"111 Centre on Biological Computing and Artificial Intelligence" , Dalian University (DLU)

Advanced Artificial Intelligence Technologies and Applications

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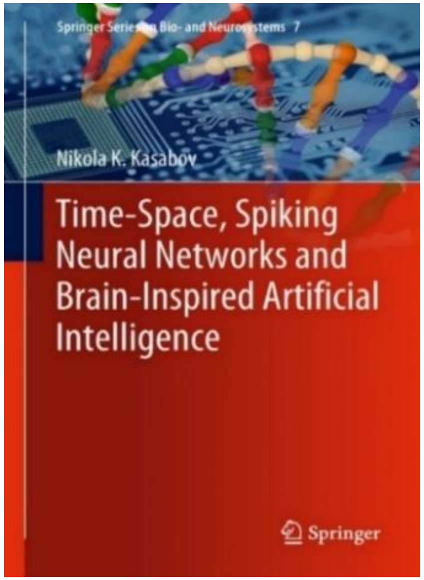
Full course DLU, 2023, Lecture Content

Advanced Artificial Intelligence Technologies and Applications

1. AI and the evolution of its principles. Evolving processes in Time and Space (Ch1, 3-19)
2. From Data and Information to Knowledge. Fuzzy logic. (Ch1,19-33 + extra reading)
3. Artificial neural networks - fundamentals. (Ch2, 39-48). Computational modelling with NN. Tut1: NeuCom.
4. Deep neural networks (Ch.2, 48-50 + extra reading).
5. Evolving connectionist systems (ECOS) (Ch2, 52-78). Tutorial 2: ECOS in NeuCom.
6. Deep learning and deep knowledge representation in the human brain (Ch3)
7. Spiking neural networks (Ch4). Evolving spiking neural networks (Ch5)
8. Brain-inspired SNN. NeuCube. (Ch.6). Tutorial 3: NeuCube software (IA)
9. Evolutionary and quantum inspired computation (Ch.7)
10. AI applications in health (Ch.8-11)
11. AI applications for computer vision (Ch.12,13)
12. AI for brain-computer interfaces (BCI) (Ch.14)
13. AI for language modelling. ChatBots (extra reading)
14. AI in bioinformatics and neuroinformatics (Ch15,16, 17,18)
15. AI applications for multisensory environmental data (Ch.19)
16. AI in finance and economics (Ch19)
17. Neuromorphic hardware and neurocomputers (Ch20).



Course book: N.Kasabov, Time-Space, Spiking Neural Networks and Brain-Inspired Artificial Intelligence Springer, 2019, https://www.springer.com/gp/book/9783662577134

Additional materials: https://www.knowledgeengineering.ai/china

N. Kasabov Foundations of Neural Networks, Fuzzy Systems, and Knowledge Engineering, MIT Press, 1996.
ZOOM link for all lectures: https://us05web.zoom.us/j/4658730662?pwd=eFN0eHRCN3o4K0FaZ0lqQmN1UUgydz09

Lecture 7

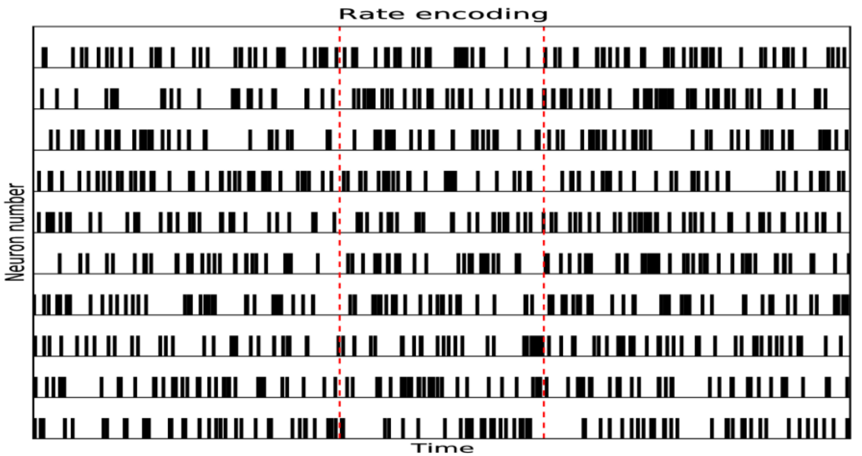
Spiking neural networks (Ch4).
Evolving spiking neural networks (Ch5)

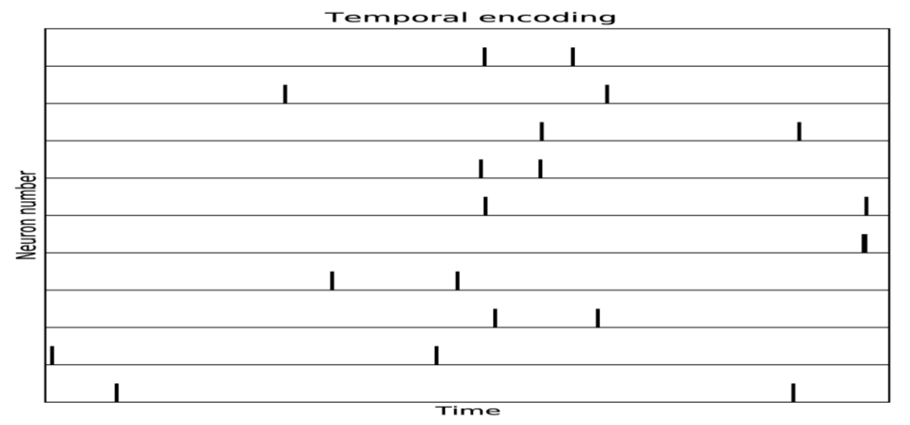
1. Encoding information as spikes
2. Spiking neuron models
3. Evolving spiking neural networks
4. Questions

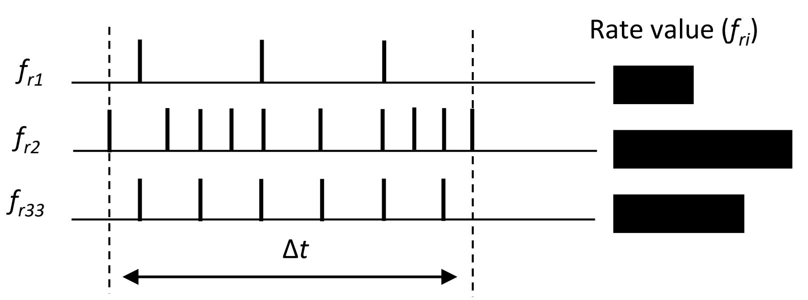
1. Encoding information as spikes (Ch.3)

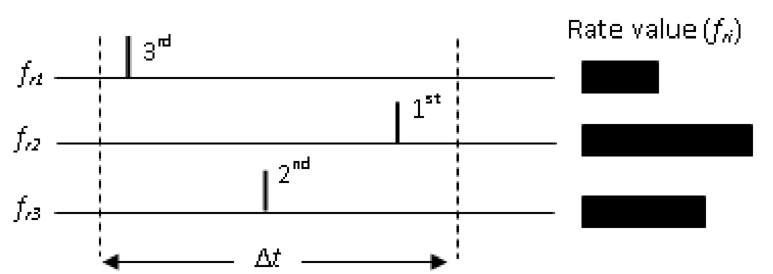
Spike encoding:

- Rate-based coding: A spiking characteristic within a time interval, e.g. frequency.
- Time-based (temporal) coding: Information is encoded in the time of spikes. Every spike matters and its time - too!







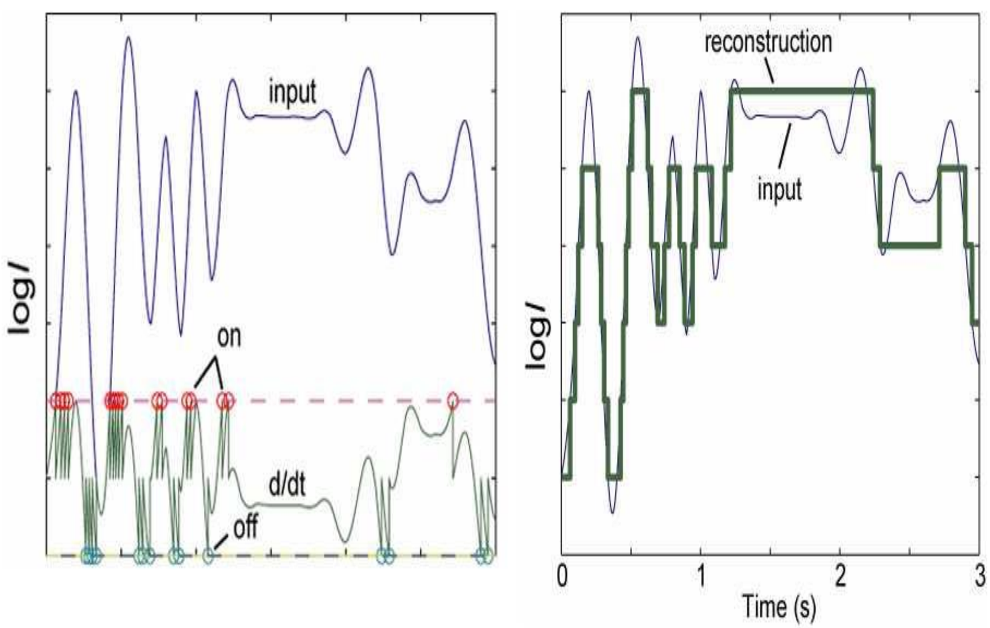


Spike encoding methods

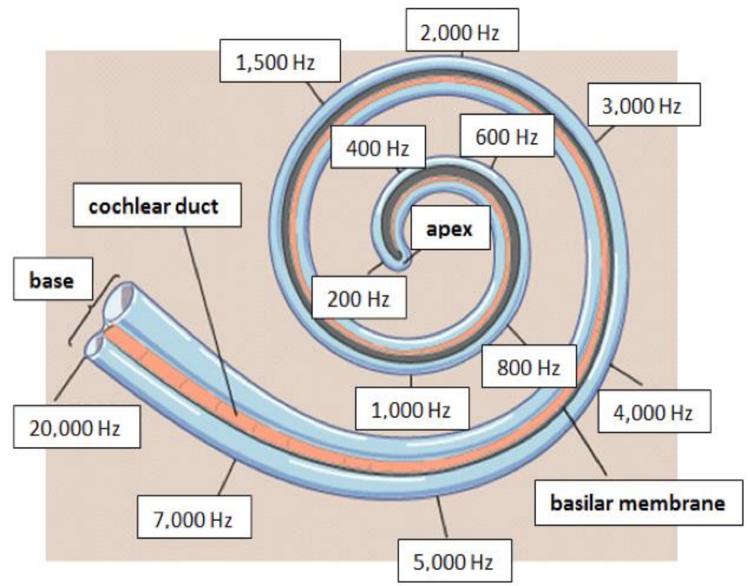
A spike is generated only if a change in the input data occurs beyond a threshold

Silicon Retina (Tobi Delbruck, INI, ETH/UZH, Zurich), DVS128: Retinotopic

Silicon Cochlea (Shih-Chii Liu, INI, ETH/UZH, Zurich): Tonotopic



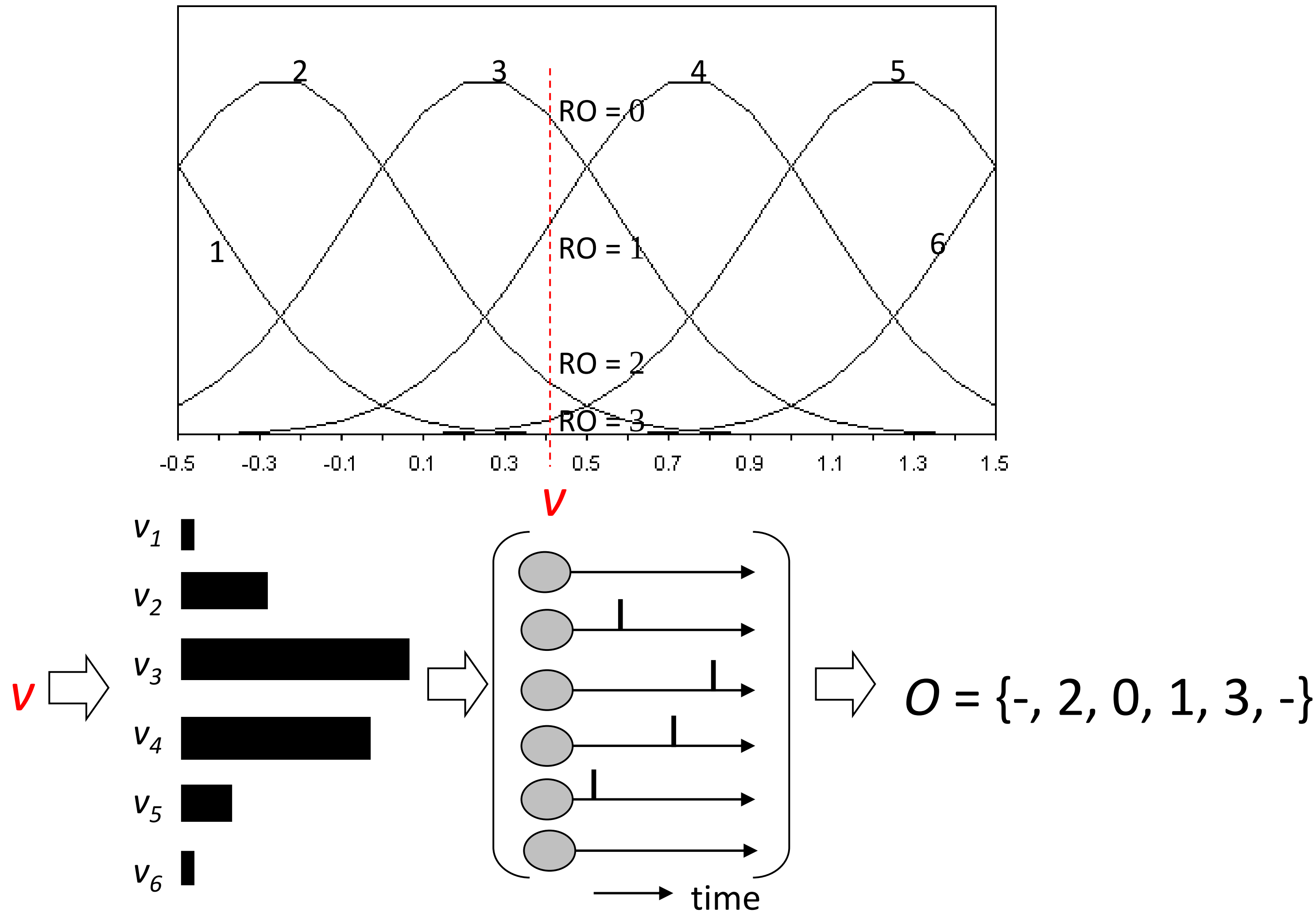
Threshold-based encoding – retinotopic



Tonotopic organization of the cochlea:
https://sites.google.com/site/jayanthinyswebite

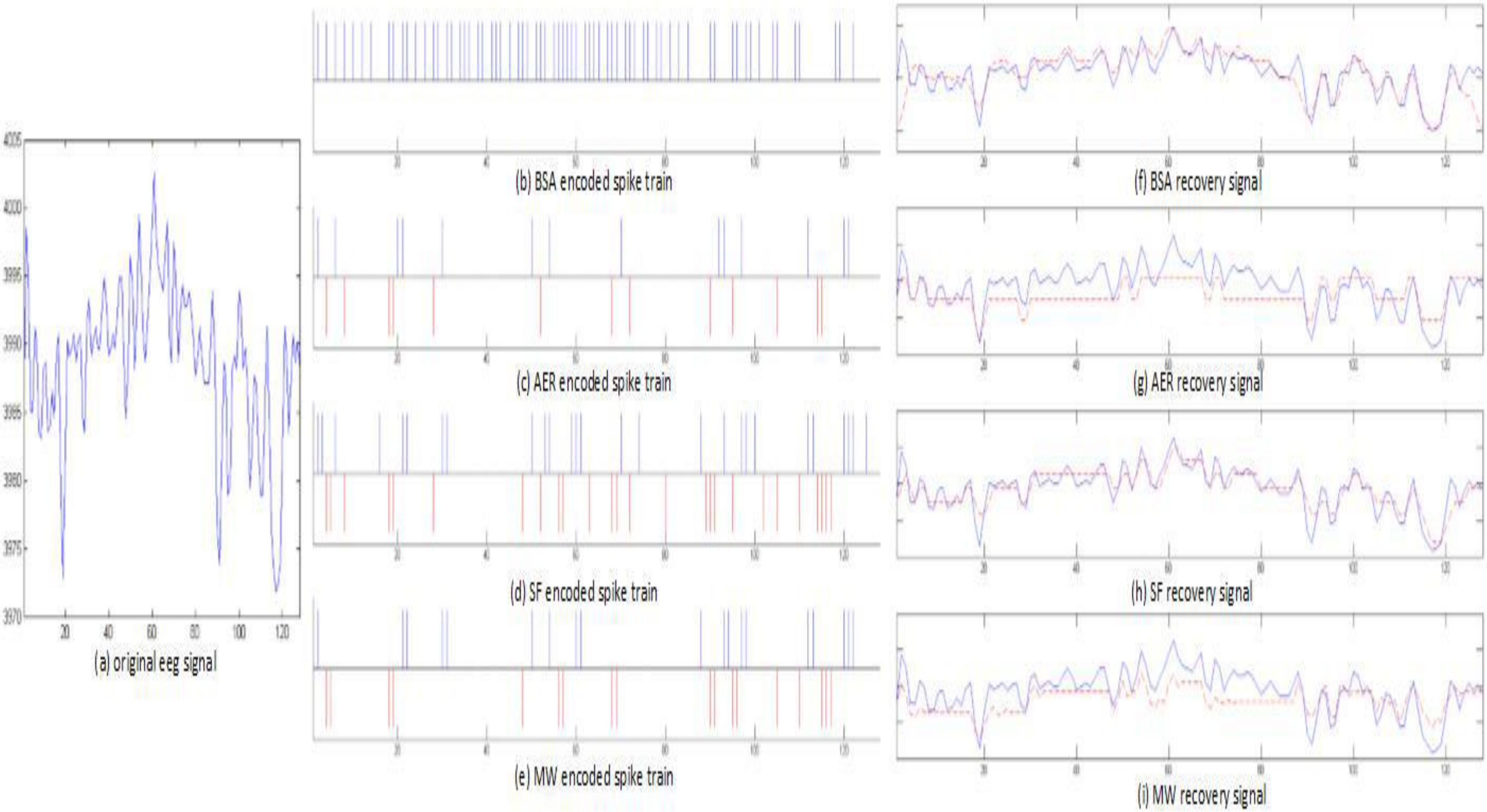
RO population coding(RO-POP C)

Distributes a single real input value V to multiple neurons and may cause the excitation and firing of several responding neurons depending on the membership to the receptive fields.
Implementation based on Gaussian receptive fields introduced by Bothe *et al* . 2002



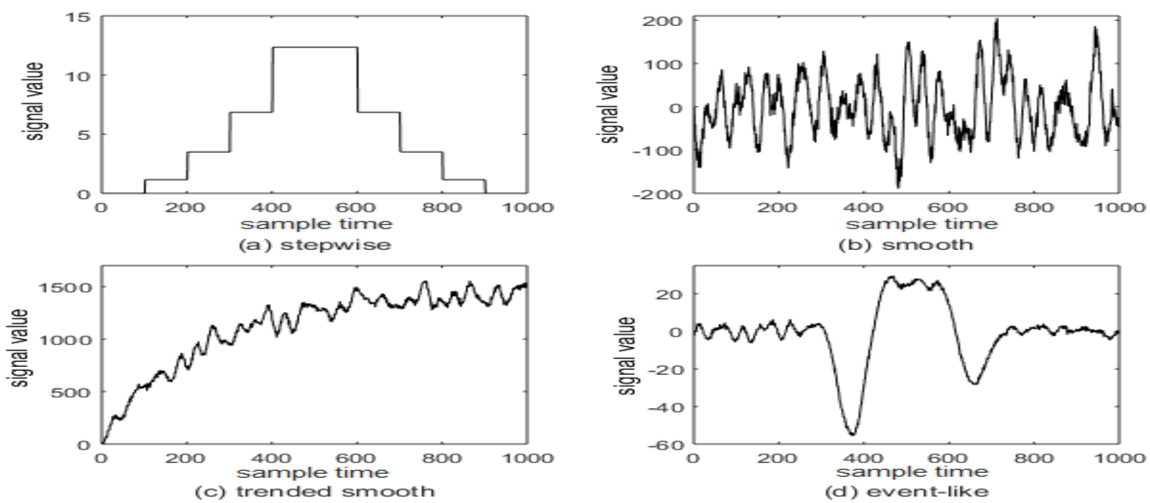
Input data encoding

(Lei Zhou, N. Kasabov, J.Yang)



Selection and optimisation of spike encoding method

((B.Petro, N.Kasabov, R.Kiss, Selection and optimisation of spike encoding methods for spiking neural networks, algorithms, IEEE Transactions of Neural Networks and Learning Systems, April 2019, DOI:10.1109/TNNLS.2019.2906158))



Four encoding methods are analyzed: one stimulus estimation [Ben’s Spiker algorithm (BSA)] and three temporal contrast [threshold -based, step-forward (SF), and moving-window (MW)] encodings.

BSA can follow smoothly changing signals if filter coefficients are scaled appropriately.

SF encoding was most effective for all types of signals as it proved to be robust and easy to optimize.

Signal-to-noise ratio (SNR) can be recommended as the error metric for parameter optimization.

Free software: https://github.com/KEDRI-AUT/snn-encoder-tools (Balint Petro, BU Hungary)

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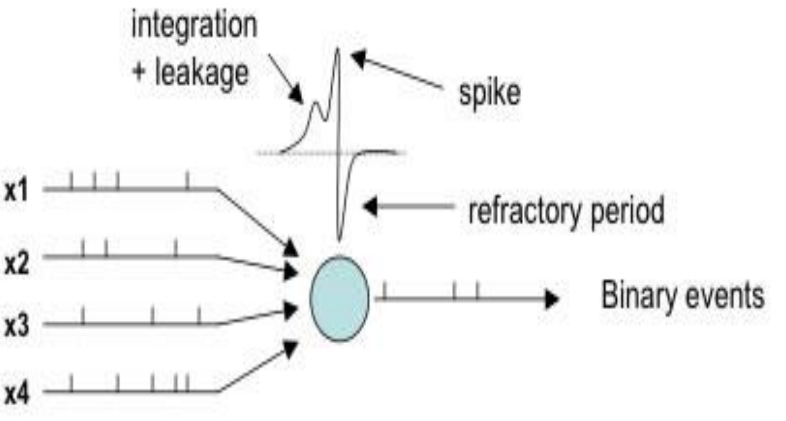
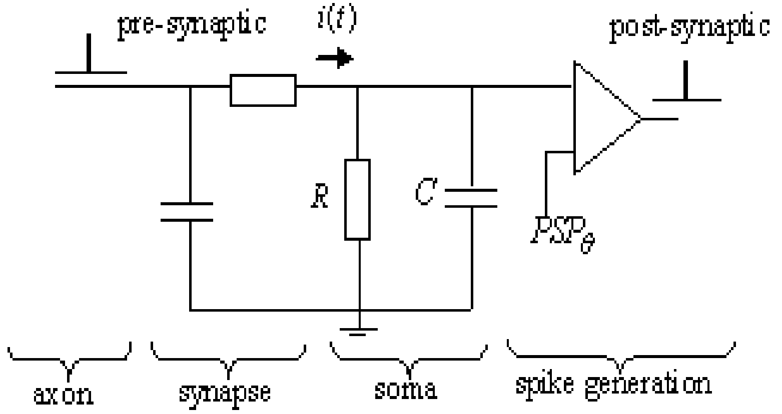
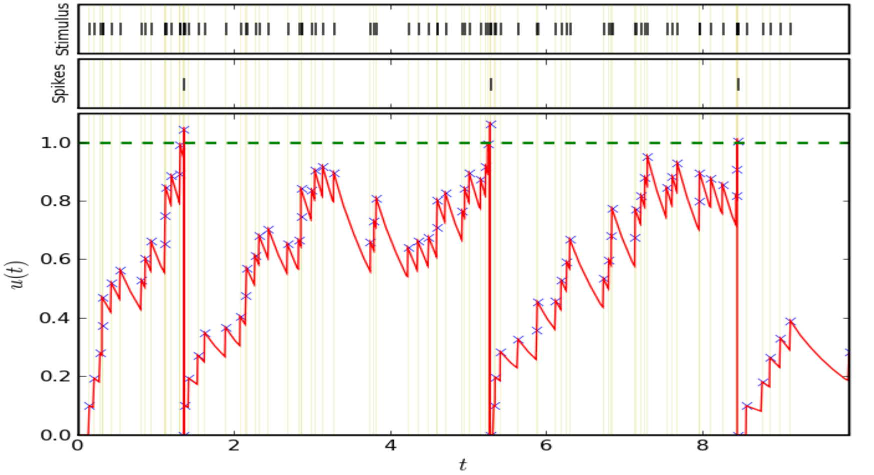
2. Spiking neuron models

Models of a spiking neurons and SNN

- Hodgkin- Huxley
- Spike response model
- Integrate-and-fire ---------------->
- Leaky integrator
- Izhikevich model
- Probabilistic and neurogenetic models





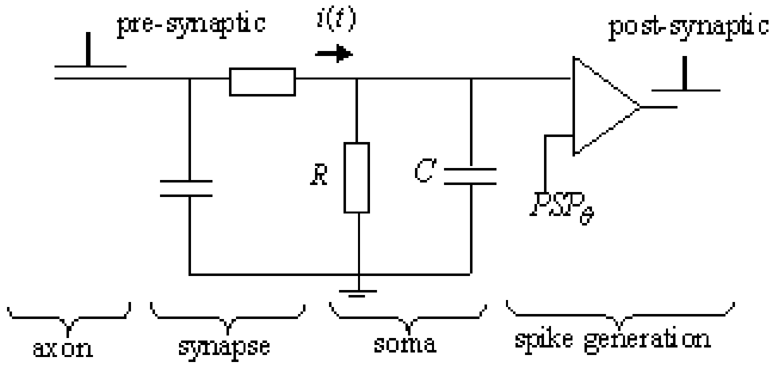


… Models of Spiking Neurons

- Spiking neurons represent the 3rd generation of neural models, incorporating the concepts of *space* and *time* trough neural connectivity and plasticity
- Neural modeling can be described at several levels of abstraction
- **Microscopic Level:** Modeling of ion channels, that depend on presence/absence of various chemical messenger molecules
  - Hodgkin-Huxley Model
  - Izhikevich model
  - Compartment models describe small segments of a neuron separately by a set of ionic equations
- **Macroscopic Level:** A neuron is a homogenous unit, receiving and emitting spikes according to defined internal dynamics
  - Integrate-and-Fire models
  - Probabilistic models

Leaky Integrate-and-Fire Neuronal Model

- Model consists of capacitor *C* in parallel with resistor *R*, driven by a current I(t) = $I_R + I_{cap}$

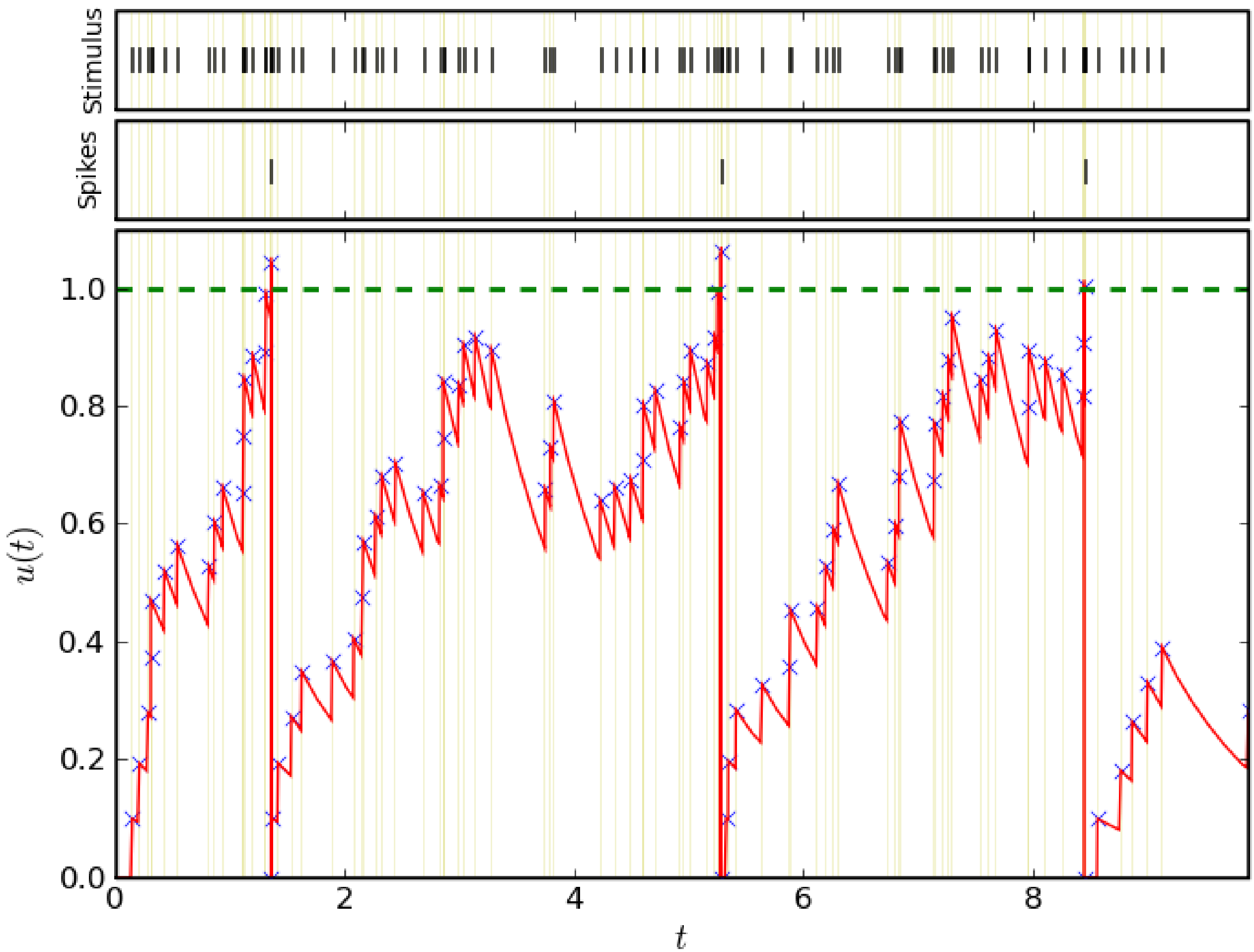


Standard form of the model:

$$\tau_m \frac{du}{dt} = -u(t) + RI(t)$$

- τ_m = RC is the membrane time constant
- Shape of action potentials are not explicitly modeled
- Spikes are events characterized by a firing time $t^{(f)}$: $u(t^{(f)}) = \vartheta$
- After $t^{(f)}$ the potential is reset to a resting potential u_r
- In a more general form the LIF model can also include a refractory period, in which the dynamics are interrupted for an absolute time Δ^{abs}

Dynamics of the LIF neuron



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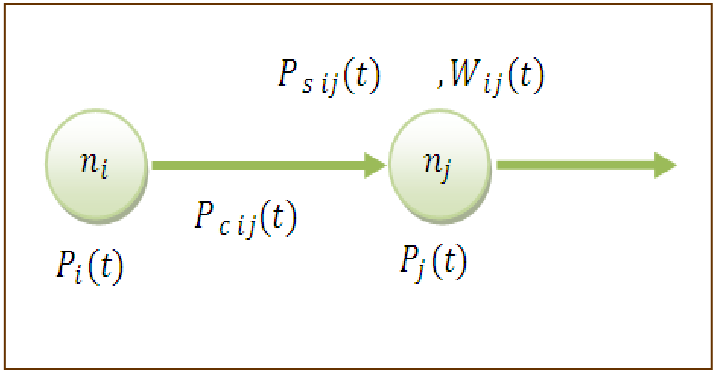
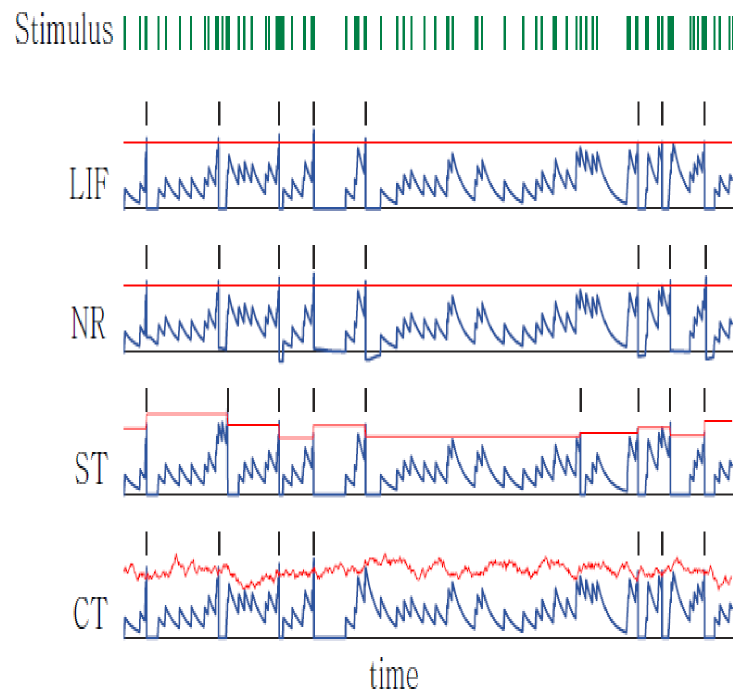
A probabilistic spiking neuron model

(Kasabov, Neural Networks, Jan. 2010)





The information is represented as connection weights and probabilistic parameters.

The PSPi(t) is calculated using a formula:

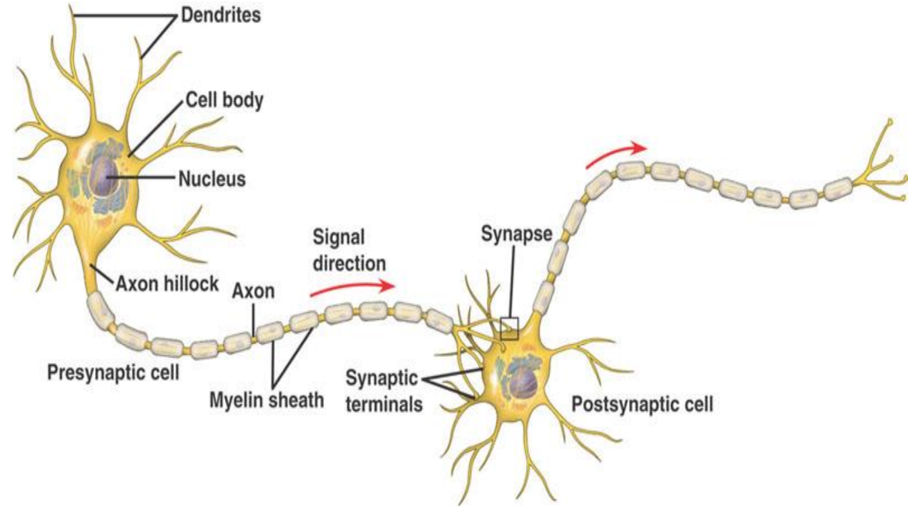
$$PSP_i(t) = p_i(t) \sum_{p=t_0,..,t} \sum_{j=1,..,m} e_j \, g(p_{cj,i}(t-p)) \, f(p_{sj,i}(t-p)) \, w_{j,i}(t) - \eta(t-t_0)$$

As a special case, when all probability parameters are “1”, the model is reduced to LIF model.

Methods for unsupervised learning in SNN

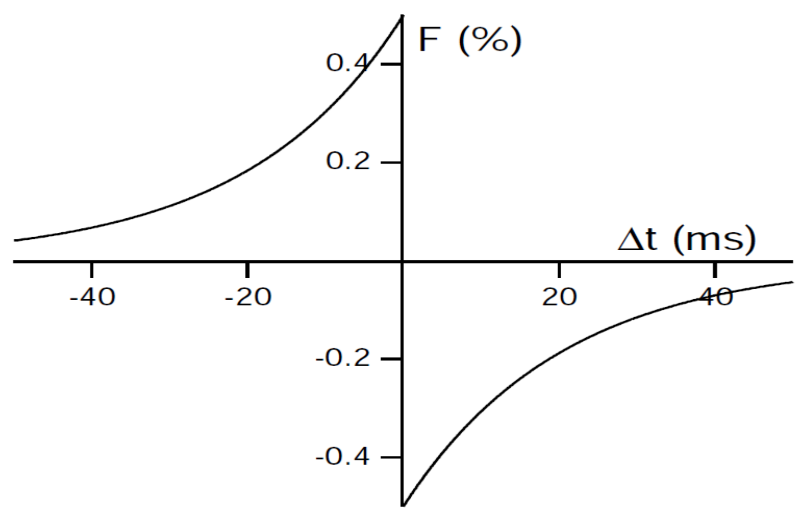
Spike-Time Dependent Plasticity (STDP) (Ch.4.3.2)
(Abbott and Nelson, 2000).

- Hebbian form of plasticity in the form of long-term potentiation (LTP) and depression (LTD)
- Effect of synapses are strengthened or weakened based on the timing of pre-synaptic spikes and post-synaptic action potential.
- Through STDP connected neurons learn consecutive temporal associations from data.
- Variations of the STDP



Pre-synaptic activity that precedes post-synaptic firing can induce LTP, reversing this temporal order causes LTD:

$\Delta t = tpre - tpost$



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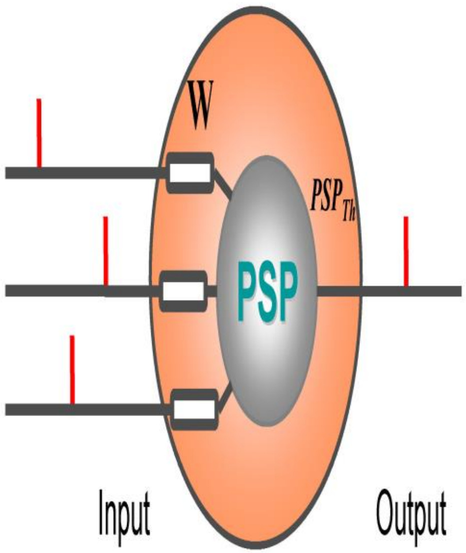
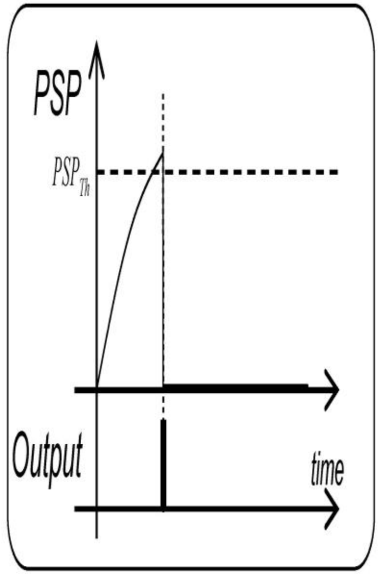
Methods for supervised learning in SNN

Rank order (RO) learning rule (Thorpe et al, 1998) (Ch.4.3.4)





$$\Delta w_{ji} = m^{\mathrm{order}(j)}$$

$$u_i(t) = \begin{cases} 0 & \text{if fired} \\ \sum_{j|f(j)<t} w_{ji} m_i^{\mathrm{order}(j)} & \text{else} \end{cases}$$

PSP max (T) = SUM [($m^{\text{order (j(t)}}$) $w_{j,i}$(t)], for j=1,2.., k; t=1,2,...,T;

PSP_{Th}=C. PSPmax (T)

- Earlier coming spikes are more important (carry more information)
- Early spiking can be achieved, depending on the parameter C.

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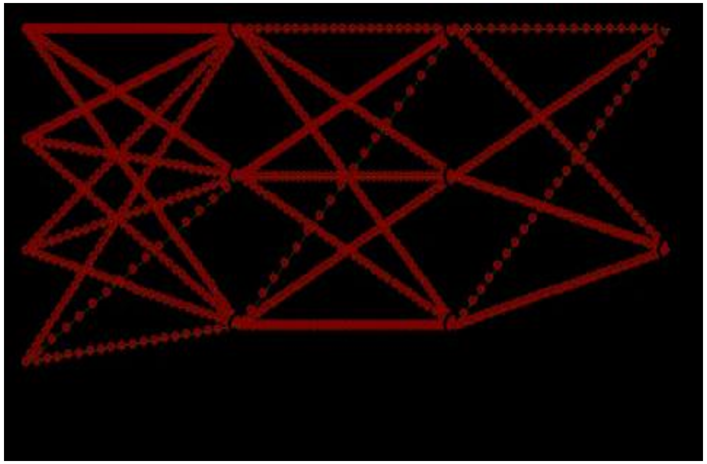
Spiking neural network architectures: From local neuronal learning to global knowledge representation through building connectivity

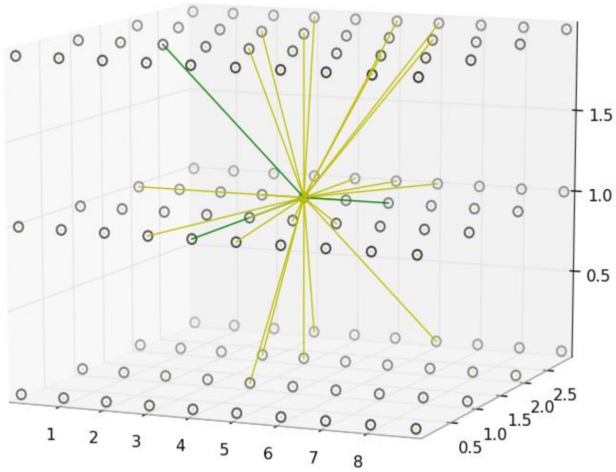
Generic SNN structures:

- Feedforward
- Recurrent
- Evolving
- Convolutional
- Reservoir
- Liquid sate-machines

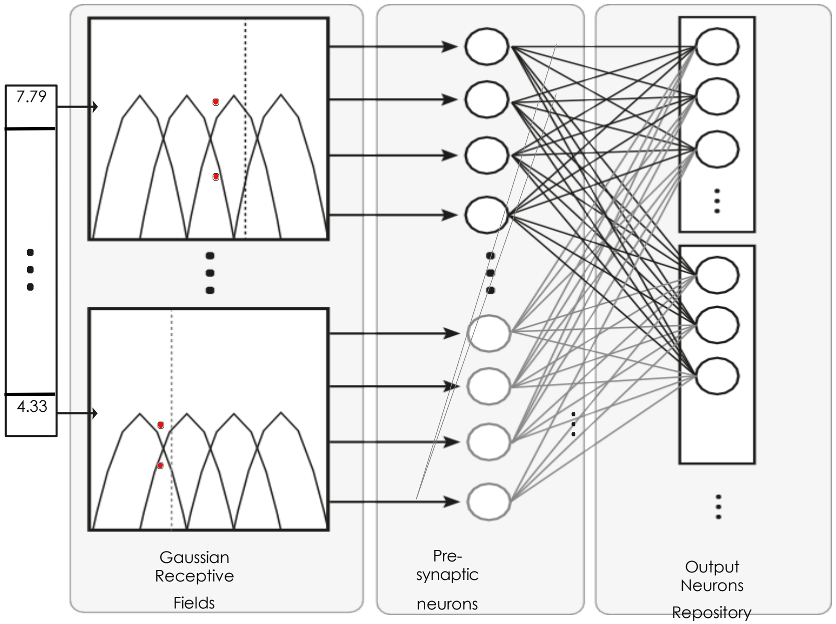


Task oriented structures:

- Classification
- Regression
- Prediction



3. Evolving Spiking Neural Networks (eSNN)



Kasabov, Evolving connectionist systems, Springer, 2007

Kasabov, N. Evolving connectionist systems for adaptive learning and knowledge discovery: Trends and Directions, Knowledge Based Systems, 2015, (2015), http://dx.doi.org/10.1016/j.knosys.2014.12.032.

Kasabov, N., Dhoble, K., Nuntalid, N., & Indiveri, G. (2013). Dynamic evolving spiking neural networks for on-line spatio- and spectro-temporal pattern recognition. Neural Networks, 41, 188-201 (236 citations).

J. L. Lobo, J. Del Ser, A. Bifet, N. Kasabov, Spiking Neural Networks and online learning: An overview and perspectives, Neural Networks, 121 (2020), 88-110, https://doi.org/10.1016/j.neunet.2019.09.004

J. L. Lobo, I.Laña, J. Del Ser, M.N.Bilbao, N.Kasabov Evolving Spiking Neural Networks for online learning over drifting data streams, Neural Networks, 108, 1-19 (2018).

Jesus L. Lobo, Izaskun Oregi, Albert Bifet, Javier Del Sera, Exploiting the Stimuli Encoding Scheme of Evolving Spiking Neural Networks for Stream Learning, Neural Networks, 2019

Evolving SNN (eSNN)

- ECOS: Evolving clusters as evolving neurons and functions (Kasabov,1998)
- eSNN: ~ for spiking neurons (Wysoski, Benuskova, Kasabov, 2006-2010);
- Uses the first spike principle (Thorpe et al.) for fast on-line training
- For each input vector

a) Create (evolve) a new output spiking neuron and its connections

b) Propagate the input vector into the network and train the newly created neuron

$$u_i(t) = \begin{cases} 0 & \text{if fired} \\ \sum\limits_{j|f(j)<t} w_{ji} m_i^{\mathrm{order}(j)} & \text{else} \end{cases}$$

$$\Delta w_{ji} = m^{\mathrm{order}(j)}$$

Weights change based on the spike time arrival

c) : IF similarity between a new and old neurons > Threshold THEN merge neurons

$$W \Leftarrow \frac{W_{new} + NW}{1+N}$$

where N is the number of samples previously used to update the respective neuron.

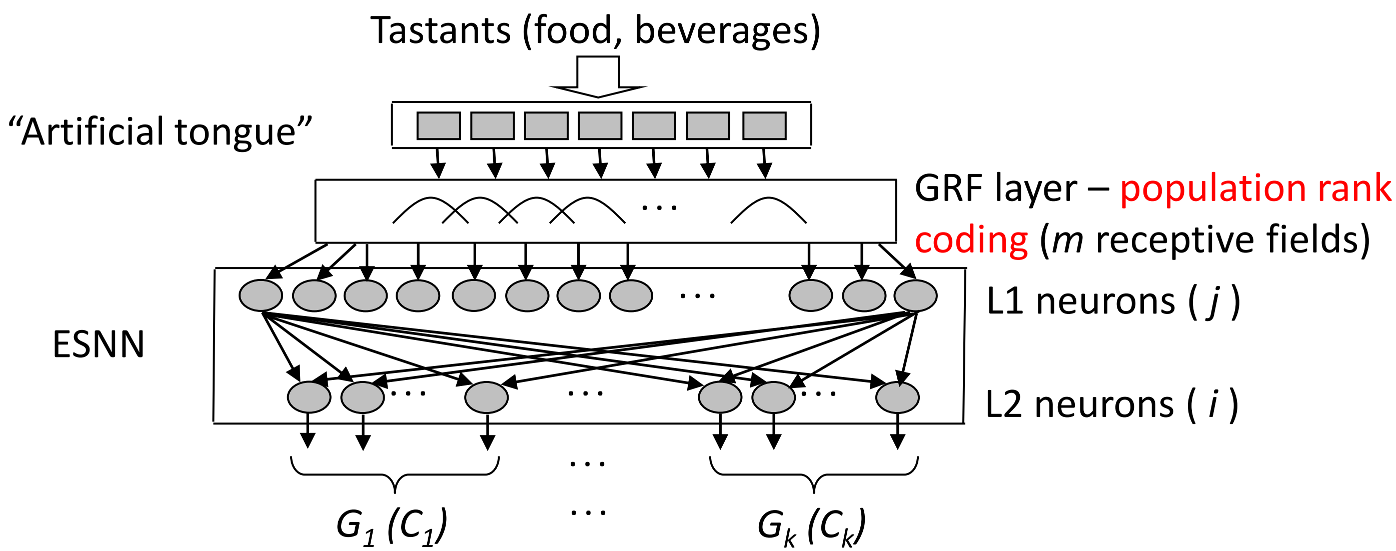
d) Update the corresponding threshold ϑ:

$$\vartheta \Leftarrow \frac{\vartheta_{new} + N\vartheta}{1+N}$$

- Schliebs, S. and N.Kasabov, Evolving spiking neural networks: A Survey, *Evolving Systems*, Springer, 2013.

eSNN for taste recognition

(S.Soltic, S.Wysoski and N.Kasabov, Evolving spiking neural networks for taste recognition, Proc.WCCI 2008, Hong Kong, IEEE Press)



- The L2 layer evolves during the learning stage (S_Θ).
- Each class C_i is represented with an ensemble of L2 neurons
- Each ensemble (G_i) is trained to represent one class.
- The latency of L2 neurons' firing is decided by the order of incoming spikes.

Dynamic Evolving SNN (deSNN)

(*Kasabov, N., Dhoble, K., Nuntalid, N., G. Indiveri, Dynamic Evolving Spiking Neural Networks for On-line Spatio- and Spectro-Temporal Pattern Recognition, Neural Networks, v.41, 188-201, 2013)*

Combine: (a) RO learning for weight initialisation based on the first spikes:

$$\Delta w_{ji} = m^{\mathrm{order}(j)}$$

(b) Learning further input spikes at a synapse through a drift – positive and negative.

wj,i(t) = ej(t) ▪ Drift

- A new output neuron may be added to a respective output repository for every new -input pattern.
- Two types of output neuron activation:
  - deSNNm (spiking is based on the membrane potential)
  - deSNNs (spiking is based on synaptic similarity between the newly created output neuron and the existing ones)
- Neurons may merge.

Dynamic Evolving SNN (deSNN) for classification or regression

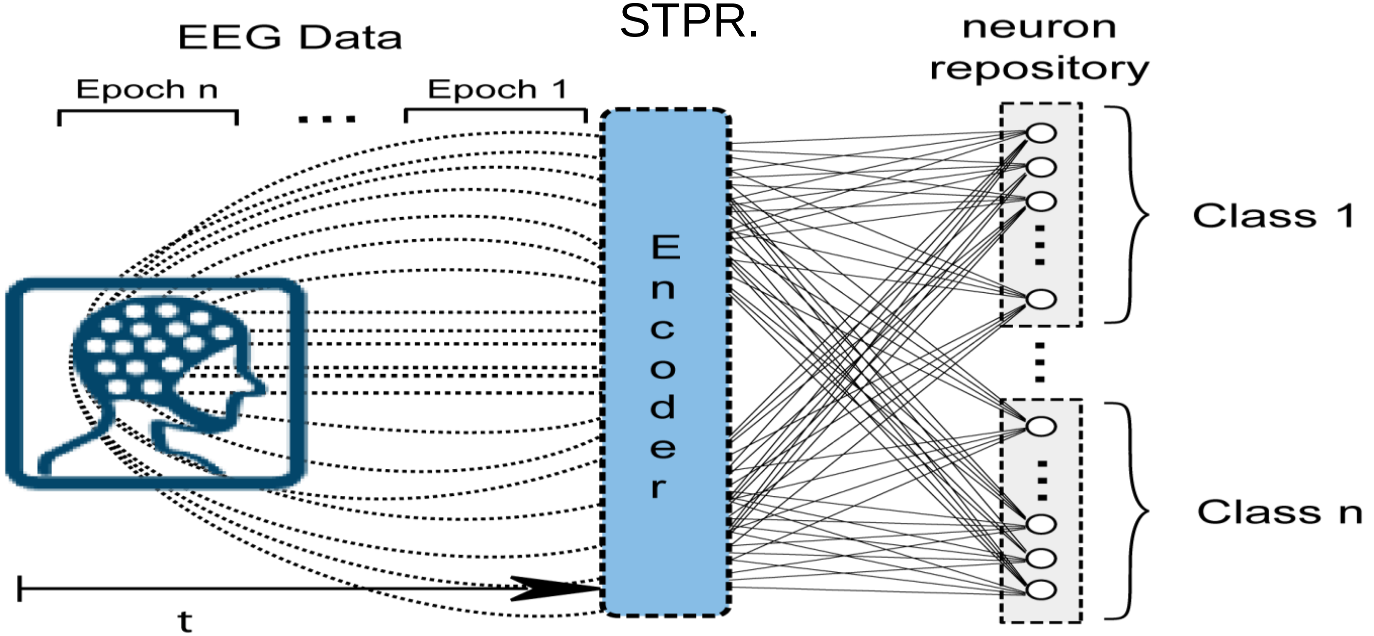
(Kasabov, Dhoble, Nuntalid, Indivery, Neural Networks, v.52, 2014)

- Combine: (a) RO learning for weight initialisation based on the first spikes:

$$\Delta w_{ji} = m^{\mathrm{order}(j)}$$

(b) SDSP for learning further input spikes at a synapse.

- A new output neuron is added to a respective output repository for every new - input pattern learned. Neurons may merge.
- The figure below shows the deSNN architecture on a case study for EEG STPR.



Course References

1. N.Kasabov, Time-Space, Spiking Neural Networks and Brain-Inspired AI, Springer 2019 (course book).
2. N. Kasabov Foundations of Neural Networks, Fuzzy Systems, and Knowledge Engineering, MIT Press, 1996 (additional reading)
3. N.Kasabov, Evolving connectionist systems, Springer 2003 and 2007 (additional reading)
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5. NeuCube: http://www.kedri.aut.ac.nz/neucube/
6. NeuCom: https://theneucom.com
7. KEDRI R&D Systems available from: http://www.kedri.aut.ac.nz
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17. Nikola K. Kasabov, Iman AbouHassan, Vinayak G.M. Jagtap, Parag Kulkarni, Spiking neural networks for predictive and explainable modelling of multimodal streaming data on the Case Study of Financial Time Series Data and on-line news, SREP, Nature, pre-print on the Research Square, DOI: https://doi.org/10.21203/rs.3.rs-2262084/v1, licence CC BY 4.0,

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4. Questions, exercises, assignments and project work

1. How is information encoded into spikes?
2. What are spiking neuron models?
3. What are evolving SNN?