Learning Spike time codes through Morphological Learning with Low Resolution Synapses

Subhrajit Roy
Prof. Arindam Basu

OUTLINE

- Motivation for low-power machine learners
- Motivation for a new Spiking Neuron Model
- Mathematical models of neurons and capacity analysis
- Task Selection
- Learning rule
- Results

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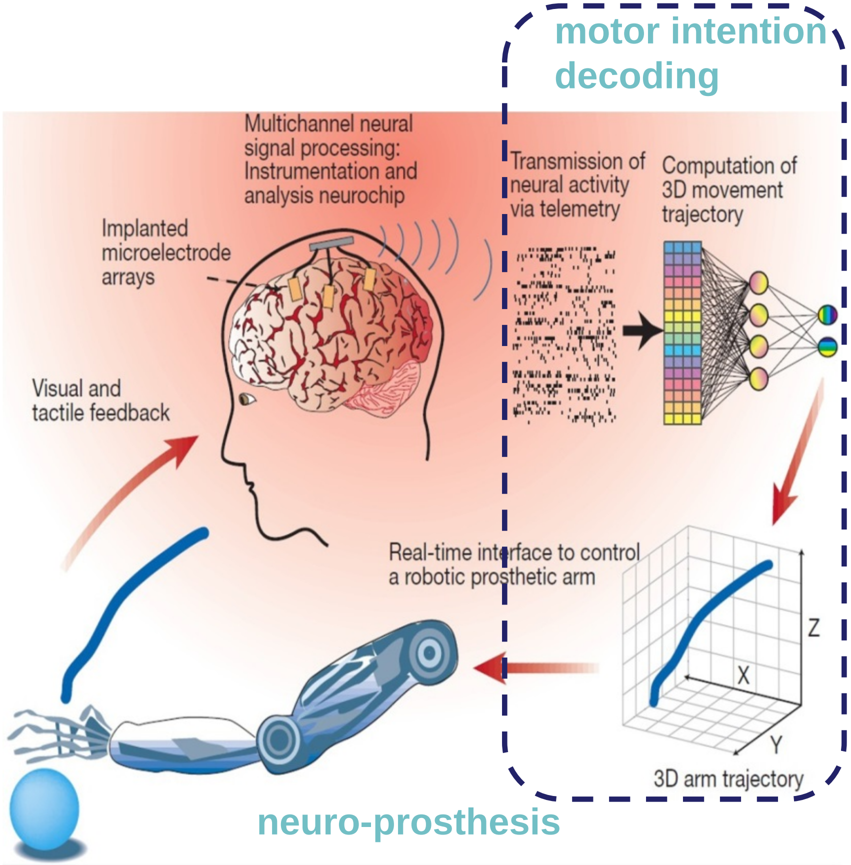
Motivation for developing low-power, machine-learners



PROBLEMS

- Data rate / channel ~ 200 Kbps
- 1000 channels → 200 Mbps
- Huge power dissipation

UNSUSTAINABLE

SOLUTIONS

- On chip neural processing unit
- Requirement for low-power hardware implementations of supervised classifiers

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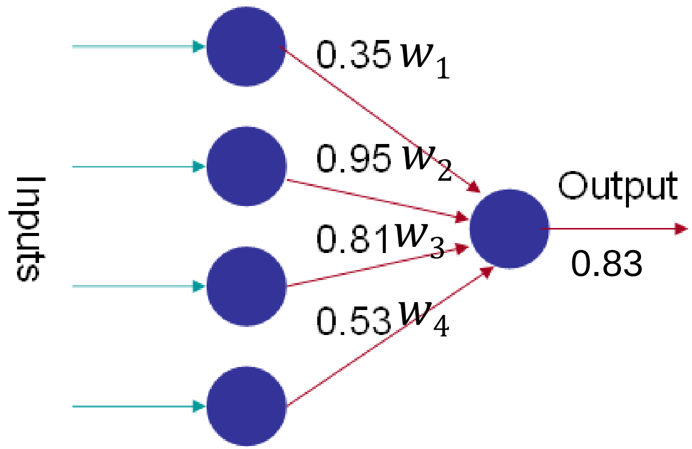
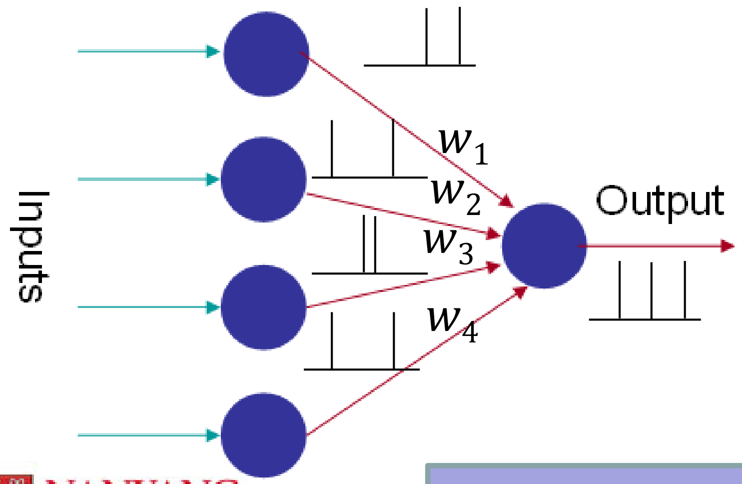
Motivation for the a new SNN



Assumes that neurons communicate through rate of spikes



Communication through exact time of spikes - **BIOREALISTIC**

LOW RESOLUTION SPIKING NEURON

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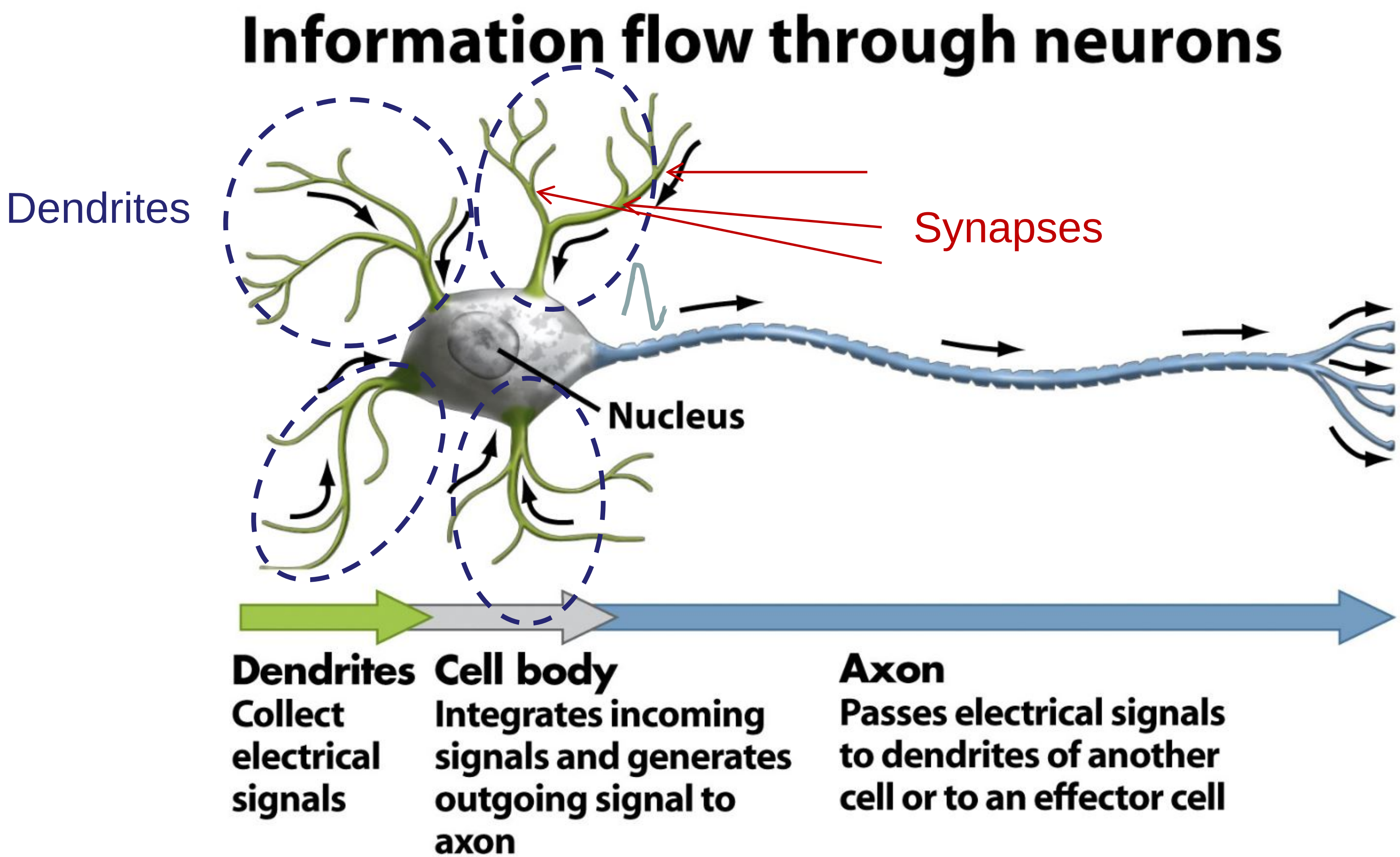
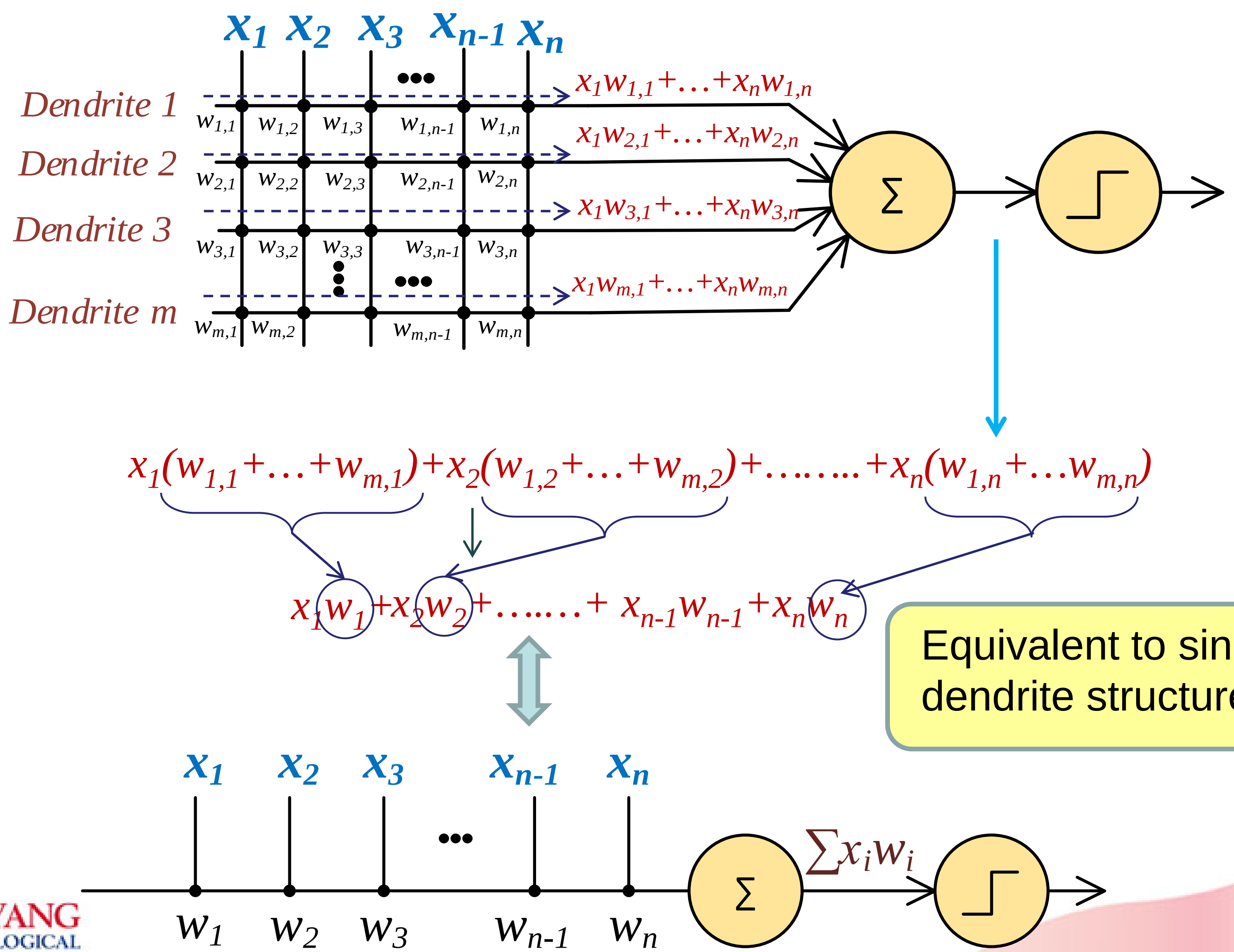
A biological neuron



Neuron Abstraction



Equivalent to single dendrite structure

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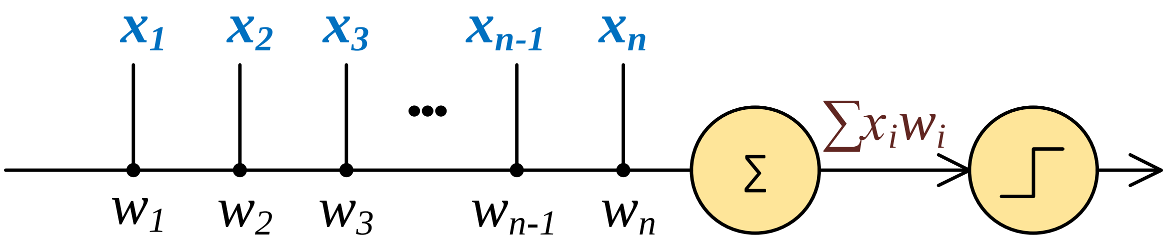
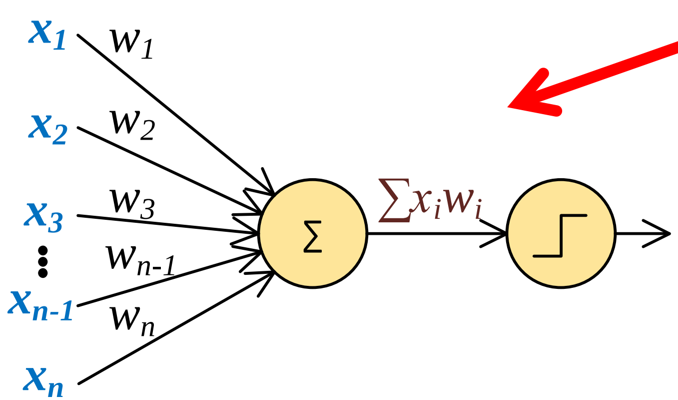
Neuron Abstraction

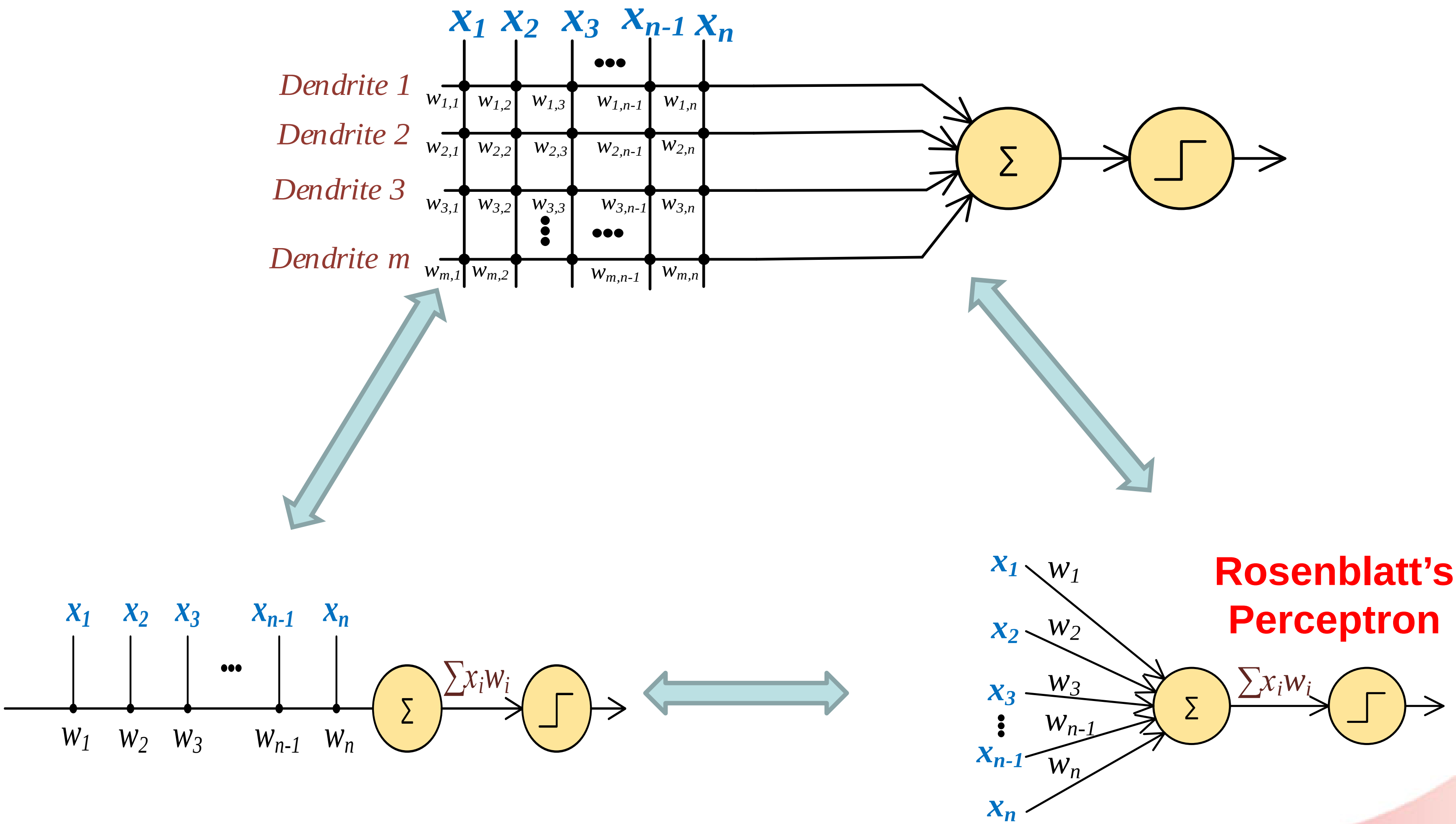




Rosenblatt's Perceptron

Model independent of dendrites – **Naive?**

Neuron Abstraction



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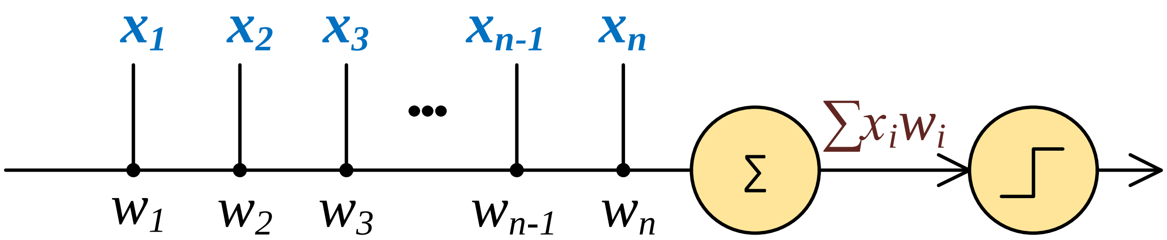
Capacity analysis



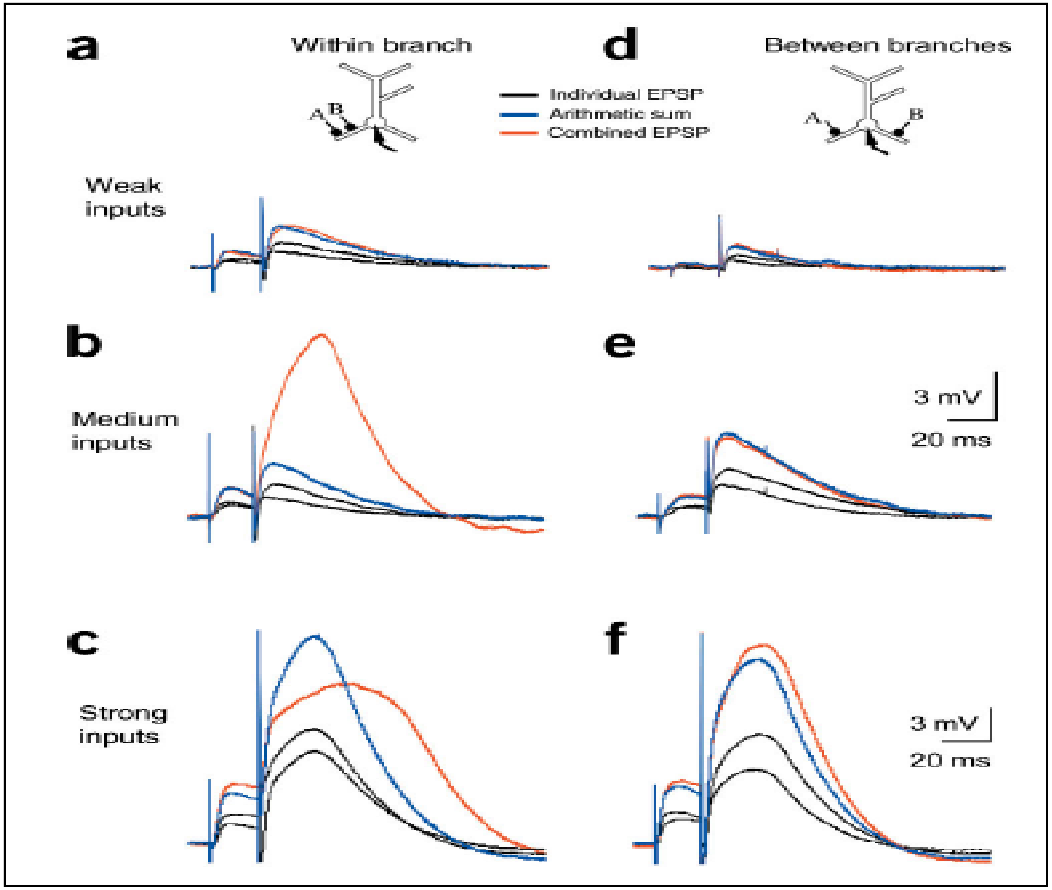
CONSTRAINTS

Constraint 1 - Weights are non-negative integers i.e. w=0/1/2/3….

Constraint 2 - Sum of the weights = *r*

$$\text{Capacity} = log_2\binom{n+r-1}{r}$$

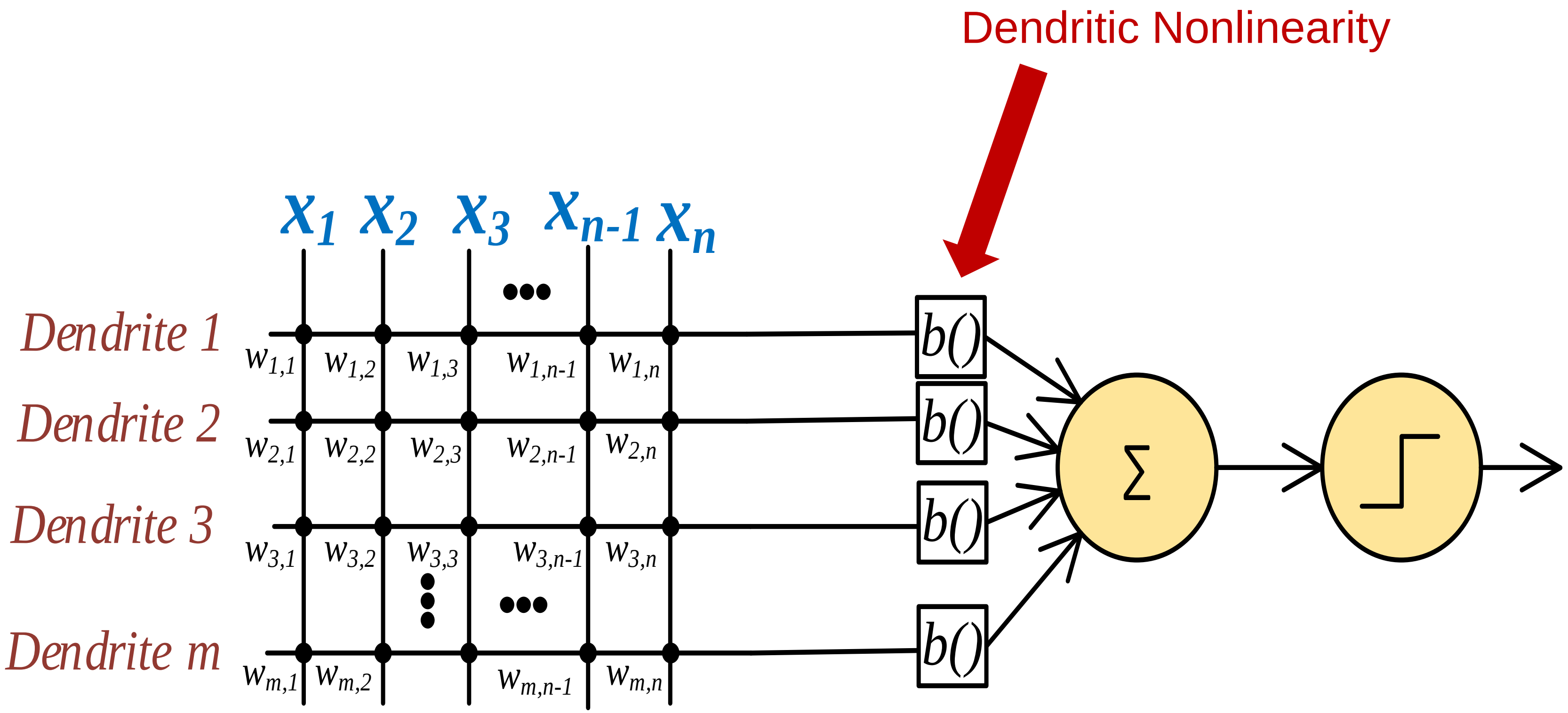
Dendritic Processing



Source: Polsky et al., 2004

Presence of saturating non-linearity in dendrites

Increasing the capacity



Enhanced Capacity ?

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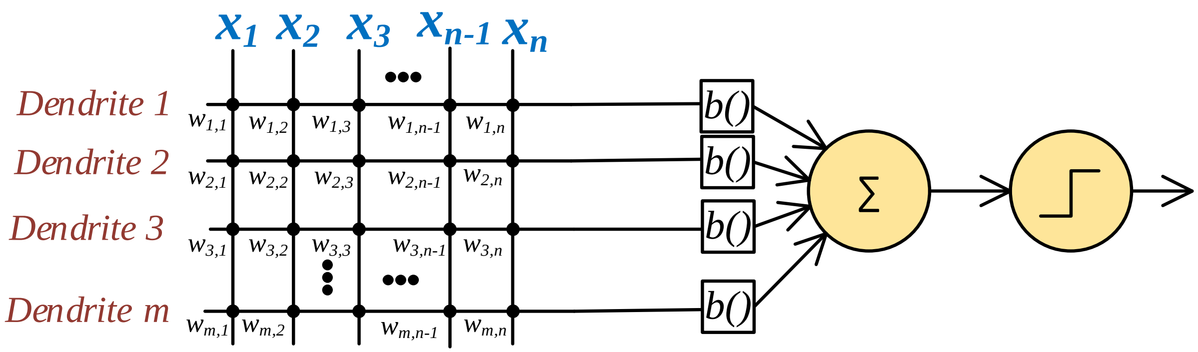
Increasing the capacity



Constraint 1 - Weights are non-negative integers i.e. w=0/1/2/3….

Constraint 2 - Sum of the weights on a dendrite = *k*

How many ways can we create a dendrite? $\binom{n+k-1}{k}$

Select "*m*" of these : $\binom{\binom{n+k-1}{k}+m-1}{m}$

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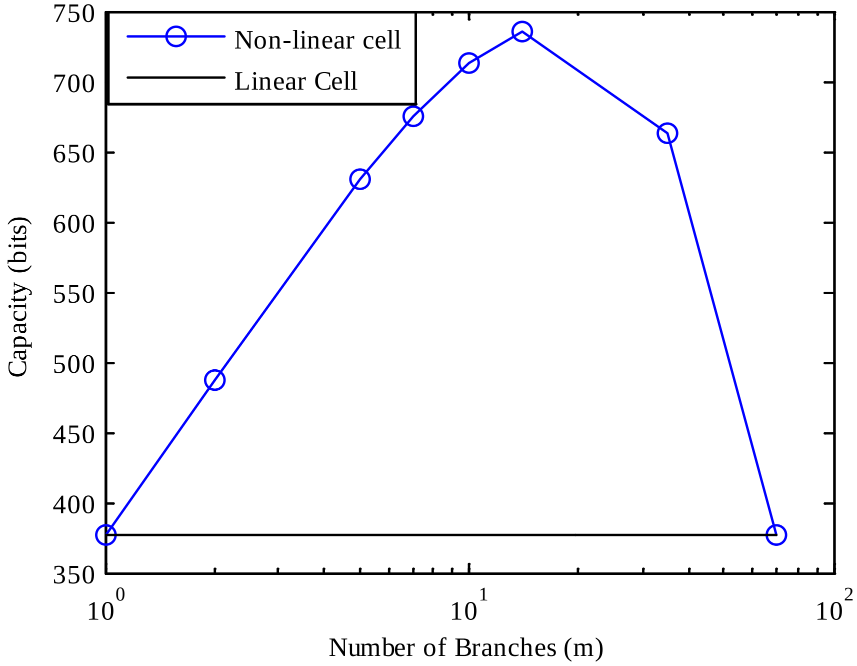
Capacity comparison

Without dendritic non-linearity : $\boldsymbol{log_2\binom{n+r-1}{r}}$

With dendritic non-linearity : $\boldsymbol{log_2\left(\binom{n+k-1}{k}+m-1 \atop m\right)}$



$r = k * m$

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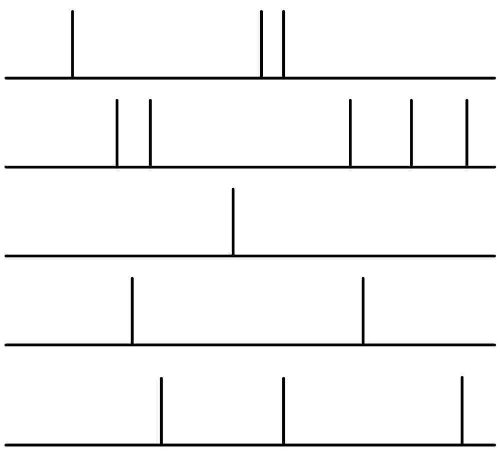
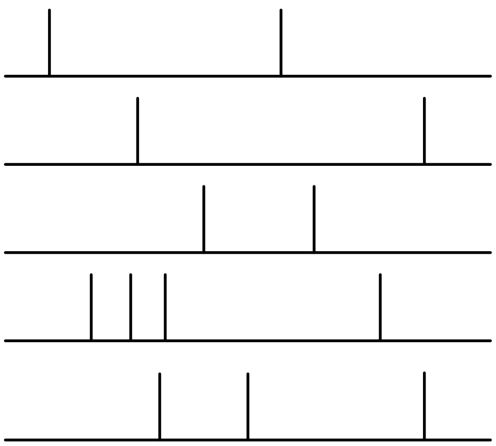
Task Selection



$$\begin{bmatrix}3\\5\\1\\2\\3\end{bmatrix}$$

Positive pattern

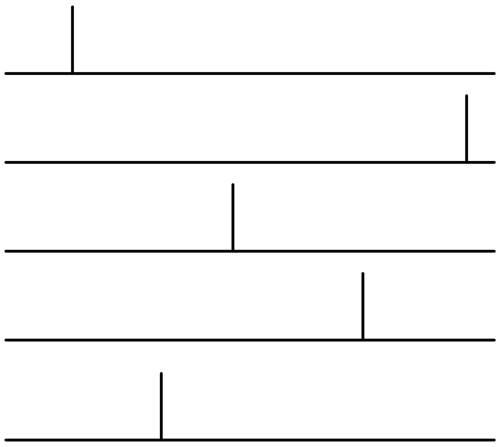


$$\begin{bmatrix}2\\2\\2\\4\\3\end{bmatrix}$$

Negative pattern

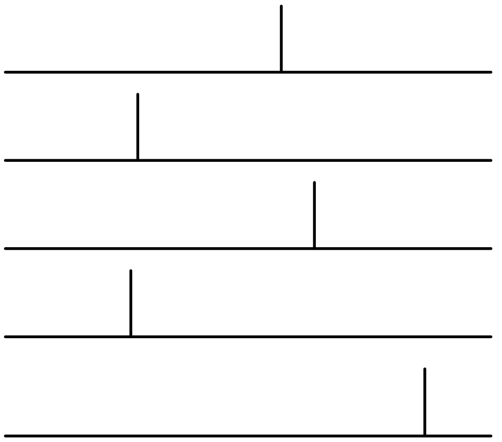
Can apply Perceptron Learning Algorithm, Back propagation, Extreme Learning Machine, etc. for classification

Task Selection



$$\begin{bmatrix}1\\1\\1\\1\\1\end{bmatrix}$$

Positive pattern

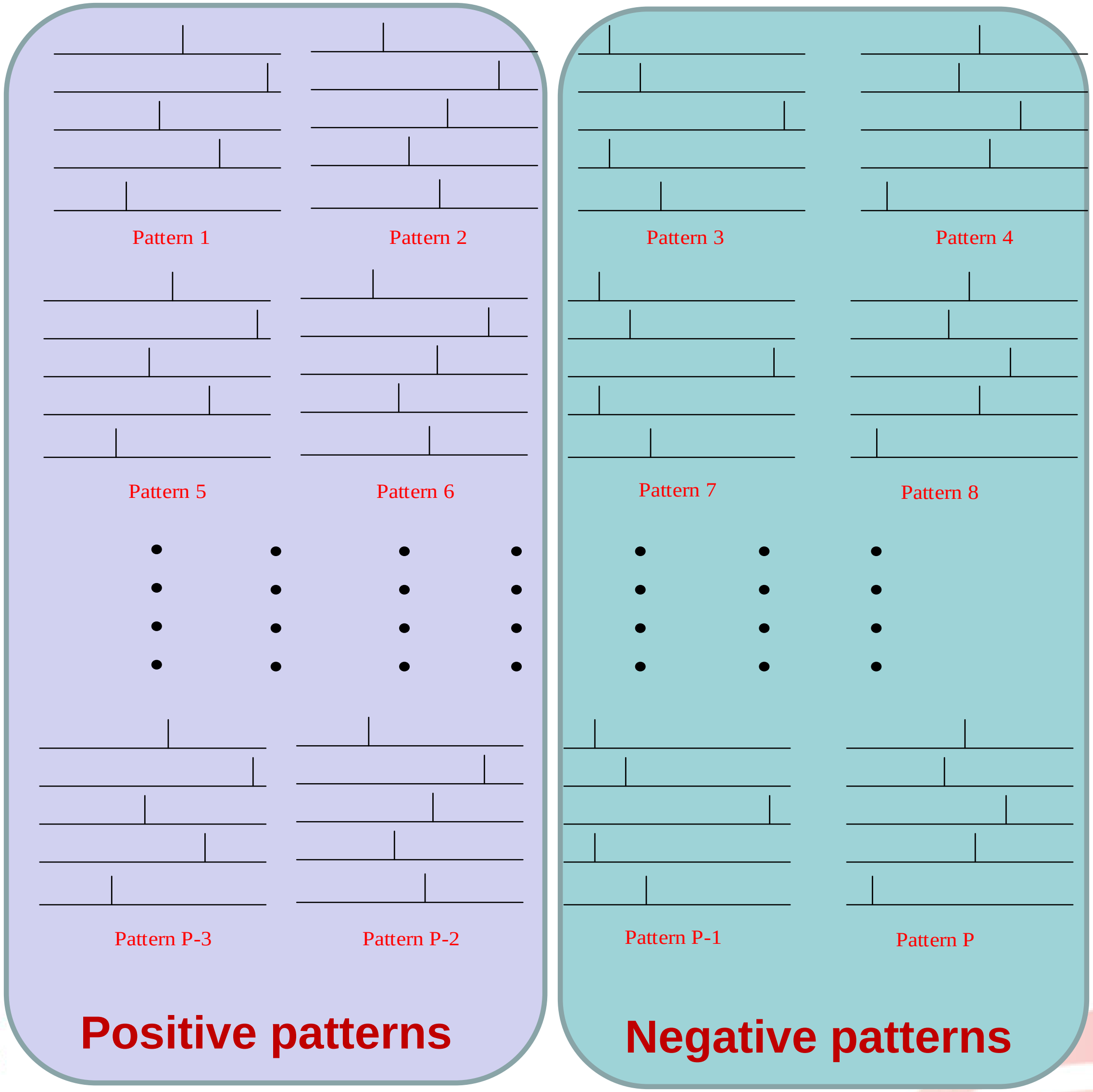


$$\begin{bmatrix}1\\1\\1\\1\\1\end{bmatrix}$$

Negative pattern

Rate based algorithms will **FAIL!!**

Task Selection



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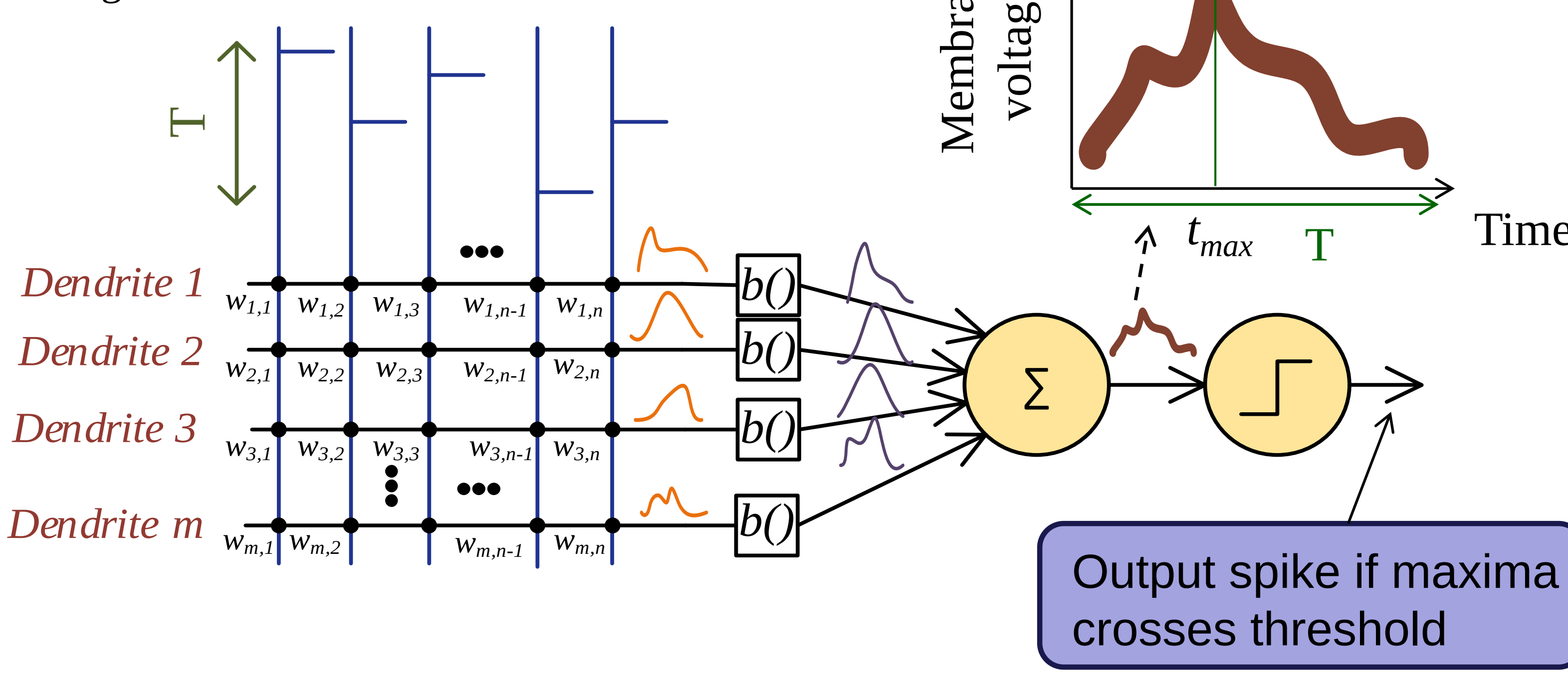
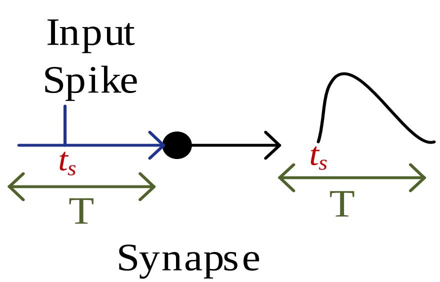
Learning rule

1. Weights : Non-negative integers
2. Sum of weights on each dendrite = k





1. $V_{max} > V_{thr}$ for Positive patterns
2. $V_{max} < V_{thr}$ for Negative patterns

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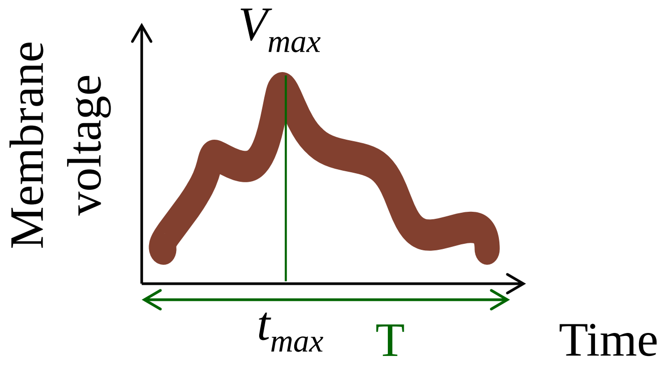
Learning rule



For each synapse

$$\underbrace{(x_{ij})_{tmax}}_{\text{Contribution of synapse to } V_{max}} * \underbrace{(x_j)_{tmax}}_{\text{Contribution of dendrite to } V_{max}}$$

Contribution of synapse to V_{max}

Contribution of dendrite to V_{max}

For j^{th} synapse of i^{th} dendrite:

$(x_{ij})_{tmax}$ = Output of the synapse at t_{max}

$(x_j)_{tmax}$ = Input to dendritic nonlinearity of i^{th} dendrite at t_{max}

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Learning rule

1. Define fitness parameter c_{ij} for all synapses and set to 0.

2. Updating of fitness parameter – Only when error

Actual pattern	Predicted pattern	Update
Positive	Positive	No
Negative	Negative	No
Positive	Negative	$+(x_{ij})_{tmax} * (x_j)_{tmax}$
Negative	Positive	$-(x_{ij})_{tmax} * (x_j)_{tmax}$

3. After an epoch replace synapse with worst fitness

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Automatic Threshold variation

Too high V_{thr} → Threshold may **never** get crossed

Too low V_{thr} → Threshold may **always** get crossed

DEPENDS ON TOTAL SYNAPTIC WEIGHT & INPUT ISI

NOT FEASIBLE

Automatic Threshold variation

$\#False\ negatives$ = Number of positive patterns incorrectly classified as negative patterns

$\#False\ positives$ = Number of negative patterns incorrectly identified as positive patterns

$$V_{thr} \coloneqq V_{thr} - \eta(\#False\ negatives - \#False\ positives)$$

η : Learning rate

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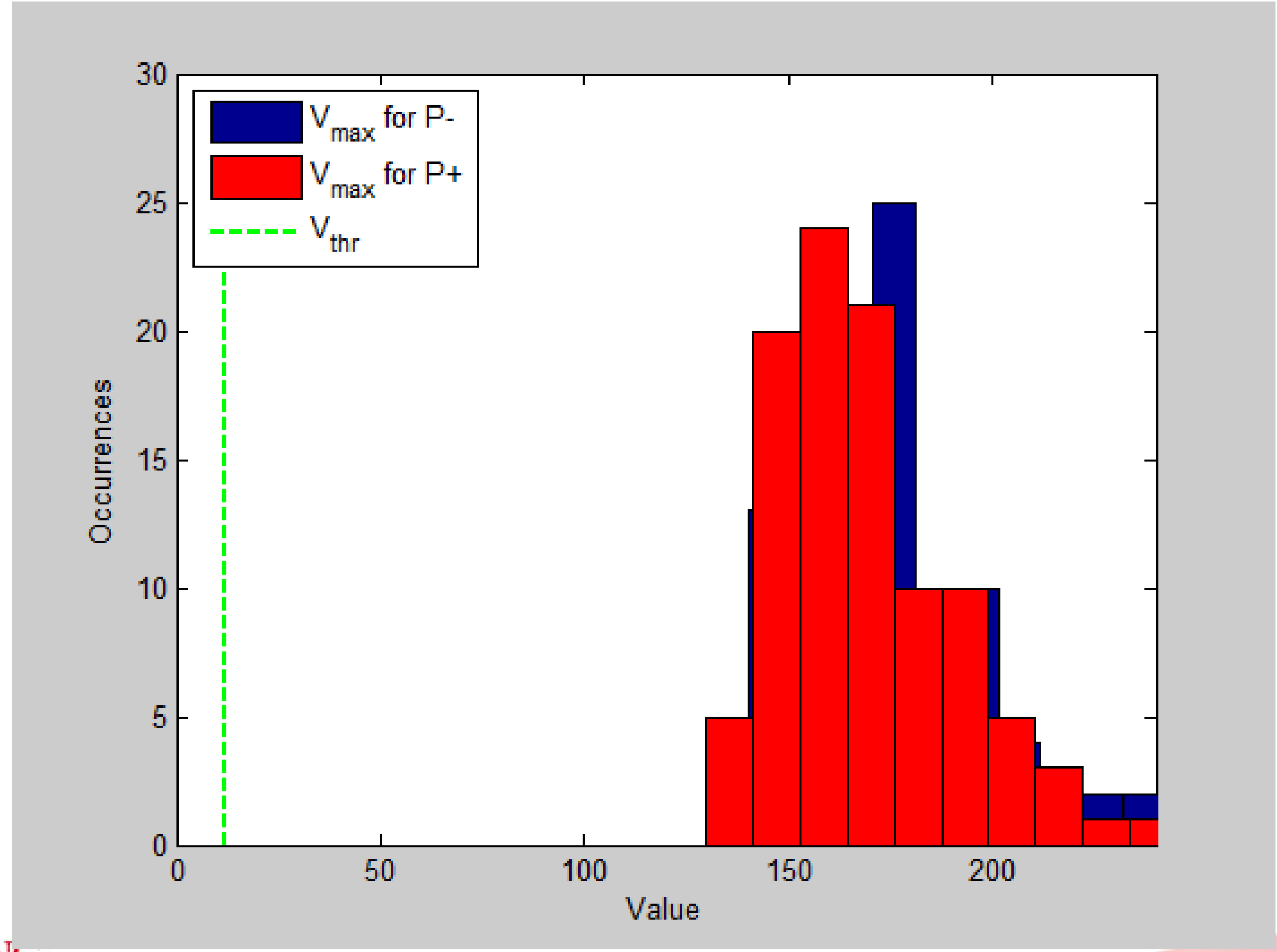
An example run



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Other results

Number of patterns	Proposed method	ReSuMe [1]
100	100%	100%
500	95.6%	89.58%
1000	86.3%	82.65%

*Averaged over 10 trials

1. F. Ponulak and A. J. Kasinski, “Supervised Learning in Spiking Neural Networks with ReSuMe: Sequence Learning, Classification, and Spike Shifting.’, Neural Computation, vol. 22, no. 2, pp. 467-510, 2010.

Conclusion

- Proposed a spiking neuron with nonlinear dendrites and low-resolution synapses
- Proposed a morphology optimizing learning rule
- Hardware friendly architecture and learning rule
- Superior performance in classification task

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Ongoing / Future Work

- Algorithmic developments:
  - Development of unsupervised morphological adaptation
  - Introduction of better generalization capabilities
  - Multi-class expansion of the proposed method
  - Combination of random weight stage and the proposed architecture.

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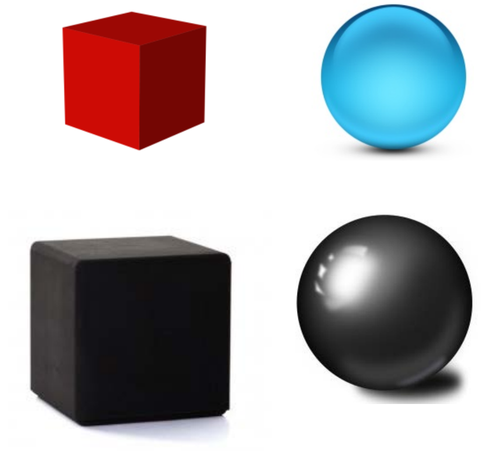
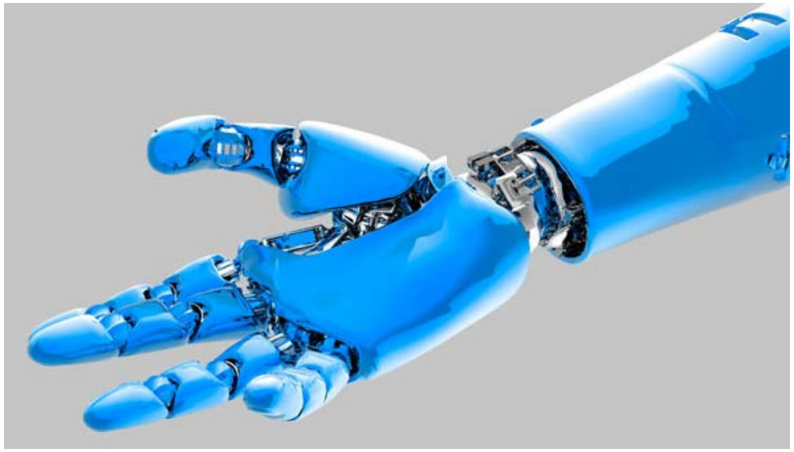
Ongoing / Future Work

Real life applications: Computer Vision, Speech Recognition, Brain Machine Interfaces, etc

- Isolated Word Recognition: Classifying the isolated spoken digits of TI46 speech corpus database
- Tactile Sensing: Classifying objects of different shape and size sensed by a prosthetic arm
- Asynchronous decoding of finger movements of monkeys.





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THANK YOU

QUESTIONS?