**The Neurotron, an Atomic Neural Computing Unit**

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## *Abstract*

*We introduce the* Neurotron*, an atomic neural computing unit to build hierarchical temporal sequence memory as a basis for machine intelligence. Sequence memory is capable of learning sequences, and to predict the next item, when only part of a sequence is presented.*

*The Neurotron is a quasi-digital computing unit, which means that the most of signal processing is purely digital. Only the learning process is based on analog* permanences*, which represent the development state of the modeled synapses. The quasi-digital approach in combination with sparse representations of patterns lead to highly efficient algorithms with fast execution time and low memory need.*

*As the concept of the Neurotron has been strongly influenced by Numenta’s architecture of Hierarchical Temporal Memory (HTM), the underlying HTM key concepts have been incorporated into the Neurotron.*

*Finally, we benchmarked the performance of a Neurotron based sequence memory layer with the performance of transformer based neural network alternatives, when both systems predict the continuation of text sequences from "Tiny Shakes­peare".*

# Introduction

The neuron model used in most artificial neural networks is known as the perceptron [1], proposed by Frank Rosenblatt in 1957. It has few synapses and no modelling of dendrites (figure 1/A). The perceptron attempts to model the proximal area of the neuron and represents de-facto a mapping of input information arriving at the proximal synapses to the neuron’s *output.* There is evidence that the proximal synapses, those closest to the soma (cell body), have a large effect on the likelihood of the cell generating an *action potential,* which is bursting along the neuron’s axon to synapses of other neurons of the network. Notably the perceptron model is a pure mapping model with absence of any memory.

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Automatisch generierte Beschreibung

Figure 1: comparison of neuron models

In contrast, an excitation of a distal (non-proximal) synapse has little effect at the soma (cell body). For this reason, it was hard to understand how the thousands of distal synapses can play a role for the cell’s responses [2].

After development of advanced research methods [3], however, re­searchers could unlock the secret of internal dendritic NMDA (N-methyl-D-aspartate) spikes, which are caused by synaptic excitation in spatial and temporal neighborhood and lead to a depolarization of the soma. Such depolarization subsequently enables the neuron to fire earlier than neighbor neurons with comparable proximal excitation, which gives such neuron the benefit to inhibit “competing” neurons.

Since NMDA spikes have a much longer duration than the action potential spikes of soma and axon, this mechanism acts like memory based on a depolarized soma state. In addition to the (perceptron like) mapping functionality of the neuron, the availability of memory in neural models offers capabilities like *prediction* and *bursting*, introduced in [4].

Such and other findings make it evident that biological neu­rons are very com­plex systems with complex sub-functionalities in the soma, axon, trunk and dendritic segments. A comprehensive characterization would have to involve spatial and temporal behavior of various ion concentrations as well as electrical quantities.

Such detailed models without further abstraction make it, however, hard to understand behavior in higher levels, like explanations how the brain might model sequence memory. Thus, understanding of any given neuron requires the right level of abstraction [2].

Inspired by such findings regarding distal dendrite func­tion­ality a group around Jeff Hawkins developed the HTM approach [4,5], which we consider a powerful conceptual abstraction of an enhanced neural layer functionality serving as an abstract building block for truly intelligent algorithms, which can run efficiently on computers. It incorporates the following concepts:

* The fundamental paradigm of sparse pattern repre­sentation
* *Quasi-digital processing*: most of the signals have binary values (0 or 1), except the use of permanence values and synaptic thresholds (analog values in the interval [0,1]).
* *Binary synaptic weights*: let a synapse behave as unconnected (weight 0) or connected (weight 1). A weight is controlled by the analog *perma­nence state* of the synapse (range [0,1]), causing the weight to take value 1 if the *permanence* exceeds a synaptic threshold, and 0 otherwise.
* *Minicolumn*: a kind of collaborative group of neurons with a mechanism for “*voluntary neuron*” selection, which causes a neuron to take over representation co-ownership for unexpected patterns.
* *Predictive neuron states:* enable those neurons of a minicolumn to fire, which are expected to do so on base of the processed input pattern, while other neurons of the minicolumn stay quiet.
* *Burst:* a state being activated during presentation of unexpected patterns. Bursting causes all neurons of a minicolumn vote for pattern representation co-owner­ship.
* *Local learning:* the learning mechanism is Hebbian like. In contrast to Hebbian learning where weight adjustment is correlated with the product of pre-synaptic input and neuron output, HTM neurons are only empowered for learning, if they were able to make a correct prediction.

There are some notable remarks: The quasi-digital nature of the algorithms in combination with sparse pattern representations allows very fast and efficient processing on digital computing hardware. The capability of *bursting* in case of a new pattern presentation increases the probability of finding voluntary neurons to take over co-representation ownership for unexpected patterns, which contributes to learning efficiency.

The HTM learning rule where synapses are only credited for learning, when a neuron made a correct prediction, provides strong learning focus on neurons with actual involved in the prediction process. It helps to avoid ruinous overwriting of well-established memory contents, which is a key challenge in the formulation of suitable synaptic plasticity hypothesis [6].

The HTM algorithm presented in [4] is formulated for a neuron-layer comprising Minicolumns as an array of “HTM-neurons”. However, the description leaves it fuzzy how the algorithm might be implemented on the granularity of neurons. Such approach is reasonable, when the intention is to provide building blocks for higher level cognitive functionality. When we designed the *Neurotron*, however, we wondered how the HTM algorithm could be broken down to the granularity of neurons.

While in [4] the “molecular” computing unit is the *minicolumn*, we are going to introduce an “atomic” computing unit, the *Neurotron*, which can be used to build *Minicolumns* on the next higher level, but also to build other next level building blocks like a *Spatial Pooler* (another functional unit consulted in the HTM approach).

# Pre-Requisites

Most artificial neural networks (ANN) are based on Rosenblatt’s Perceptron [1], which works with analog inputs, outputs and weights. The advantage of ANNs based on analog signals is that global learning can be employed, using gradient based backpropagation algorithms.

The authors of [4], however, have demonstrated, that local learning mechanisms, as they occur in biological neurons [6], lead to very efficient learning algorithms, and allow a further abstraction of neuronal functionality by using quasi-digital signal representation. Such approach is compliant with the claim to describe the salient input/output properties of a neuron using a minimal des­crip­tion [2]. Thus, we start our approach with an 80 year old neuron model proposed by McCulloch and Pitts in 1943, which describes the input output properties of a neuron on a pure digital (binary) basis.

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Figure 2: augmented neuron model based on the proposal of McCulloch and Pitts in 1943

Figure 2a shows a McCulloch-Pitts neuron model with scalar binary inputs *v1, v2, …, vl*, and a scalar output *s*. Notably the input/output functionality is a pure mapping without any presence of state (memory). As will be shown, it is useful to split the input/output mapping according to (1a) into a composition of two partial functions *( ° )*.

*s = ( ° )(v1, v2, …, vl) (1a)*

*e = (v1, v2, …, vl) = Σi vi (1b)*

*s = (e) = (e ≥ Θ) (1c)*

In the first part the inputs *v1, v2, …, vl ∈ B, B = {0,1}* aresummed up to the *empowerment* signal *e*, an internal quantity (1b). In the second step the *empowerment e* is mapped to output *s* by taking the logical result of comparing the *empowerment e* against the *spiking-threshold* *Θ (1c)*, suggesting the instruction: “if the neuron is sufficiently empowered, then it shall spike”.

The basic McCulloch-Pitts neuron can be augmented by combining *v1, v2, …, vl* to *input vector* ***v*** *(2a)*, intro­ducing the digital weight vector ***w****∈ B,* and modifying *(1b)* to let the empowerment *e* be now a weighted sum of the input vector’s elements *(2c)*, where ***w*** ° ***v*** denotes elementwise product.

***v*** = (*v1, v2, …, vl )∈ B l (2a)*

***w*** := (*w1, w2, …, wl )∈ B l (2b)*

***e*** *= (****v****) =* ***w*** ° ***v*** *(2c)*

*s = (****e****) = (Σei ≥ Θ) (2d)*

The motivation for such augmentation (see also figure 2b) is to be prepared for the introduction of a learning mecha­nism, which allows to change an unconnected synapse (*wi* *= 0*) to a connected synapse (*wi* *= 1*) and vice versa.

It is notable that all signals and synaptic weights introduced so far are binary. Further, the augmented McCulloch-Pitts model (2a-d) is not intended to be applied to an entire neuron model. Rather we will use the augmented McCulloch-Pitts model neuron compartments, which are related to ta dendritic segment or a group of dendritic segments.

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Figure 2: Multi compartment model respecting local computations in different dendritic segments [9].

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Figure 3: Cortical microcircuit showing different input kinds applied to a principal (pyramidal) neuron [6]

There are different proposals in the literature [2][6][9] how to split a pyramidal neuron into compartments representing mea­ning­ful sub-functionalities (figure 2,3). With such background in mind, it makes sense to introduce an array of McCulloch-Pitts models (according to figure 1c) to represent a multitude of synaptic regions. The related equations are (3a-d), where *d* scalar outputs *si* are combined to output vector ***s***, and *d* input vectors ***v***i are combined to form the rows of input matrix ***V***. In a similar way this scheme is applied to *l* vectors ***e****i ,* ***w****i ,* which form the rows of matrices ***E****,* ***W****.*

***V*** = (***v****1,* ***v****2, …,* ***v****d )T ∈ B  d x l (3a)*

***W*** := (***w****1,* ***w****2, …,* ***w****d )T ∈ B  d x l (3b)*

***E*** *= (****V****) =* ***W*** ° ***V*** *∈ B  d x l (3c)*

***s*** *= (****E****) =* [*Σ* ***e****i ≥ Θ* ] *∈ B  d (3d)*

# The Neurotron

The *Neurotron* is a basic neural computing unit, serving as an atomic building block for HTM sequence memory (in the sense of [4]), for a *spatial pooler (*which is an autonomous learning map to maintain given sparsity by preserving semantics), and possibly for other higher-level functionality which has not yet been defined. The *Neuro­tron* is a well-defined abstraction of a pyramidal neuron, assigned with a well-defined algorithm deter­mining its computing process.

# References

[1] Rosenblatt, F.: „The perceptron. A probabilistic model for information storage and organization in the brain“; *Psychological Reviews*, 65 (1958): S. 386–408.

[2] Major, G., Larkum, M. E., and Schiller, J.: “Active properties of neocortical pyramidal neuron dendrites”; *Annual Review of Neuroscience* 36, 1–24 (2013).

[3] Antic, S. D., et al.: “The decade of the dendritic NMDA spike”; *J. Neurosci. Res.* 88, 2991–3001. doi: 10.1002/jnr.22444 (2010).

[4] Hawkins J., Ahmad S.: „Why Neurons Have Thousands of Synapses, a Theory of Sequence Memory in Neocortex“; *frontiers in Neural Circuits, 2016*.

[5] Hawkins J., Ahmad S., Cui Y.: „A Theory of How Columns in the Neocortex Enable Learning the Structure of the World“; *frontiers in Neural Circuits, 2017*.

[6] Magee J.C., Grienberger C.: Synaptic Plasticity Forms and Functions. *Annual Review of Neuroscience* 46, 95-117 (2020).

[7] McCulloch W.S., Pitts W.: A logical calculus of the ideas immanent in nervous activity. *Bulletin of Mathematical Biophysics,* 5, 115-133 (1943).

[8] Winding M., et all: The connectome of an insect brain. *Science 379, eadd9330* (2023).

[9] Larkum M.E., et all: Synaptic integration in tuft dendrites of layer 5 pyramidal neurons: a new unifying principle. *Science 325:756-60* (2009).

[8] Chklovskii et al.: Cortical rewiring and information storage. *Nature* 431, 782–788. doi: 10.1038/nature03012 (2004).

[1] Hawkins J., Blakeslee S.: “On Intelligence”; Owl Books (2005).

[2] Hawkins J.: “A Thousand Brains”; Basic Books, New York (2022).

[9] Stuart, G.J., Häusser, M.:. Dendritic coincidence detection of EPSPs and action potentials. *Nat. Neurosci.* 4, 63–71. doi: 10.1038/82910 (2001)

[10] Berlyand L., Jabin P.E.: „Mathematics of Deep Learning; An Introduction“; *de Gruyter Textbook, 2023*.

# Algorithm

Appendix

configure ***K,*** init ***X*** *0,* ***P*** *0*

repeat for *t = 0,1,2,3*

input ***u*** *t*

***Y*** *t = (****X*** *t + (1**-* ***1****m****max****(****X*** *t))° (****1****m* ***⋅ u*** *tT)*

***Q*** *t* = *σ(****D*** *t - η)* ° ***y*** *t(****K****)*

***X*** *t+1* = ([*||****Q****1 t ||1*, *||****Q****2 t ||1*, ... , *||****Q****n t||1*]*T ≥ θ)(m×n)*

***D*** *t+1* ***=*** ***D*** *t* ***+*** *(δ +****Q*** *t - δ -)* ° ***Y*** *t*