the biological neuron?

Hodgkin-Huxley model

- A biologically plausible LIF model based on the squid axon:
- Three parallel current channels; Na, K and Leakage

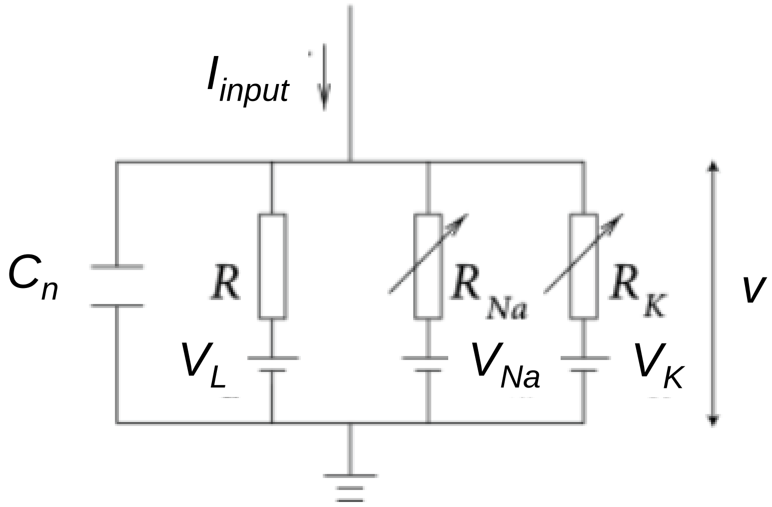
→ $C_n \frac{dv(t)}{dt} = I_{input}(t) - I_L - I_{Na} - I_K$

Na activation function $m \in f(v)$

- $I_{Na} = g_{Na} m^3 h(v(t) - V_{Na})$
- $I_K = g_K n^4 (v(t) - V_K)$
- $I_L = \frac{1}{R}(v(t) - V_L)$

Na inactivation function $h \in f(v)$

K activation function $n \in f(v)$

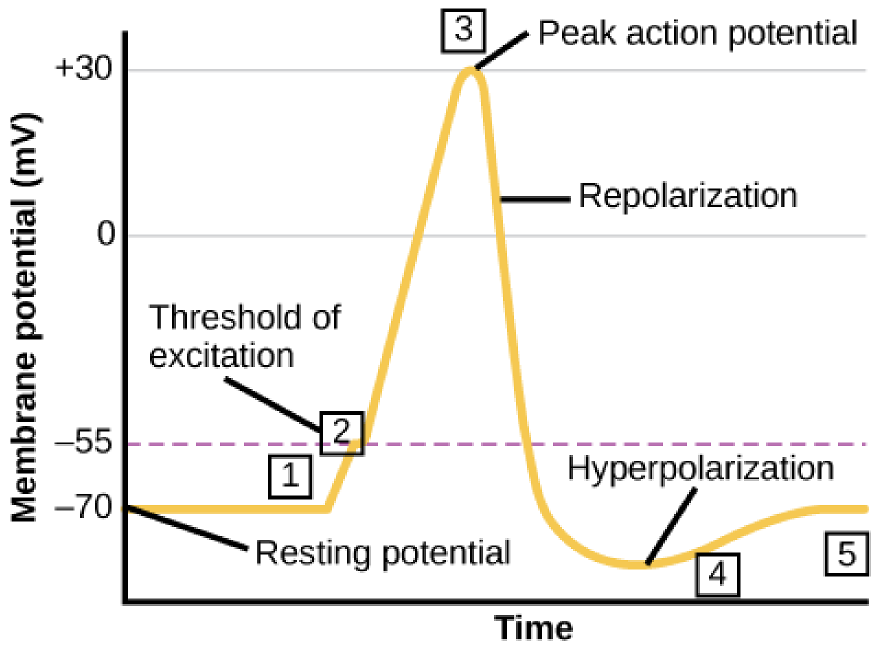


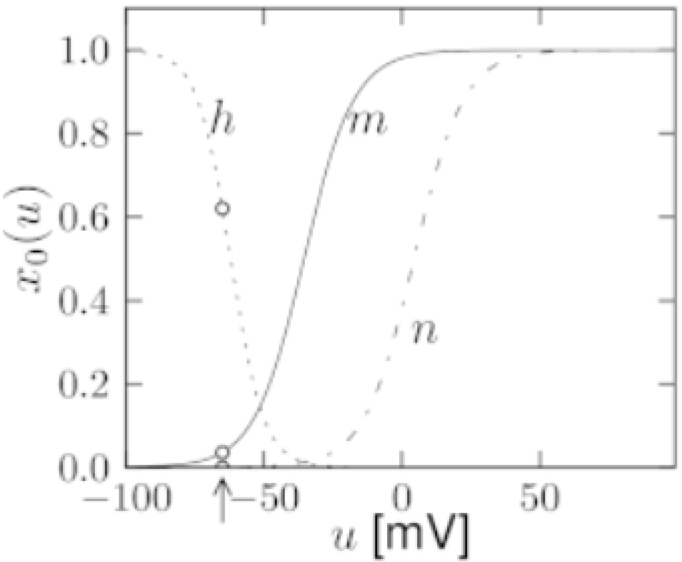
x	V_K [mV]	g_x [mS / cm^2]
Na	55	40
K	-77	35
L	-65	0.3

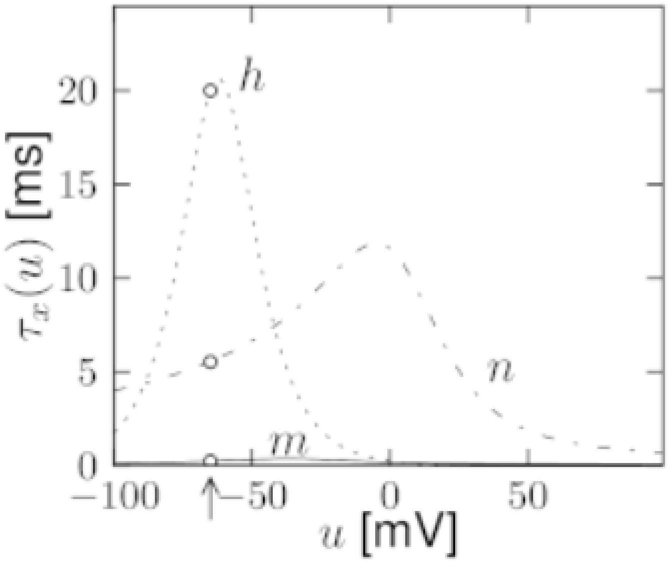
Hodgkin-Huxley parameters

- n, m and $h \in f(v,t)$
- Parameters respond with time constant!
- → possibility for a potential spike

$$\frac{dx}{dt} = \frac{\left(x - x_0(v)\right)}{\tau_x}$$





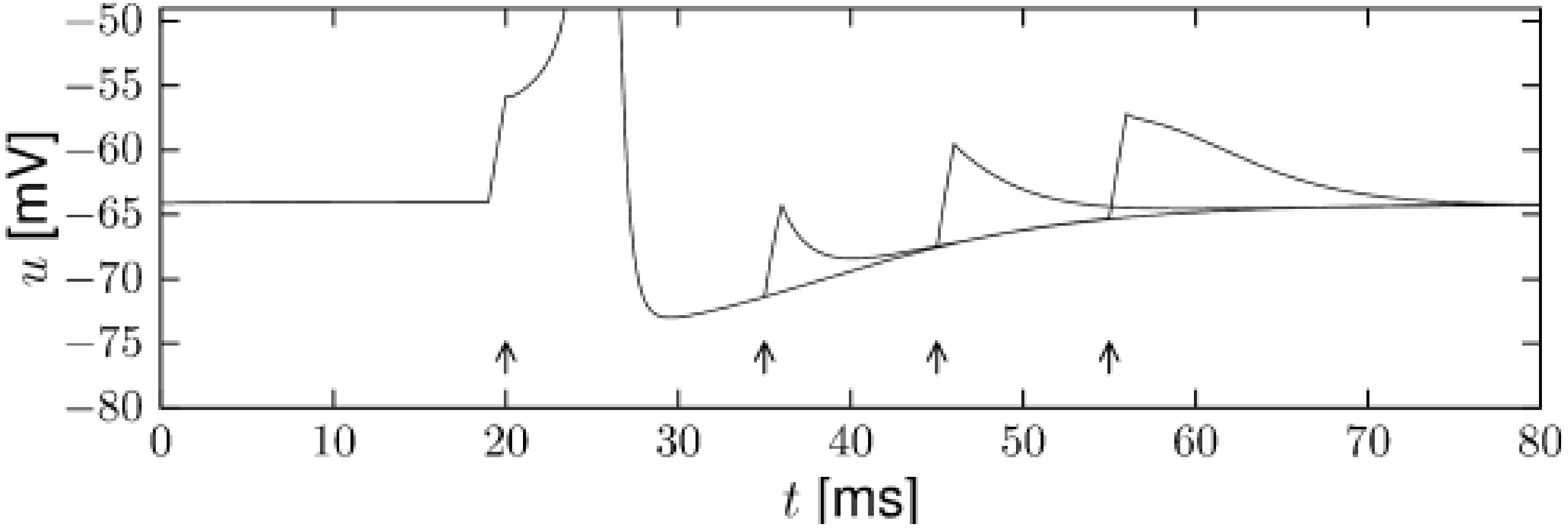


Refractory behaviour with H-H model

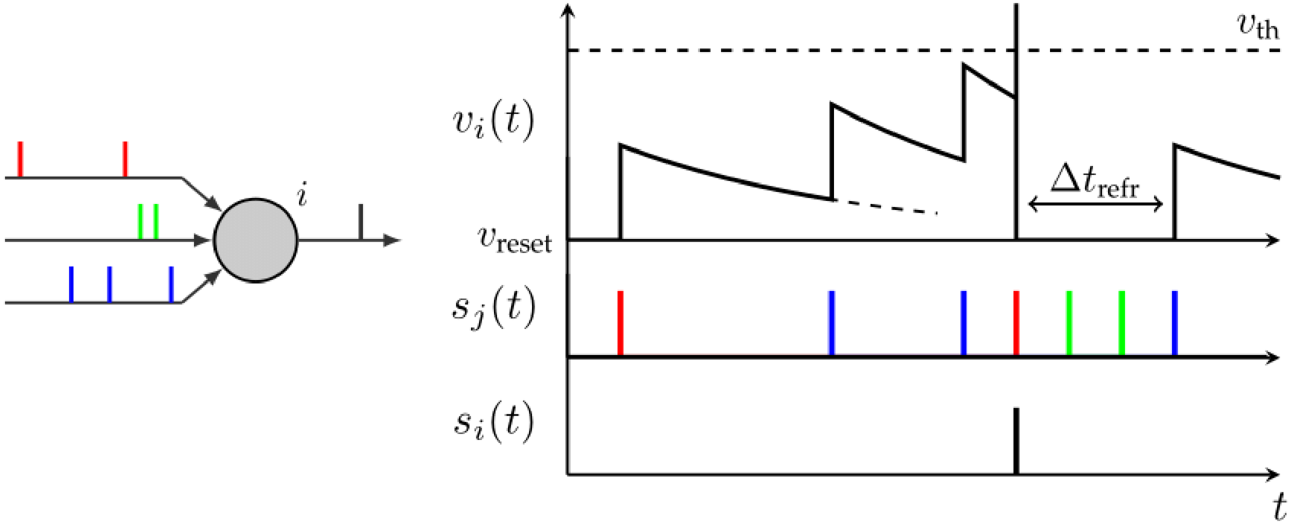
- After spiking → u < 0 → Incoming spikes have harder time to initiate new spike

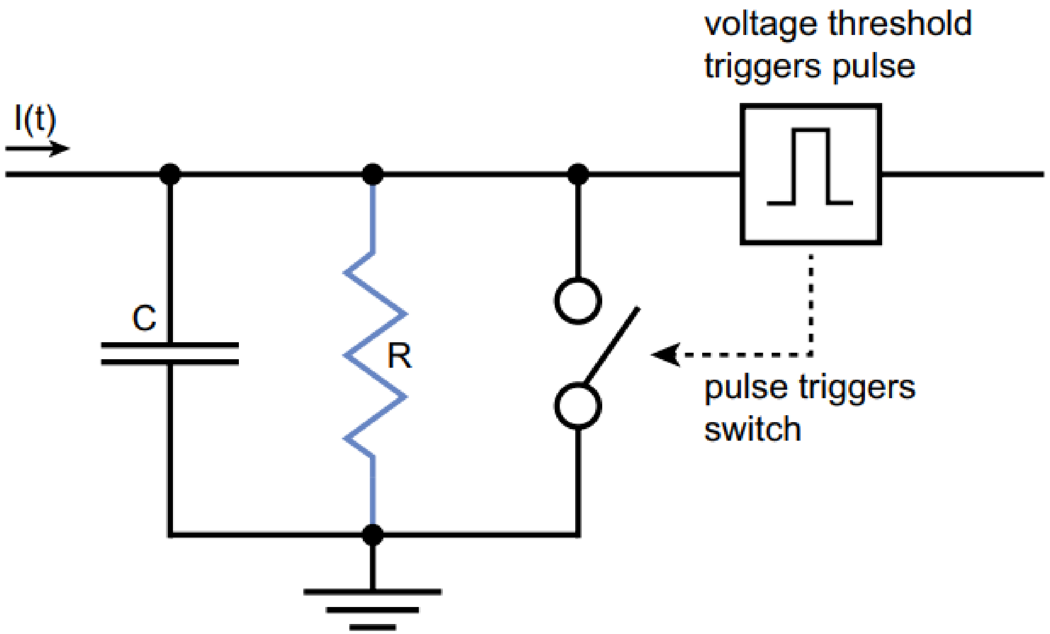
→ Refractory behaviour, although not explicitly defined

- In practical implementations often defined explicitly instead



The integrate-and-fire model





$$C_n \frac{dv(t)}{dt} = I_{input}(t) - \frac{1}{R_n}(v(t) - v_0) + I_{spike}^0 \delta(v(t) - v_t)$$

A. Thomas, J. Phys. D 2013

Adaptive threshold

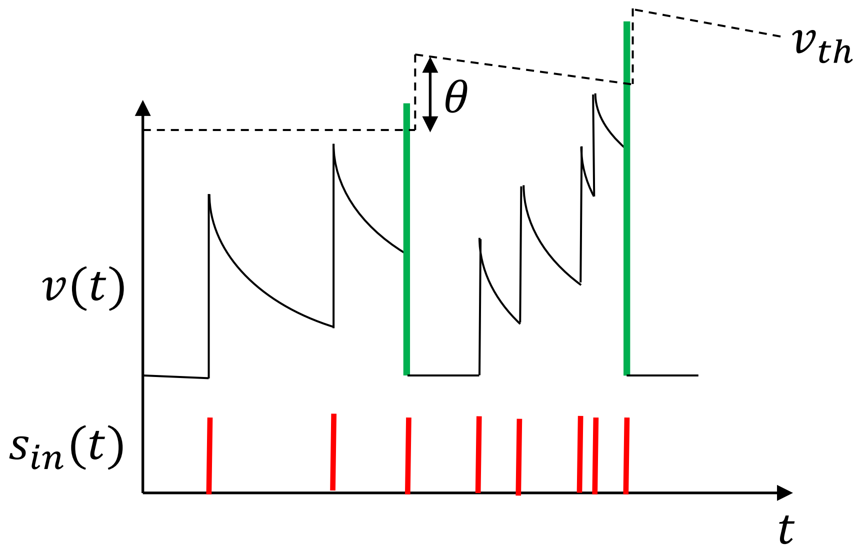
- For each spiking event → increase threshold
- Threshold decays to "resting value"

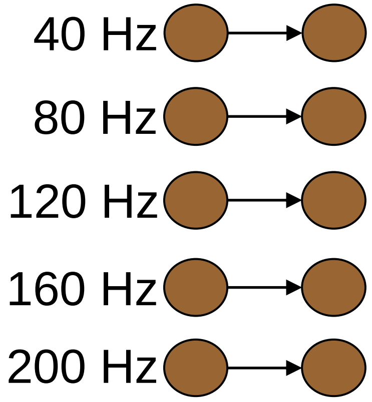
→ Hard to have high spiking rate

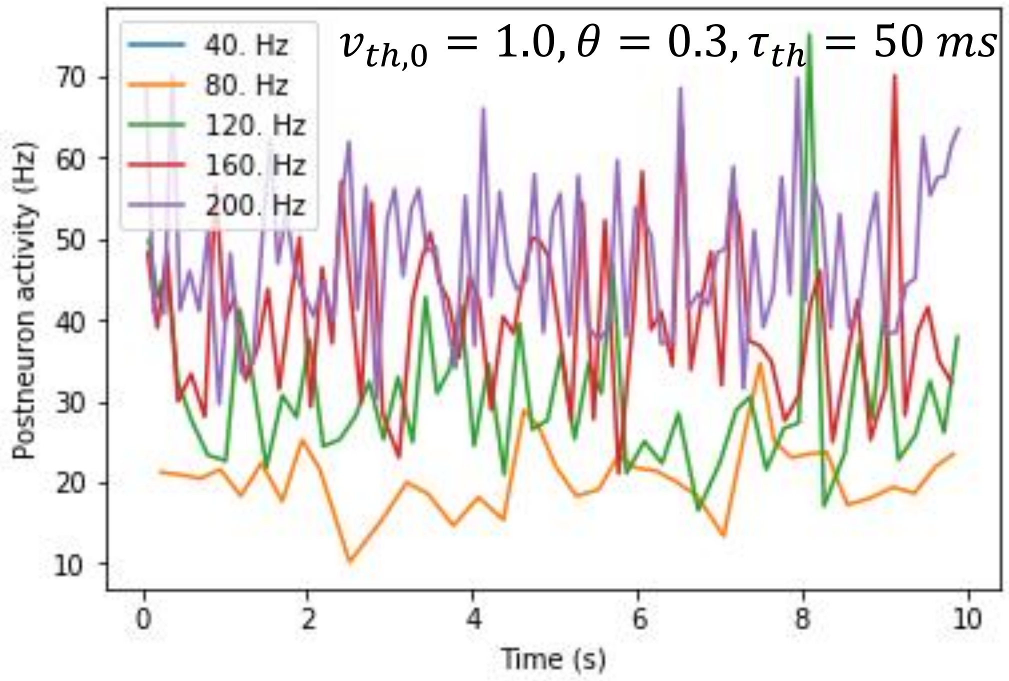
- Keeps overall spiking rate uniform

$$\frac{dv_{th}}{dt} = -\frac{(v_{th} - v_{th,0})}{\tau_{th}}$$

On spike: $v_{th} = v_{th} + \theta$

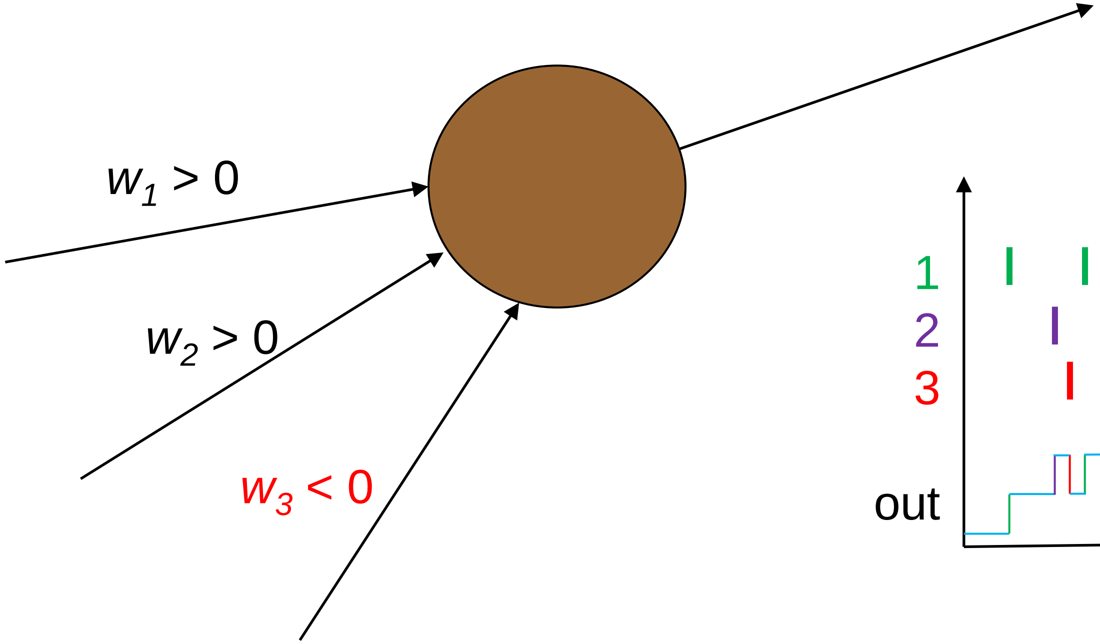


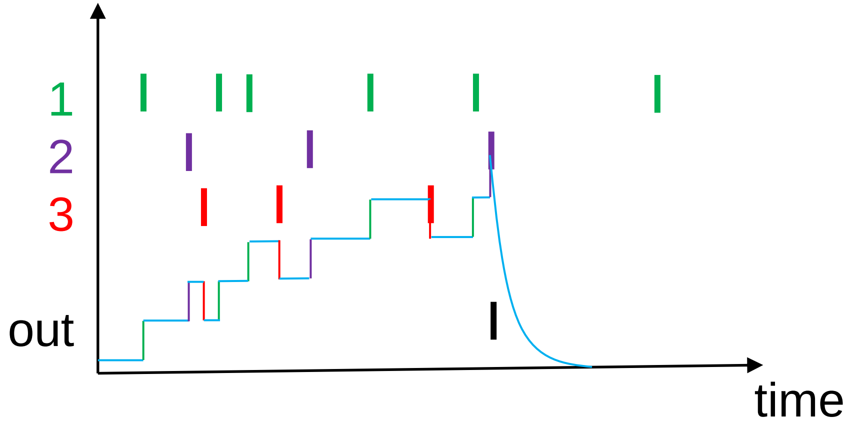




Excitatory / Inhibitory synapses

- Not all synapses shift the neuron potential towards threshold (excitation)
- Some reduce the neuron potential (inhibition)
  → Inhibition can be a crucial feature for learning in SNNs
- Inhibition can be modeled by synapse with negative weight



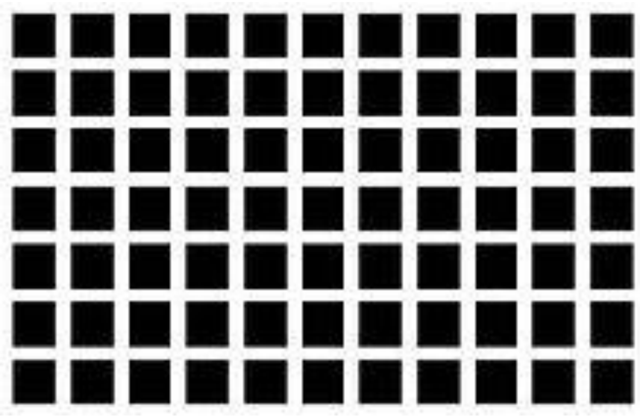


Lateral inhibition - Example

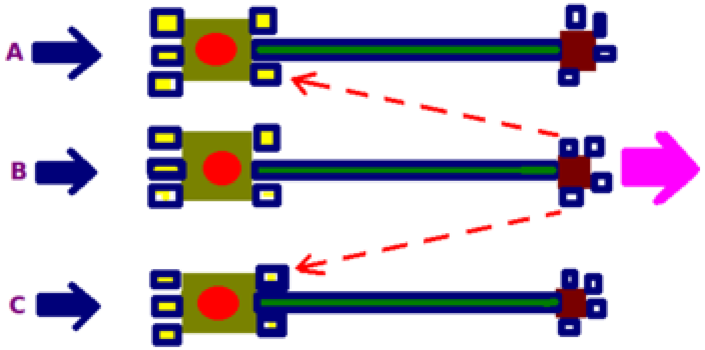
- Upon firing (activation) a neuron inhibits potentiation of neighbouring neurons (in the same layer!)

→ extra spatial contrast

Mach bands illusion
Darker areas in contact with lighter areas appear darker than they are



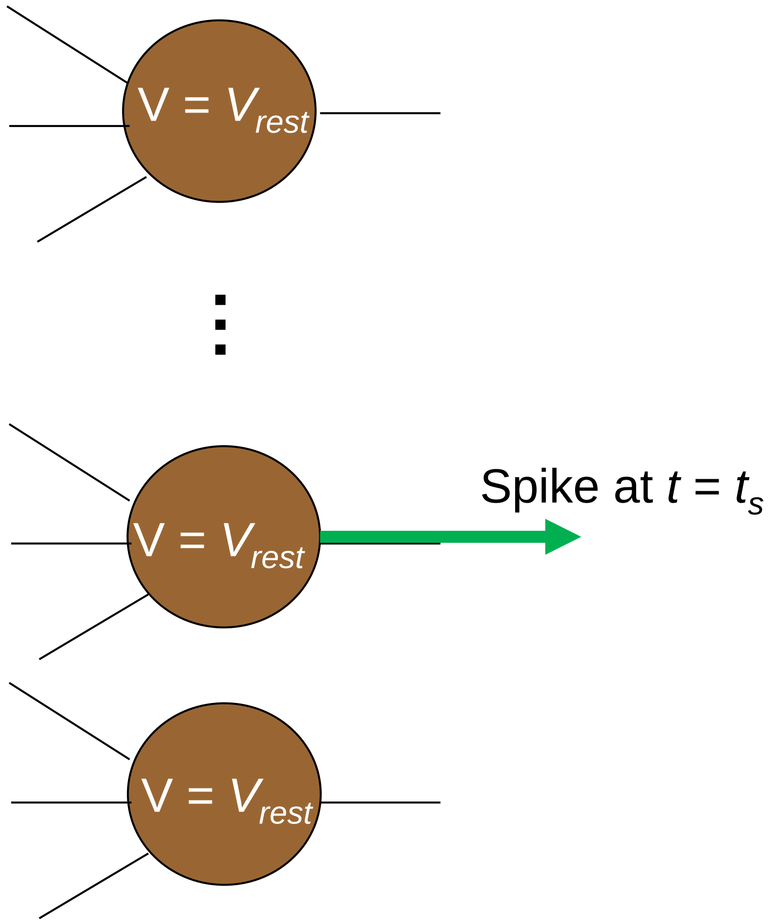
Herman grid illusion
Darker blobs appear at intersections



"Winner-takes-all"

- If all neurons in a layer can <u>completely</u> inhibit all others in the layer

  → i.e. the first to fire will be the only one to fire…
- Typically implemented as inhibition for a certain time, matching refractive period
  - $V = V_{rest}$ on all until $t = t_s + t_{refr}$

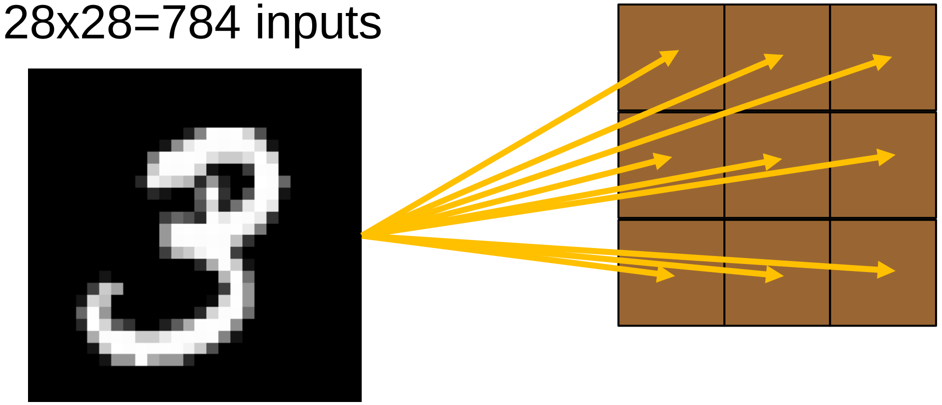


Learning prototypes

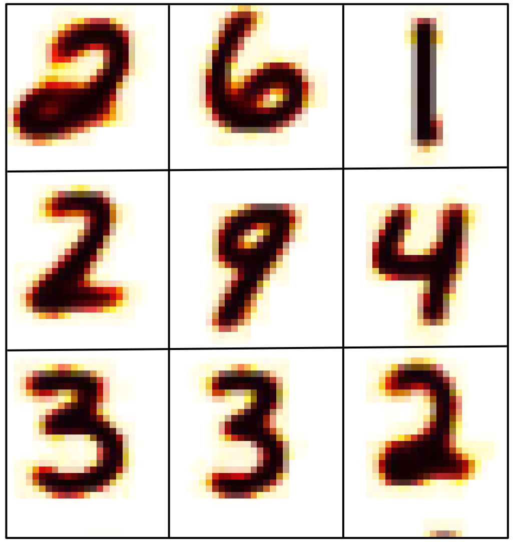
- Lateral inhibition promotes neuronal learning of specific prototypes in the data, since only a few neurons can spike and adjust their receptive field towards a specific prototype
- Lateral inhibition also prevents overfitting as the competition between neurons forces them to learn different features/prototypes

784 synapses to each neuron

28x28=784 inputs



Receptive field graph

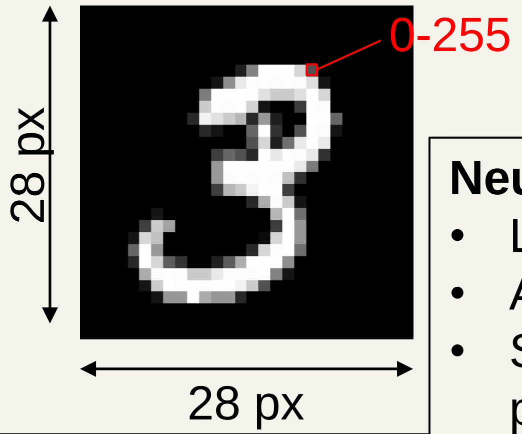


Example of SNN in action

- Classification of MNIST data set
- Rate encoding + conductance synapses

Input encoding

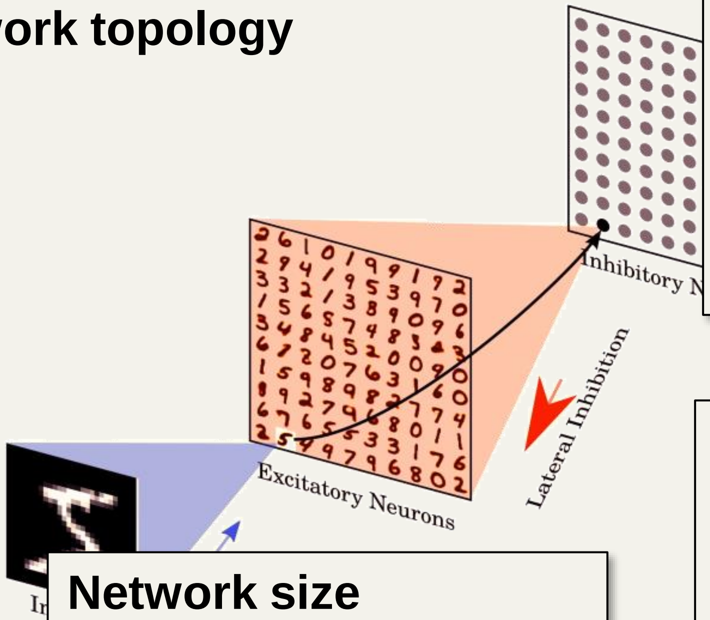
$$f = \frac{I_{ij}}{4} < 63.75 \text{ Hz}$$



Neuron features

- LIF neurons
- Adaptive threshold
- Short refractive period
- "Soft" lateral inhibition via inhibitory neurons

Network topology



Network size

- 100, 400, 1600 and 6400 excitatory neurons
- Trained on 3-15x training set

Training

- Image presented for 350 ms
- 150 ms pause between images
- Weights updated by STDP (4 variants)

Testing

- Set learning rate = 0
- Fix neuron thresholds
- Present testing set
- Each neuron is assigned a class depending on highest response over one set in training

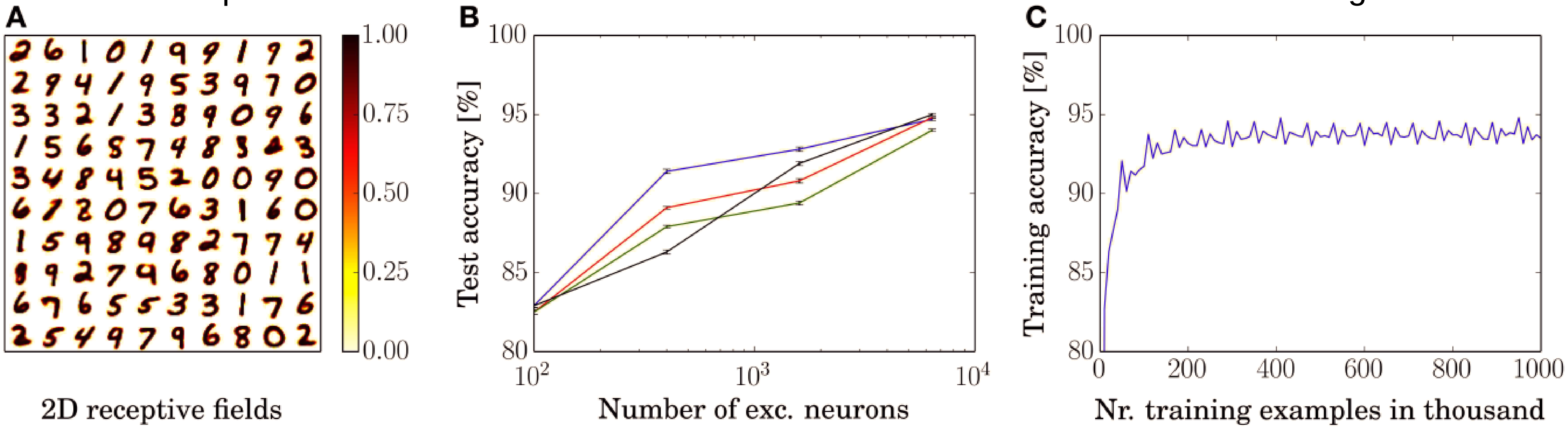
Diehl and Cook 2015

Training results of SNN

Inhibition → specialization of the neuron receptive fields

Robust with respect to the STDP variant.

Quick to converge. Maximum 95.0% for the largest network.



Possible improvements: Additional layers, localised receptive fields,…
Limitations: Few spikes + Rate-encoding limits minimum presentation time

Energy usage in SNN

- Variable threshold → keeps # pulses low
- Very sparse spiking: 17 spikes for one example (16 spikes correct class + 1 spike incorrect)

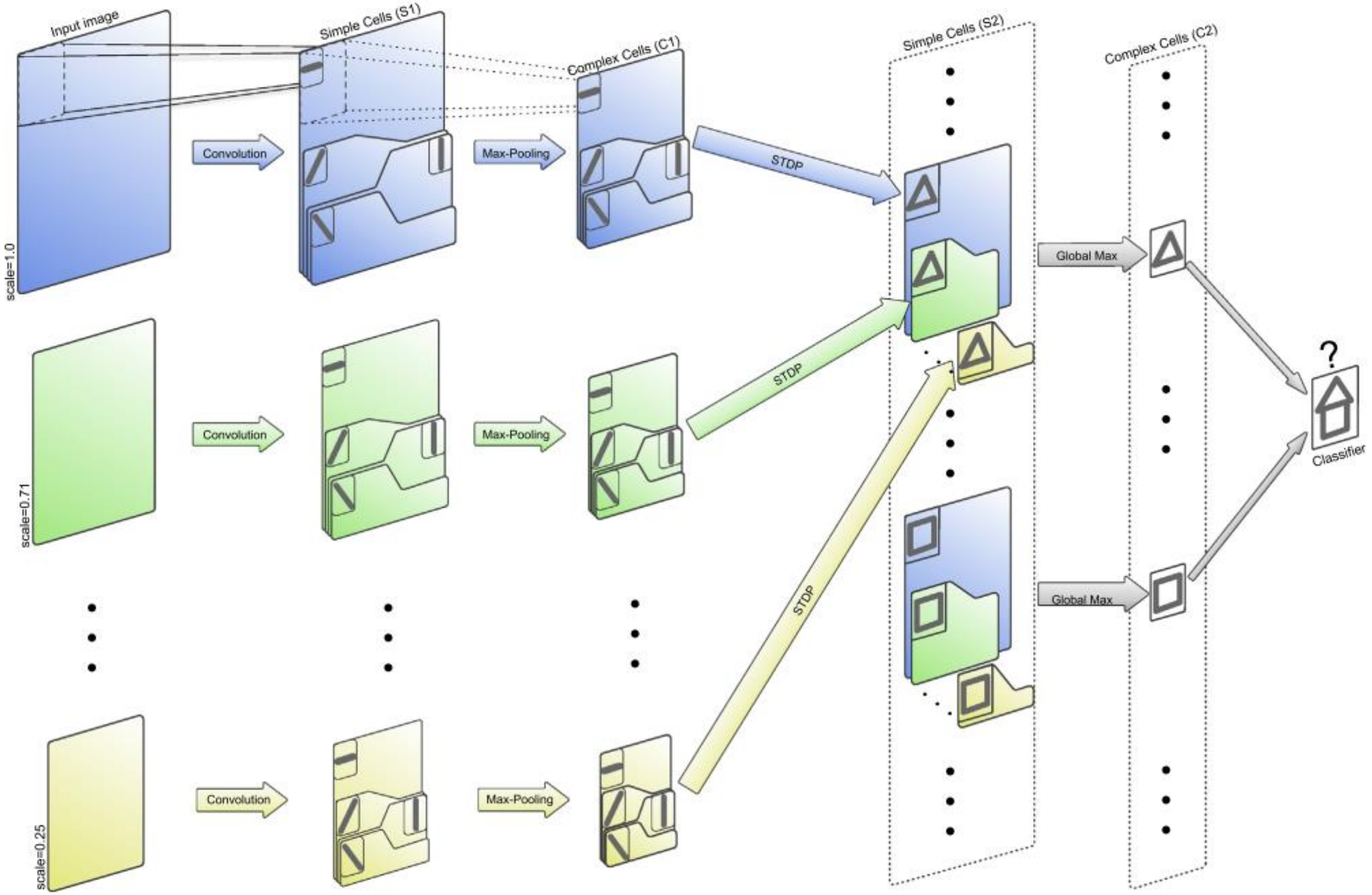
- Typical energy / spike in hardware? 1 spike ~1 pJ, synapse ~1 pW
- Authors estimate ~ 1 mW consumption! (smart phone ~ 1 W)

Compare to NVIDIA V100 GPU = 250W (at least)
→ 250 000 times better

Diehl and Cook 2015

More advanced SNN

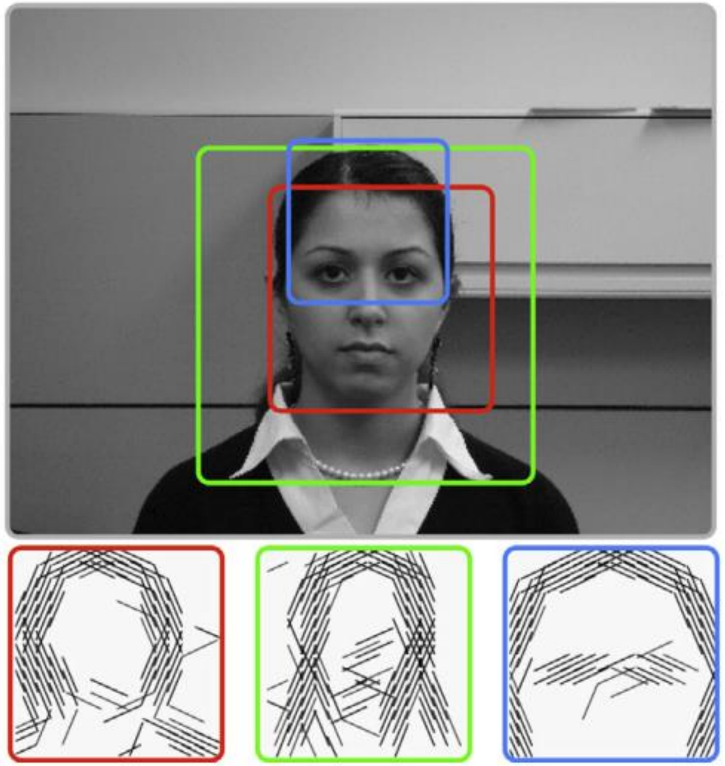
- Time-encoding
  - Darker pixel
    → Larger input spike delay
- First layer: Convolution
  - 5x5 kernels with four predefined features
  - No learning here!
- Second layer: Data pooling
  - Max pool implemented as first pulse is propagated
- Data scaling
  - 0th-2nd layers implemented at 5 scales
- STDP learning in third layer
  - Unsupervised feature learning
  - Input from all scales!



Kheradpisheh et al. Neurocomputing 2016

Performance benchmark

- Beats DeepConvNet on the 3D-object data set:
  - 10 classes of objects at 72 different conditions (various angles, scales, tilt, …)
  - The SNN got 96% vs 85.8% for DeepConvNet
- Much fewer parameters: thousands vs 60 million (DeepConvNet)
  - Allows for smaller data sets without overfitting
  - Only 3500 images used here
    (humans can generalize from a few images only).



Ex. Feature learning at three scales

Make your own quiz question!

- Come up with a good quiz question based on the topics of L4-L7
- You have until the end of the lecture/day → Send it to mattias.borg@eit.lth.se
- Quiz will be posted on Canvas for you to practise on..

What is the chance that you win on the lottery?

1. Chance? I always win
2. 1 in 100 000
3. As good as dying in a plane crash
4. I will win when pigs can fly

Lecture 4 – Machine Learning Topologies
Convolutional Neural Network
Recurrent Neural Network
Locally Connected Network

Lecture 5 – Hardware for Big Data
GPU
TPU
In-memory computing

Lecture 6 – Spiking Neural Networks 1
Plasticity
Hebbian learning
STDP

Lecture 7 – Spiking Neural Networks 2
Biological neuron
Hodgkin-Huxley
Integrate-and-fire