DD2437 – Artificial Neural Networks and Deep Architectures (annda)

Lecture 1: **Course introduction and fundamental concepts**

Pawel Herman and Erik Fransén

Computational Science and Technology (CST)

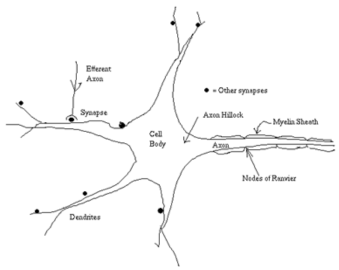
KTH Royal Institute of Technology

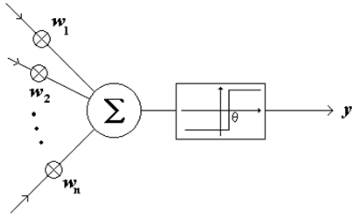
Overview

- A historical note
- Course outline
  - Learning activities
  - Assessment, grading
- Introduction to ANNs
  - Fundamental characteristics
  - Brain inspirations
  - Current developments – theory and applications

Brief history of ANNs

- McCulloch and Pitts
- Donald Hebb “The Organization of Behaviour”





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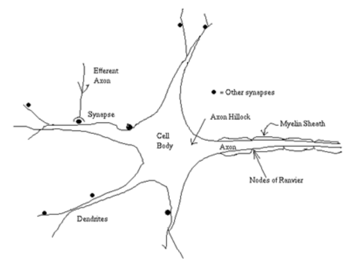

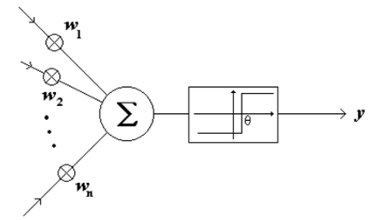

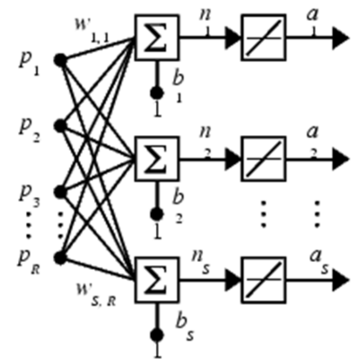

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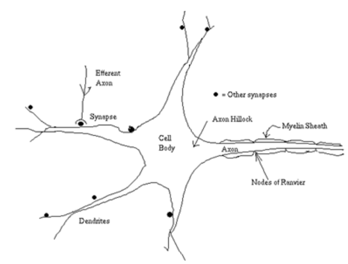
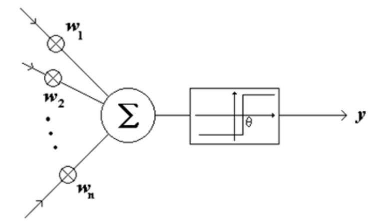
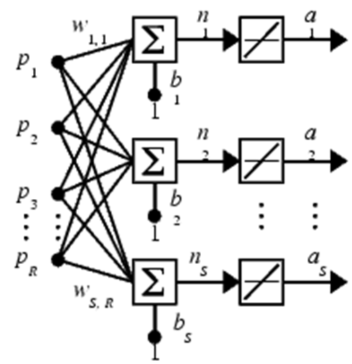
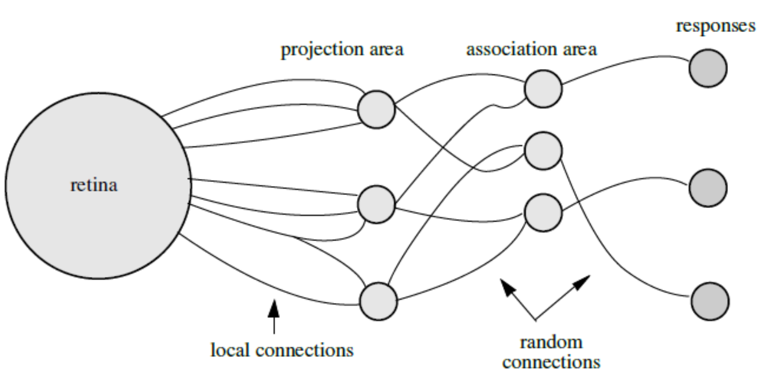
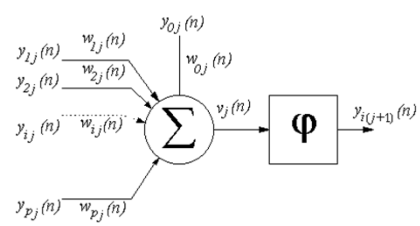
- Rosenblatt’s perceptron











After Rosenblatt (1958)

Brief history of ANNs

- McCulloch and Pitts
- Donald Hebb "The Organization of Behaviour"
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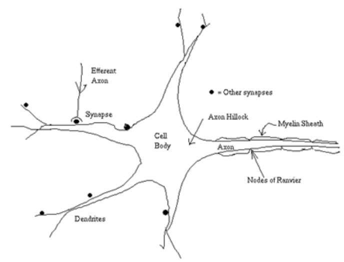
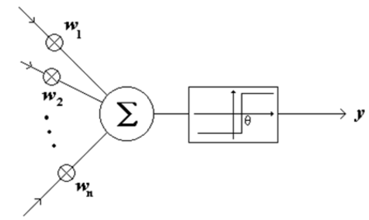
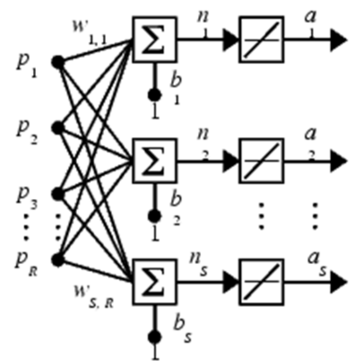
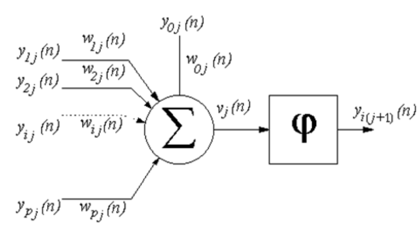
- Rosenblatt's perceptron
- Marvin Minsky and Seymour Papert's criticism (1969)
- first AI winter: fears and outrageous claims led to lower interest and poor funding



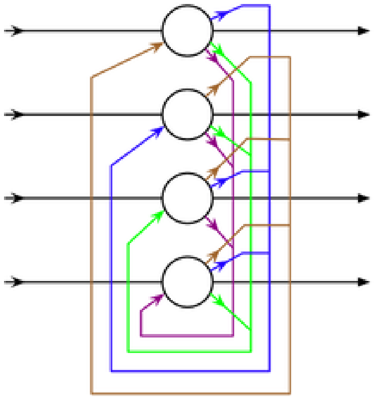






Brief history of ANNs

- Hopfield's impact



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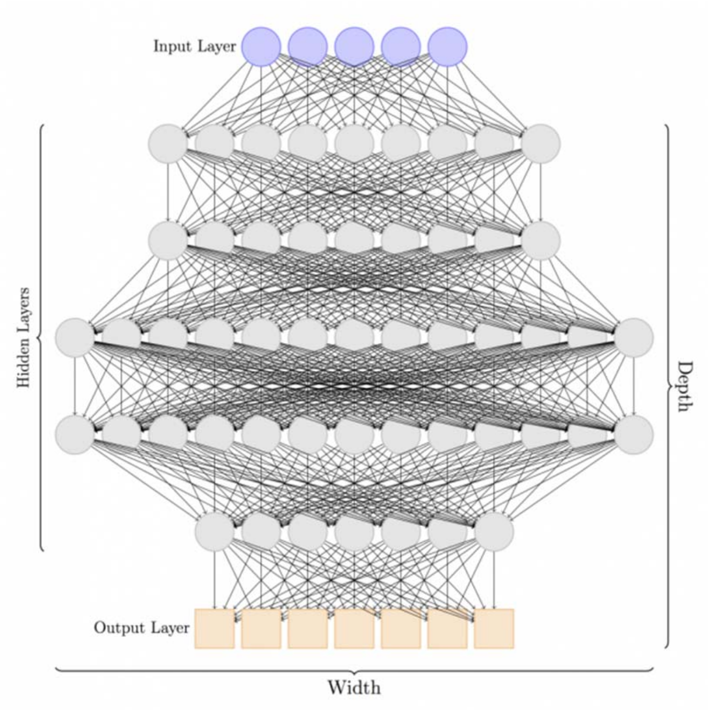
Brief history of ANNs

- Hopfield's impact
- Renewed enthusiasm in the 1980s and 1990s (backpropagation, 1986)
- interest swifts towards more mathematically rigorous statistical learning theory
- another revival of interest in deep neural networks



A wide scope of applications

- Pattern recognition: classification and clustering
- General interpolation problems (generalisation)
- Data representations, coding and compression
- Signal processing
- Time series prediction
- System identification
- Decision support (e.g. medical or industrial diagnostics)
- Memory storage, modelling
- Optimisation, combinatorial problems
- etc…….

Course outline

- Learning activities
  - 11 lectures + 1 summary and Q&A lecture + 1 reserve slot (Oct 10)
  - 10 “lab” sessions (evaluation and support)
  - 4 lab assignments (in groups of 3 students)

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  - 4 lab assignments (in groups of 3 students)
- Assessment, grading
  - 4 mandatory lab assignments with bonus point deadlines (check in Canvas: under Lab Review as well as Content, assessment)
  - lab review (redovisning) and a short report to submit in Canvas (P/F)
  - written exam: A-F

Lab review

- be prepared for short 10-min demonstration of the lab results (in groups) and 2-3 min questions, we do not tend to inspect your code
- time is short so planning and preparation are critical –
  - focus on main points, key questions – what is the lab about?
  - what are the assumptions?
  - share your insights and formulate clear conclusions
  - what did you learn?
  - are there any open questions left?
- you are in charge of the lab review but we are likely to ask questions
- please ensure the entire group is involved (time sharing)
- please demonstrate in the form of a report with clear & clean figures

Lab report

- a concise document to be uploaded to Canvas as a pdf file before your lab demonstration (bring the report with you)
- a typical layout involves (for each lab there is a template)
  - clear header (lab title, course signature, list of authors)
  - aim/scope of the lab assignment, assumptions, tools used
  - main results/findings supported with figures or tables (with captions, and always referred to in the main text) along with short commentary, your interpretations
  - reflections, open questions and conclusions (to the point)
  - no code needed and please do not add any appendices – there is an upper limit for the number of pages, e.g. 6 for lab 1.
- follow instructions on Canvas

Course content

Lectures

L1: Course introduction and fundamental concepts

L2: From perceptron learning rule to backpropagation in feedforward networks – supervised learning

L3: Generalization, regularization, model selection and validation

L4: Practical aspects of ANN approaches to pattern recognition problems

L5: Radial basis function networks and introduction to unsupervised learning

L6: Self-organising maps

Course content

Lectures

L7: Temporal processing with ANNs: feedforward vs recurrent network architectures

L8: Hopfield networks and introduction to stochastic networks

L9: Deep learning fundamentals: general philosophy and a review of deep architectures

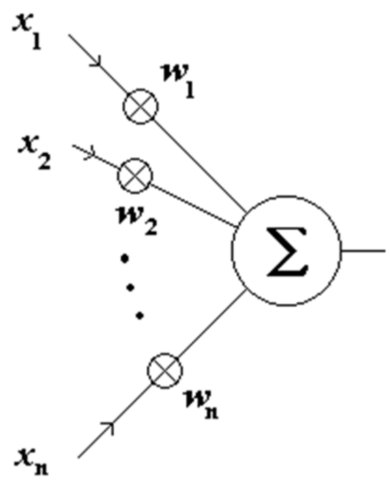
L10: Representation learning and deep generative models

L11: Deep neural networks: practicalities, challenges and current trends

L12: Course summary, old exam questions, Q&A

Fundamental characteristics

- **nodes, units**
- activation function
- learning rule
- topology, network architecture
- data



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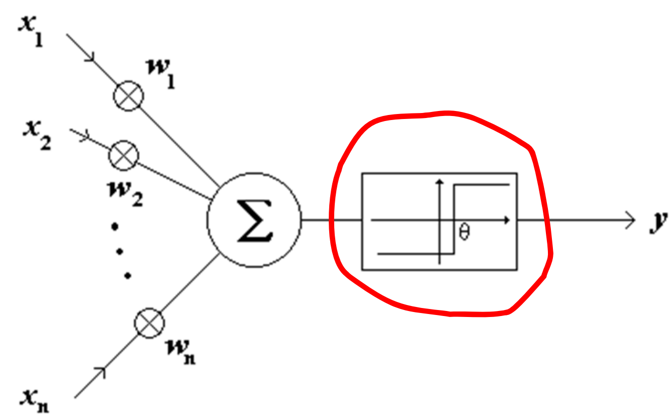

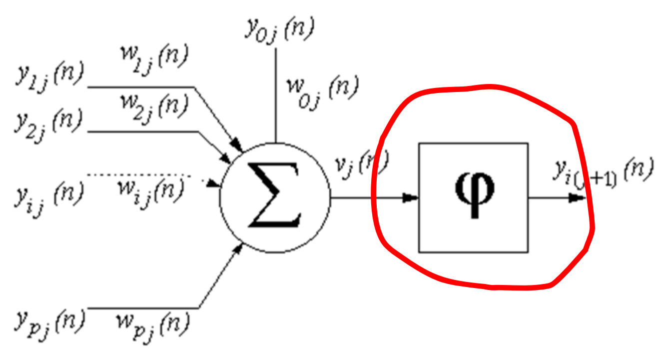

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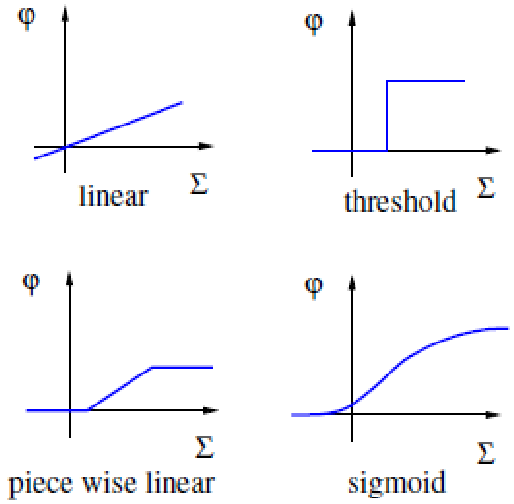
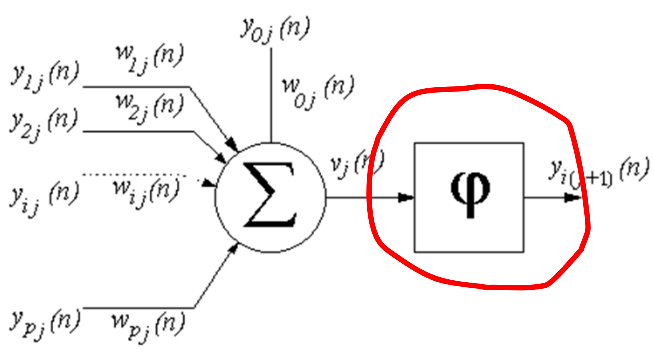
activation function





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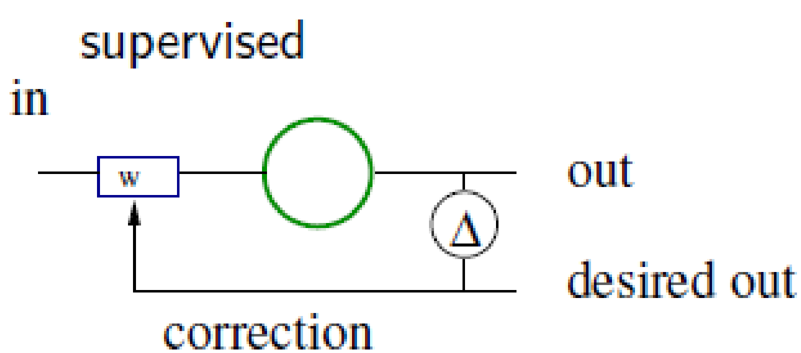

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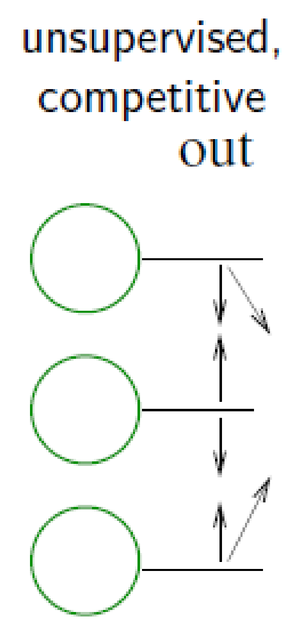

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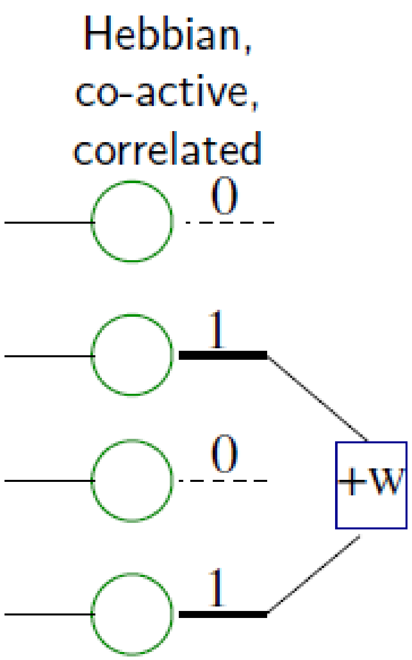

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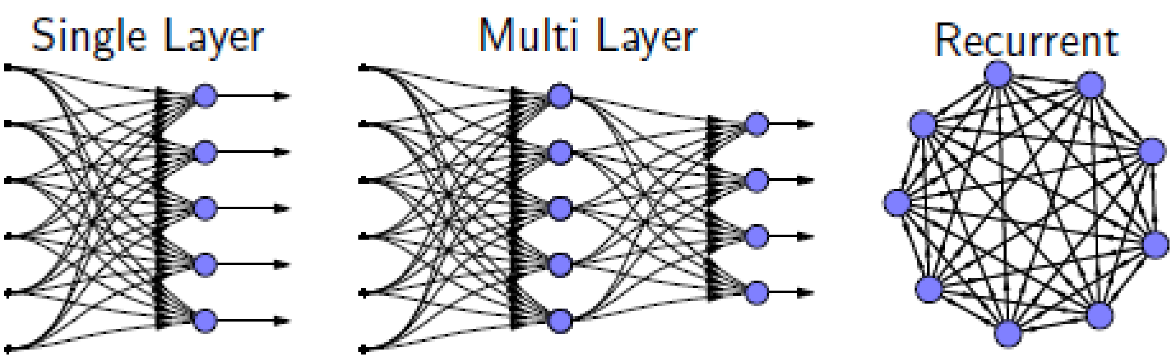

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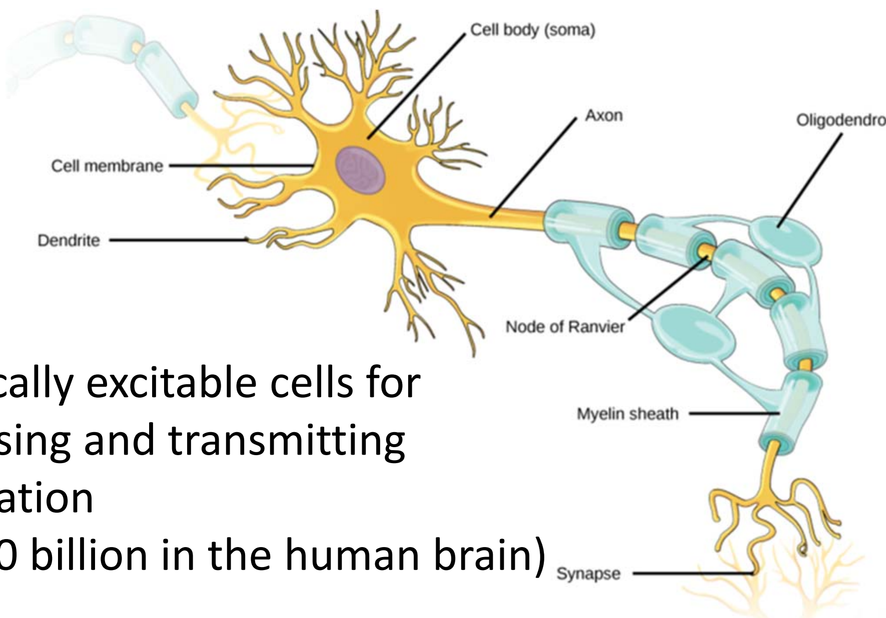
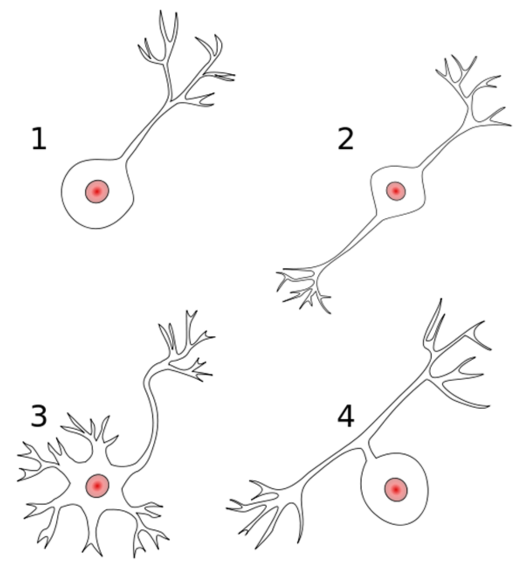
Biomimetic nature of ANNs

Inspirations from biology



electrically excitable cells for processing and transmitting information
(ca. 100 billion in the human brain)

Multitude of neuron types in the brain



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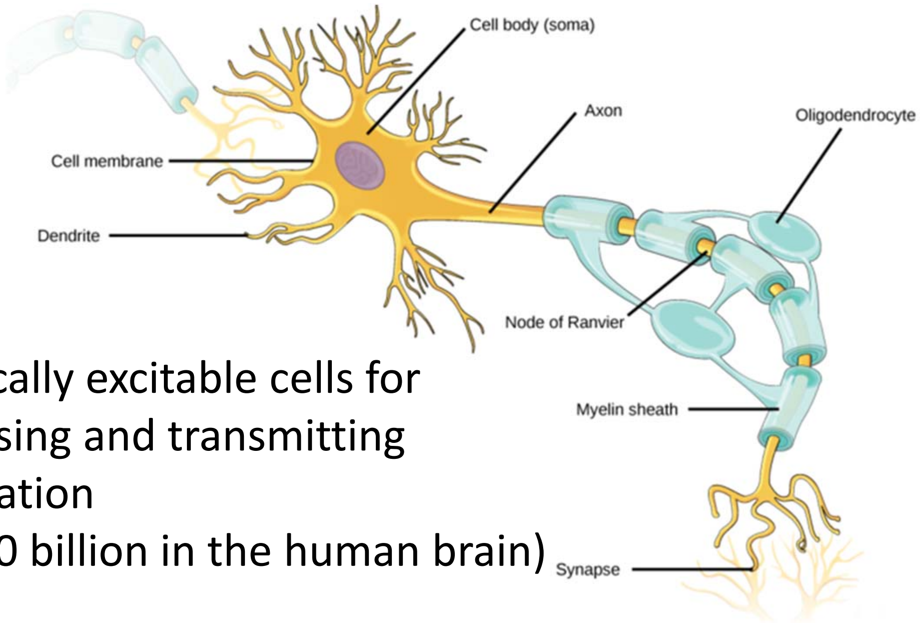

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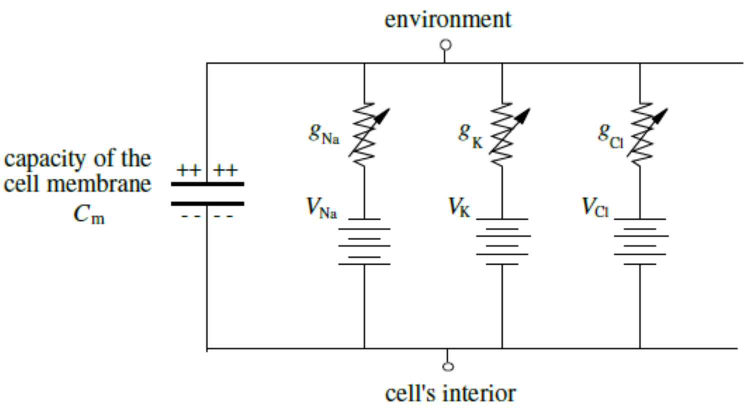
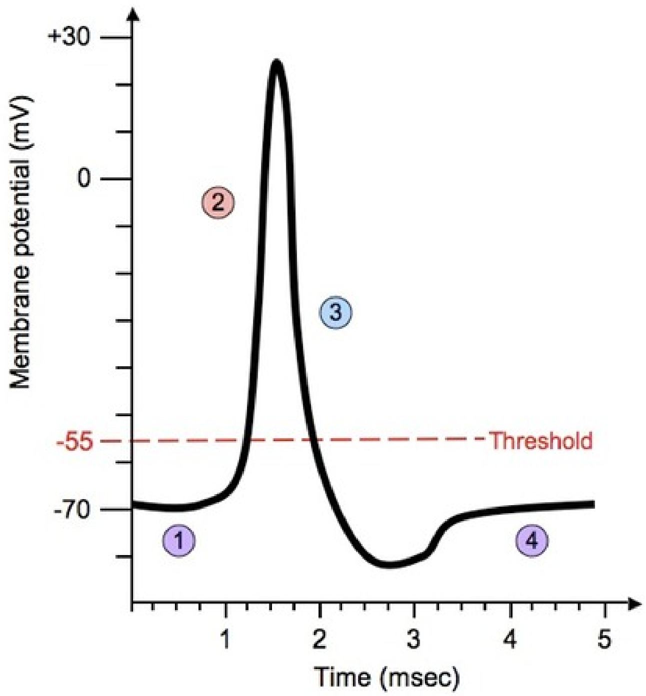
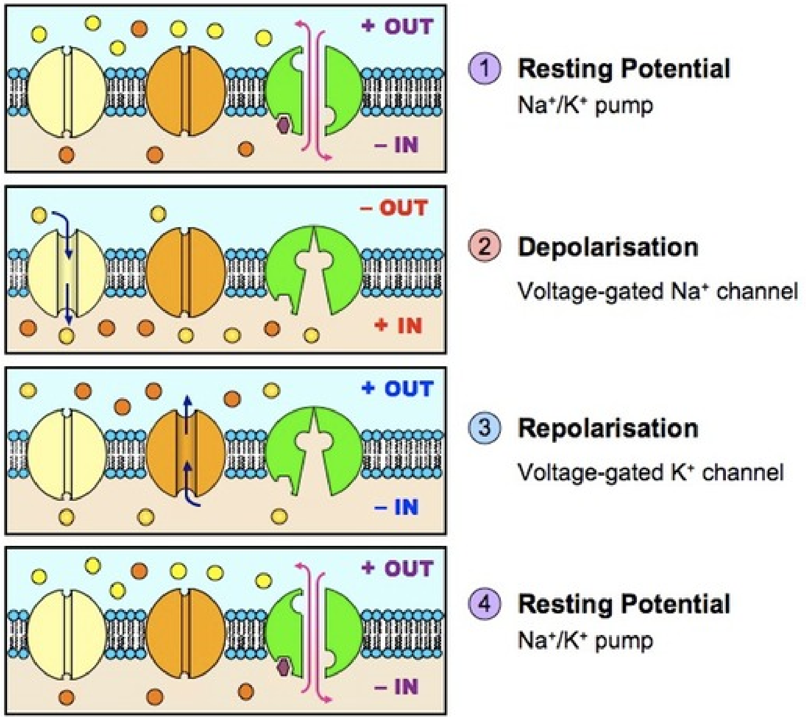


Biomimetic nature of ANNs

Inspirations from biology – action potential (firing)





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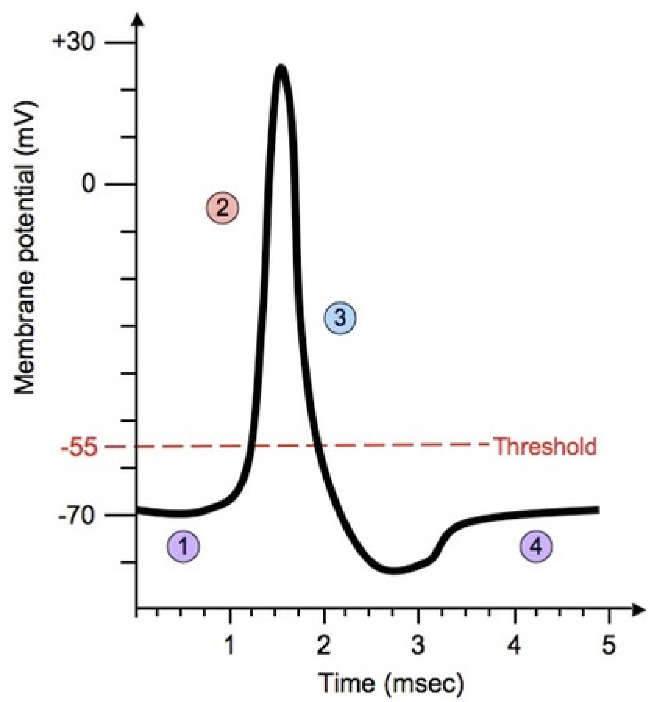

- commonly referred to as "spike" (nerve impulse)
- threshold phenomenon accounts for "all-or-nothing" paradigm
- spike (action potential of fixed amplitude) travels along the axon

Biomimetic nature of ANNs

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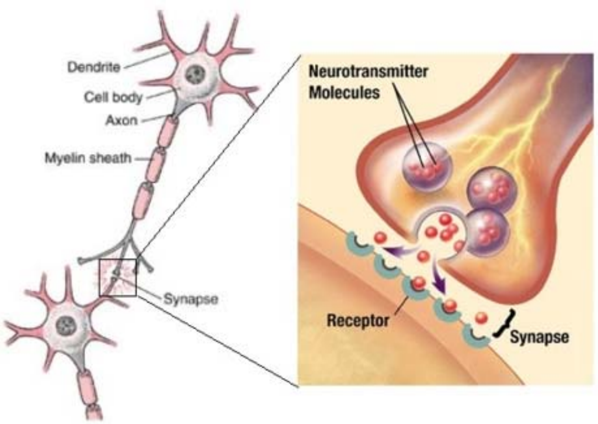

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- when spike reaches synaptic terminal, it contributes to post-synaptic potentials

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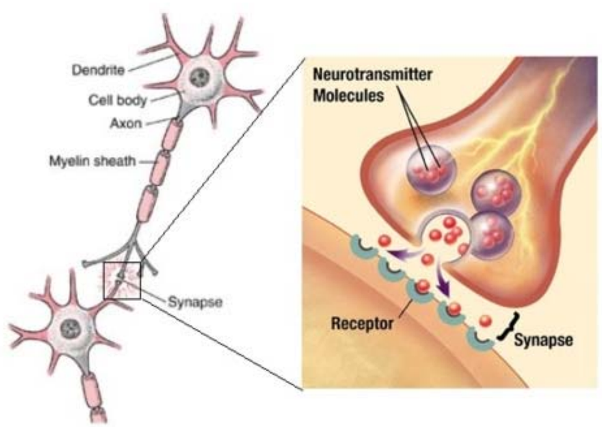
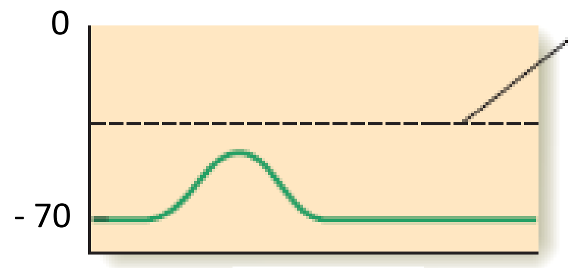
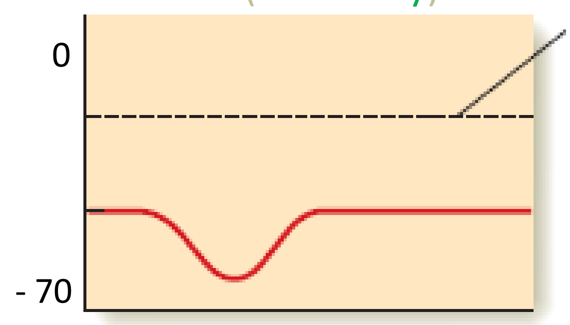




Level of depolarization needed to trigger an action potential

Depolarization
(Excitatory)



Level needed to trigger an action potential

Hyperpolarization
(Inhibitory)

Biomimetic nature of ANNs

Biological neurons and networks – computational aspects

- numerous simple units (type of integrators)
- binary communication – spike (“all-or-nothing”)
- but analog transmission in synapse (connection weight)
- many inputs, interconnect
- summation (integration) of inputs

Biomimetic nature of ANNs

Biological neurons and networks – computational aspects

- local processing, learning (based on local information)
- synaptic memory (memory stored in weights)
- synaptic plasticity – weight adaptation according to learning rules (largely phenomenological)
- weights can be positive and negative (but Dale's law)
- fast nature of parallel processing
- tolerance to errors/noise in data, weights etc.