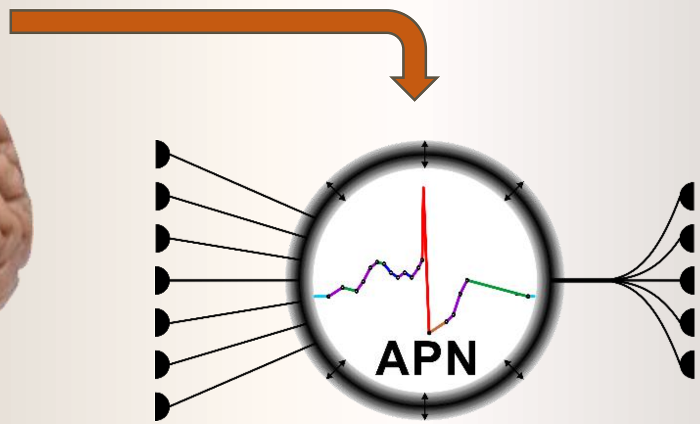
METODY INŻYNIERII WIEDZY

Asocjacyjne Neurony Pulsujące i Asocjacyjne Pulsacyjne Sieci Neuronowe



Akademia Górniczo-Hutnicza
w Krakowie

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Mózg i Neurony

Jak w rzeczywistości działają?

Mózg i Neurony

- ✓ **Uruchamiają wewnętrzne procesy równolegle i często asynchronicznie**
- ✓ **Wykorzystują czas do temporalnych i kontekstowych obliczeń**
- ✓ **Integrują pamięć z procedurami (algorytmami)**

Jak w rzeczywistości działają?

Mózg i Neurony

- ✓ Automatycznie i kontekstowo kojarzą dane i obiekty
- ✓ Tworzą samo-organizujące reprezentacje danych i obiektów
- ✓ Agregują dane i obiekty podobne

Jak w rzeczywistości działają?

Mózg i Neurony

- ✓ **Wykorzystują złożone pamięci o neuronowej strukturze grafowej**
- ✓ **Nie są ograniczone modelem obliczeniowym maszyny Turinga**
- ✓ **Automatycznie powracają do stanu spoczynku neuronów**

Jak w rzeczywistości działają?

Mózg i Neurony

- ✓ **Kojarzą różne informacje w celu uformowania wiedzy**
- ✓ **Agregują reprezentacje takich samych i bliskich obiektów**
- ✓ **Łączą reprezentacje powiązanych obiektów**

Jak w rzeczywistości działają?

Fundamentalne Pytanie i Cele Neurobiologii

Jak informacje są kodowane i dekodowane za pośrednictwem serii impulsów przesyłanych przez aktywowane neurony po ich potencjałach czynnościowych?

Podstawowym celem neurobiologii jest wyjaśnienie czy neurony komunikują się poprzez częstotliwość pulsów czy poprzez różnice w czasie pomiędzy impulsami?

Asocjacyjne Neurony Pulsacyjne dowodzą, że upływ czasu pomiędzy kolejnymi impulsami, jak również częstotliwość tych impulsów mają wpływ na wynik asocjacji oraz obliczeń neuronowych.

Jak w rzeczywistości działają?

Objectives and Contribution

- Implementation of **associative self-organizing mechanisms** inspired by brains which **speed up and simplify** functional aspects of spiking neurons.
- Introduction of **a new associative pulsing model of neurons (APNs)** that can quickly point out related data and objects, and be used for inference.
- Construction of **APN neural networks** implementing associative spiking mechanisms of associative pulsing neurons and **conditional plasticity**.

Neuron Models Evolution

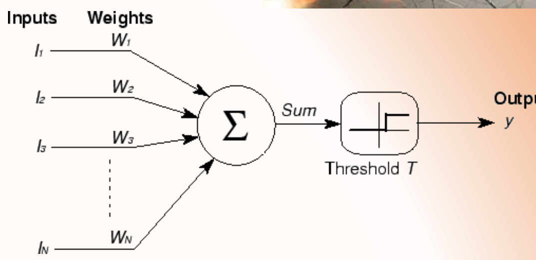
GENERATIONS OF NEURON MODELS:

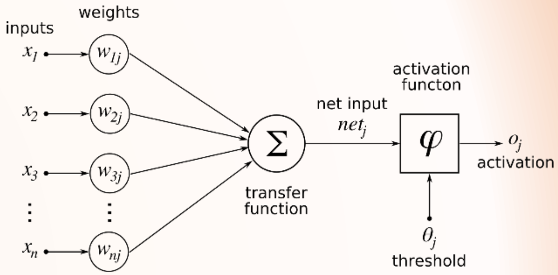
1. **The McCulloch-Pitts model of neurons** implements only the most fundamental mechanisms of the weighted input stimuli integration and threshold activation function leaving aside issues of time, plasticity, and other important factors.

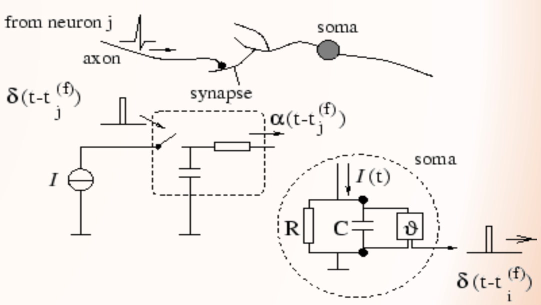
2. **The model of neurons using non-linear continuous activation functions** enables us to build multilayer neural networks (e.g. MLP) and adapt such networks to more complex tasks and non-linear separable training data.

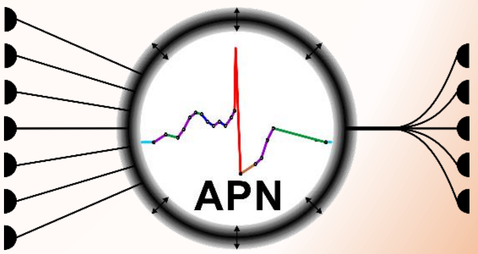
3. **The spiking models of neurons** enriched this model with the implementation of the approach of time which is very important during stimuli integration and modeling of subsequent processes in time.

4. **The associative pulsing model (APN) of neurons** produces series of pulses (spikes) in time which frequency determines the association level. Moreover APNs enrich the model with automatic plastic mechanisms which let neurons to conditionally connect and configure an associative neural structure representing data, objects, and their sequences.



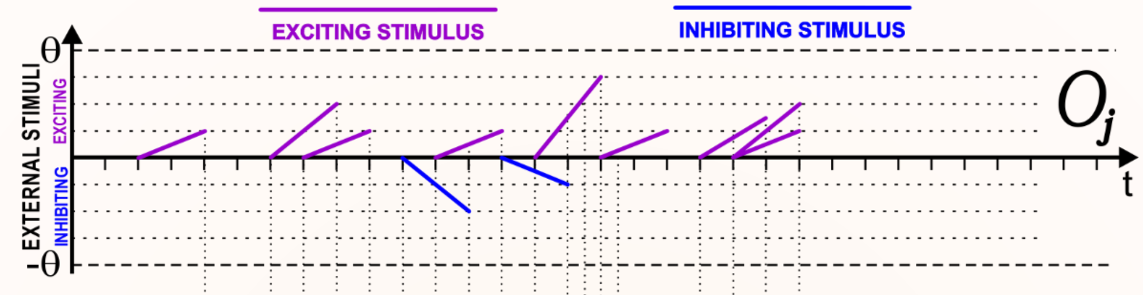




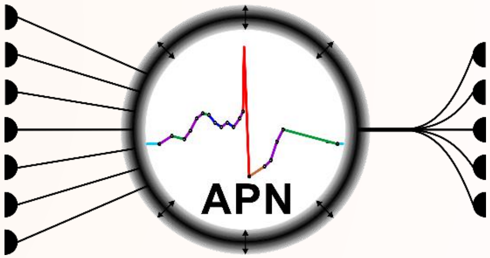


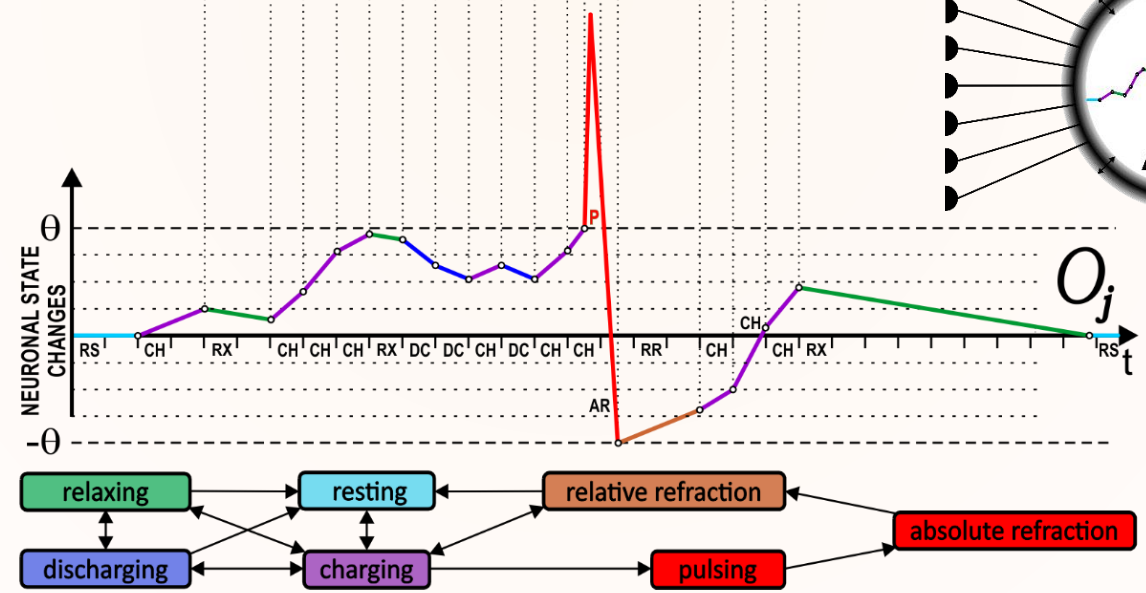
Real neurons are plastic as well!

Associative Pulsing Neurons



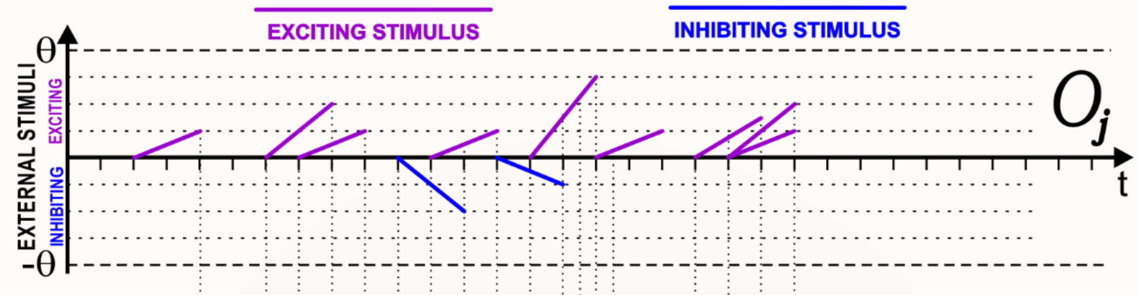
- ✓ **Implement a new time-spread integration mechanism which quickly combines input stimuli in time producing an internal process queue (IPQ) of subsequent internal processes.**



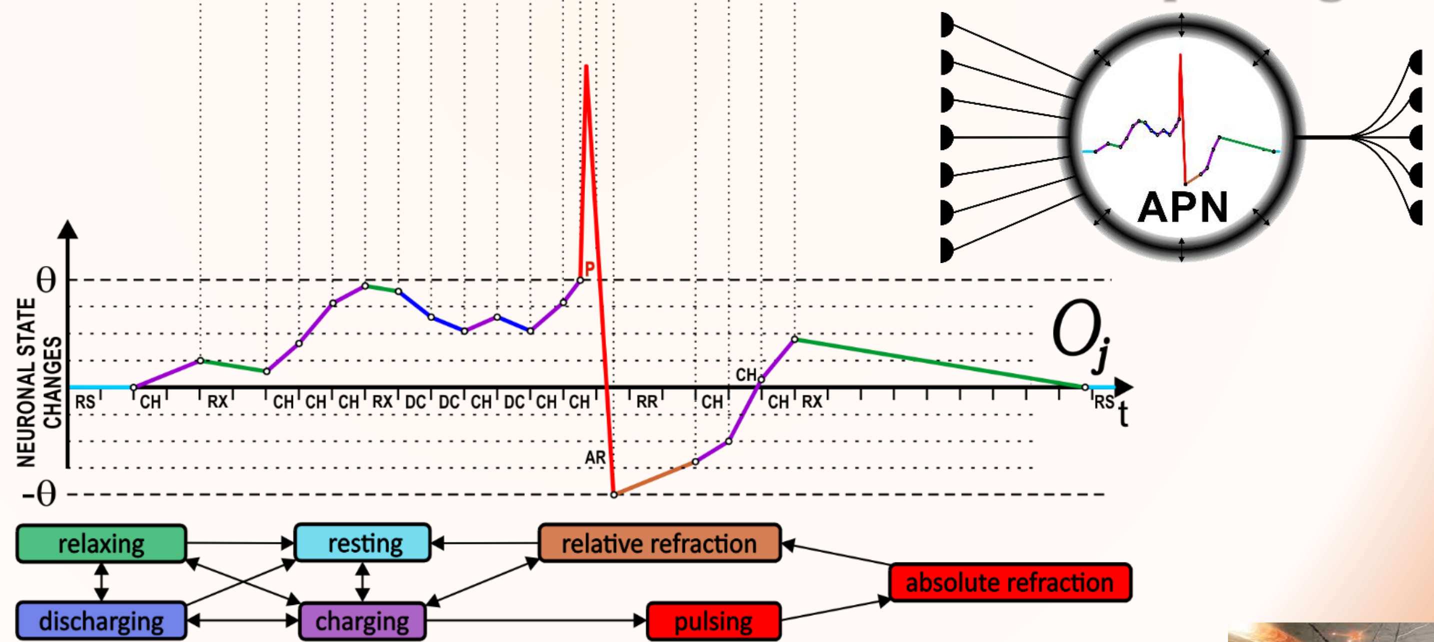


It allows for recalling of associated information.

Associative Pulsing Neurons



✓ **Model the internal processes of real neurons but allow for the update of their states in sparse discrete moments of time that is much more time-efficient than the continuous updating.**



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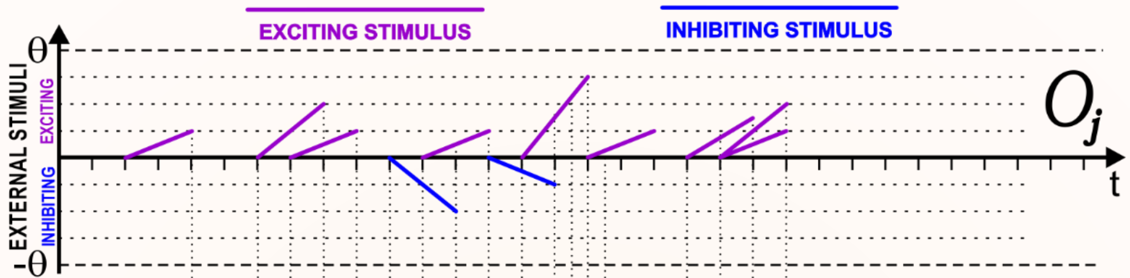
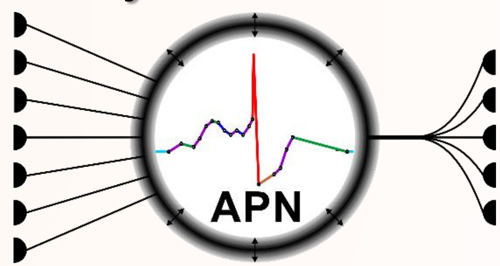
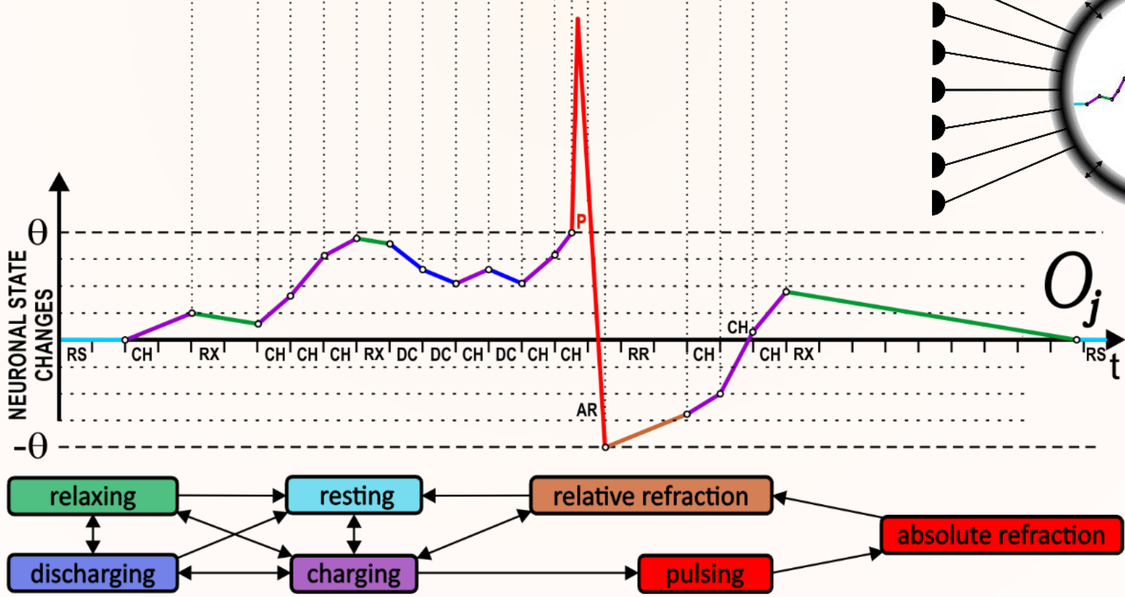
Associative Pulsing Neurons



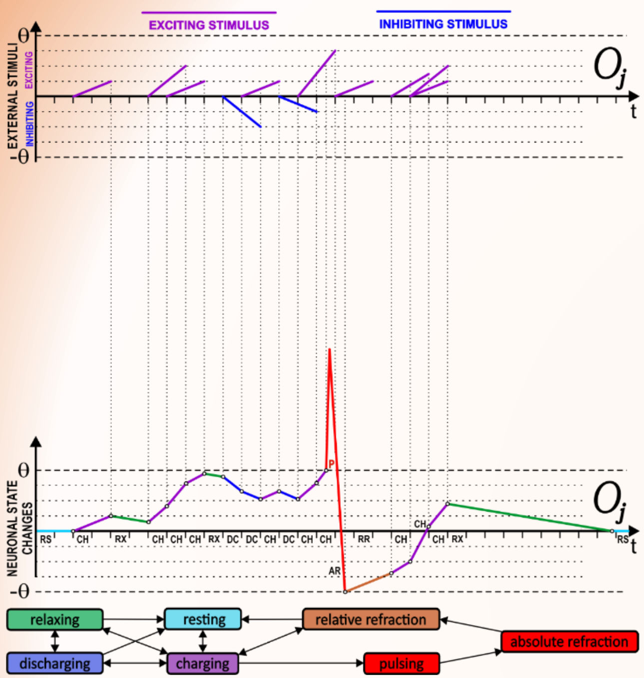
- ✓ **Implement plastic mechanisms of real neurons which allow for adaptive self-organization of the neuronal structure thanks to the conditional creation of connections between activated neurons, and for the association of the information encoded by these neurons.**

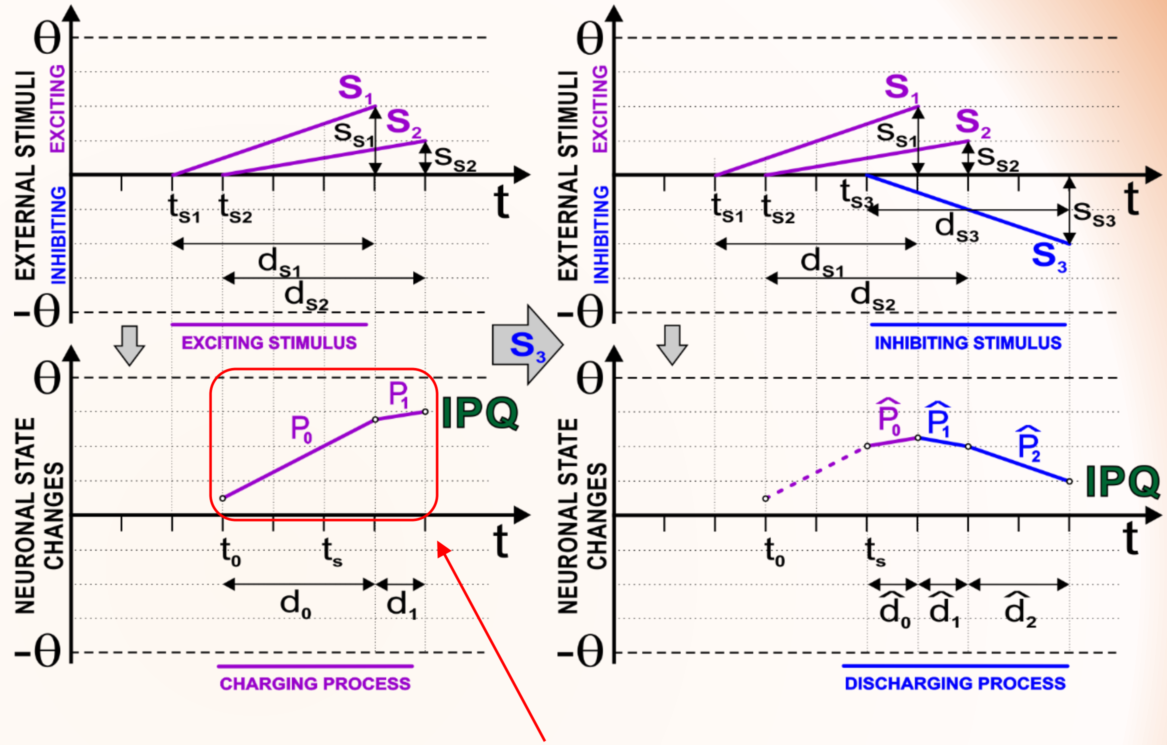


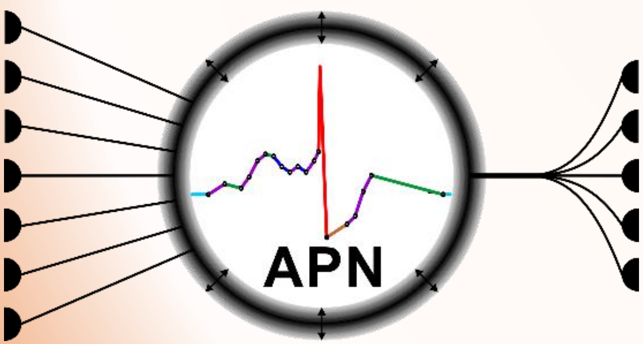


It allows for recalling of associated information.

Combining of Input Stimuli





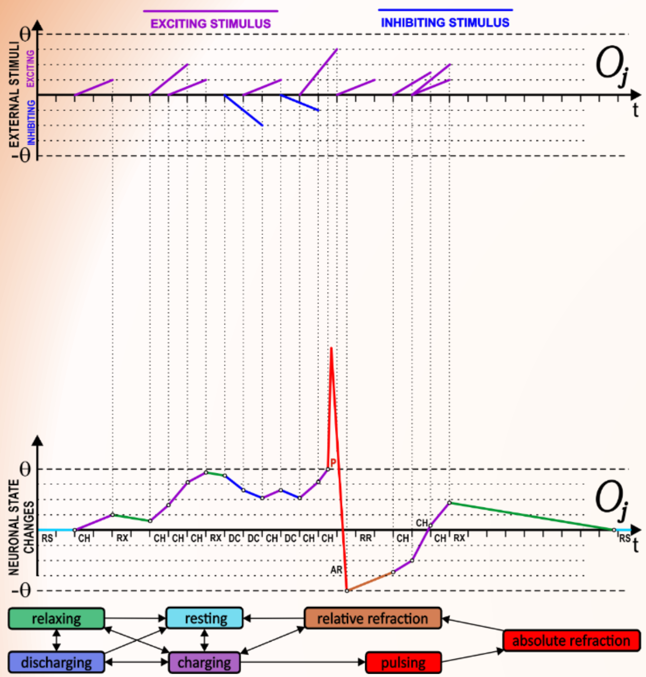


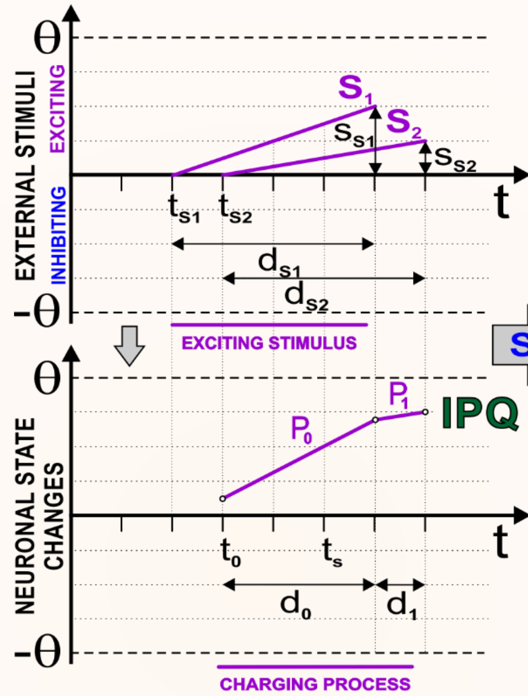
1. The stimulus S_2 occurs
   the APN internal state is updated.

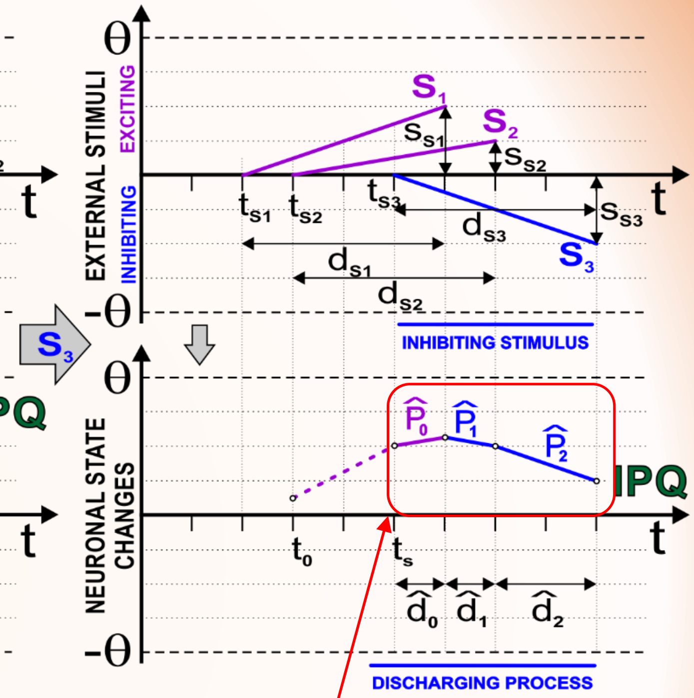
2. The remaining part of S_1 is **linearly combined** with S_2 producing IPQ consisting of the processes: P_0-P_1

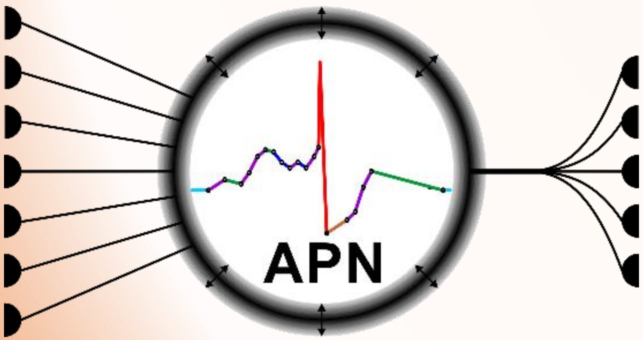
Creation of the queue of subsequent internal processes which do not overlap in time.

Combining of Input Stimuli







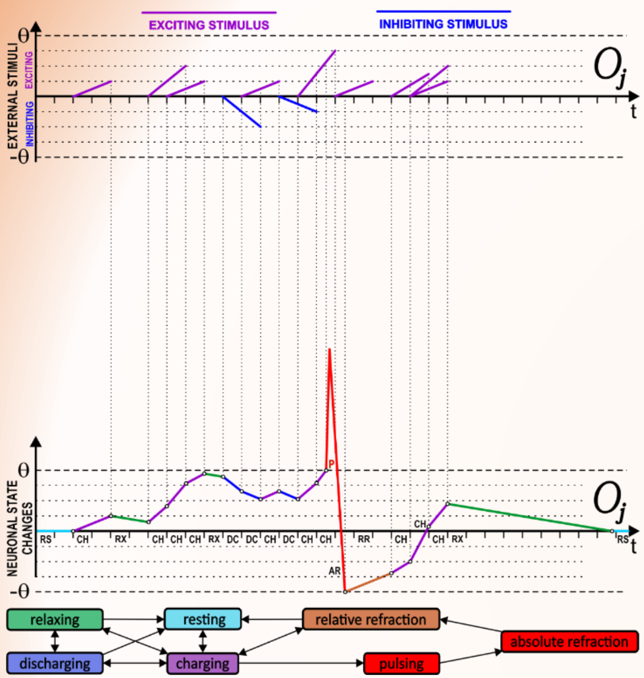


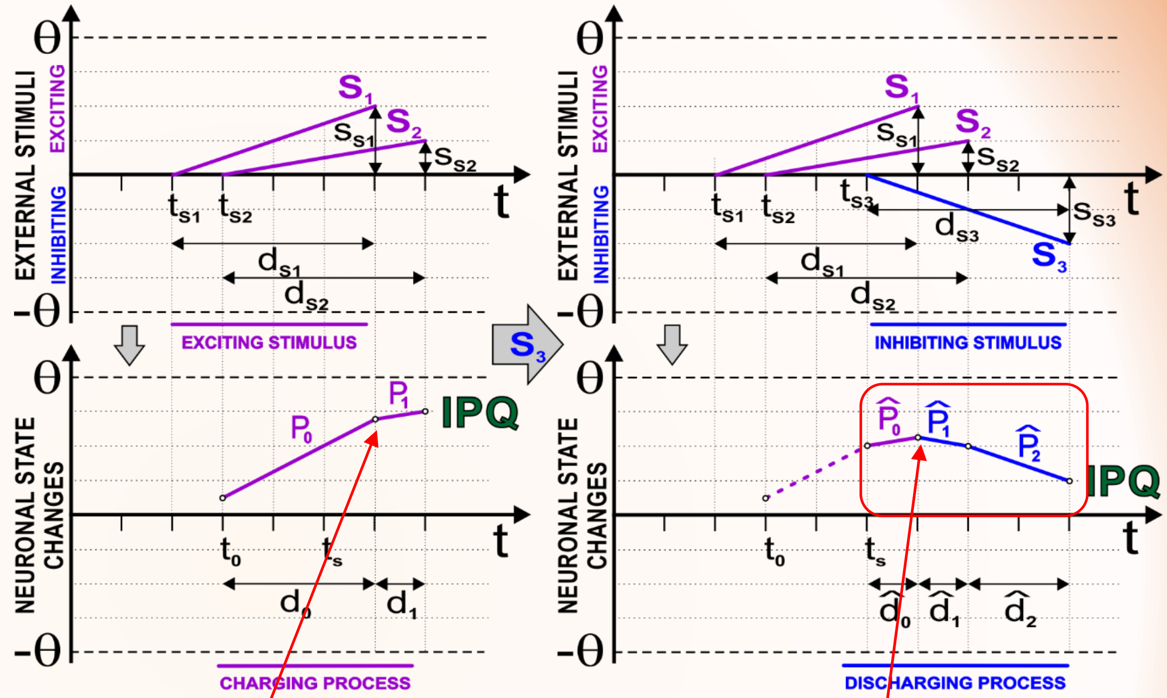
3. **When the inhibiting stimulus S_3 comes the APN is updated again at the time when this stimulus occurs.**

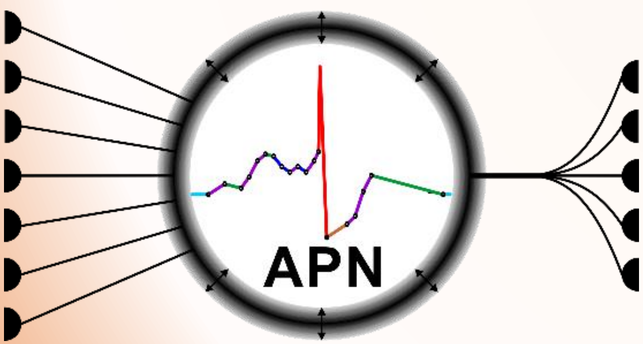
4. **Next, this stimulus is linearly combined with the existing processes P_0-P_1 in the IPQ producing a new sequence of processes.**

Creation of the queue of subsequent internal processes which do not overlap in time.

Global Event Queue





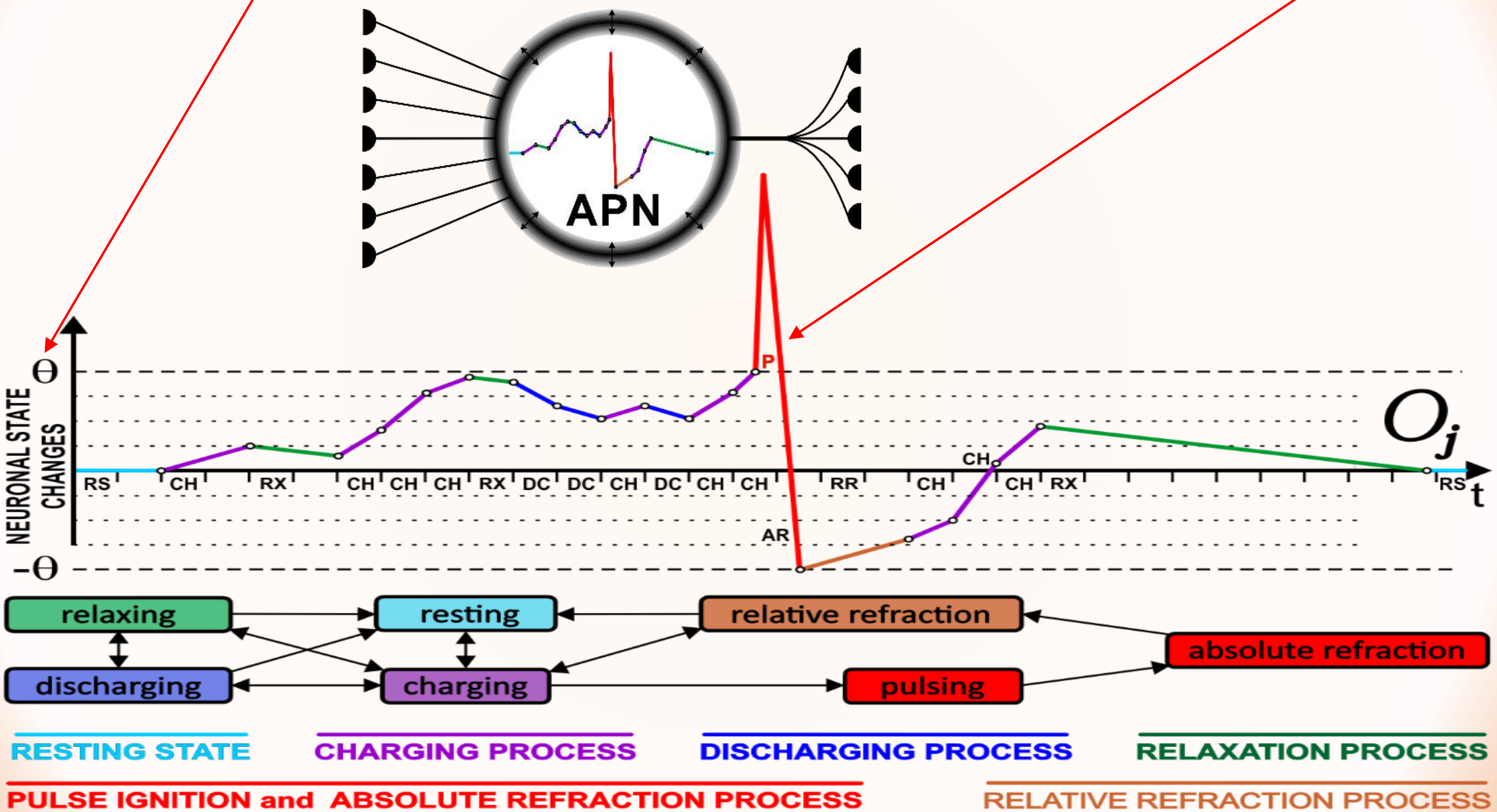


5. GEQ – Global Event Queue sorts all processes and waits for moments when the **first internal processes** of all IPQs of neurons **will finish** because in these moments, the neuronal states **must be updated** and the internal processes **must be switched** to the subsequent ones.

Watching out the discrete update moments.

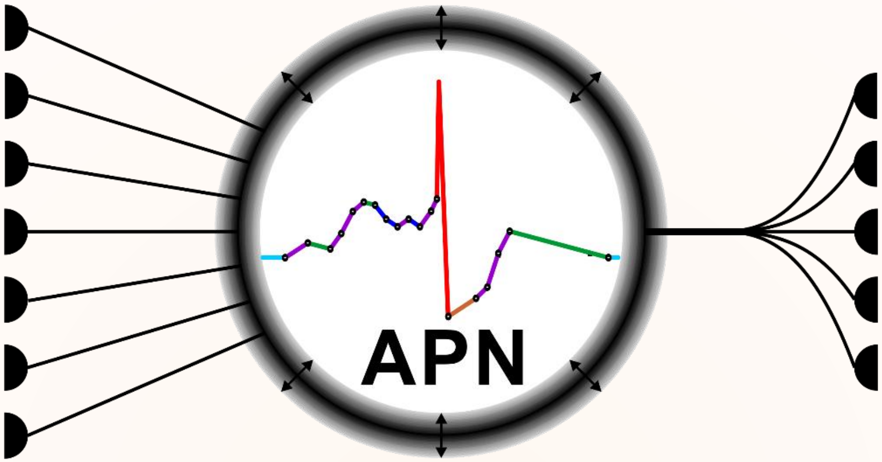
Pulsing Moments of APNs

6. GEQ – Global Event Queue also watches out the moments when the **pulsing thresholds** are achieved and when APNs should **start pulsing**.



GEQ watches out when the APNs achieve activation thresholds to make them pulsing.

Associative Pulsing Neurons



- ✓ **Conditionally connect and change their sensitivity to input stimuli.**
- ✓ **Reproduce time activity of neurons in the neural structure.**
- ✓ **Sparse connections reflect the time-spread relations between objects.**
- ✓ **Aggregate representation of the same or similar objects presented to the neural network on the receptive sensory input fields (SIFs).**
- ✓ **Represent these combinations of input stimuli which make them firing, and according to their sensitivity, they can specialize over time.**

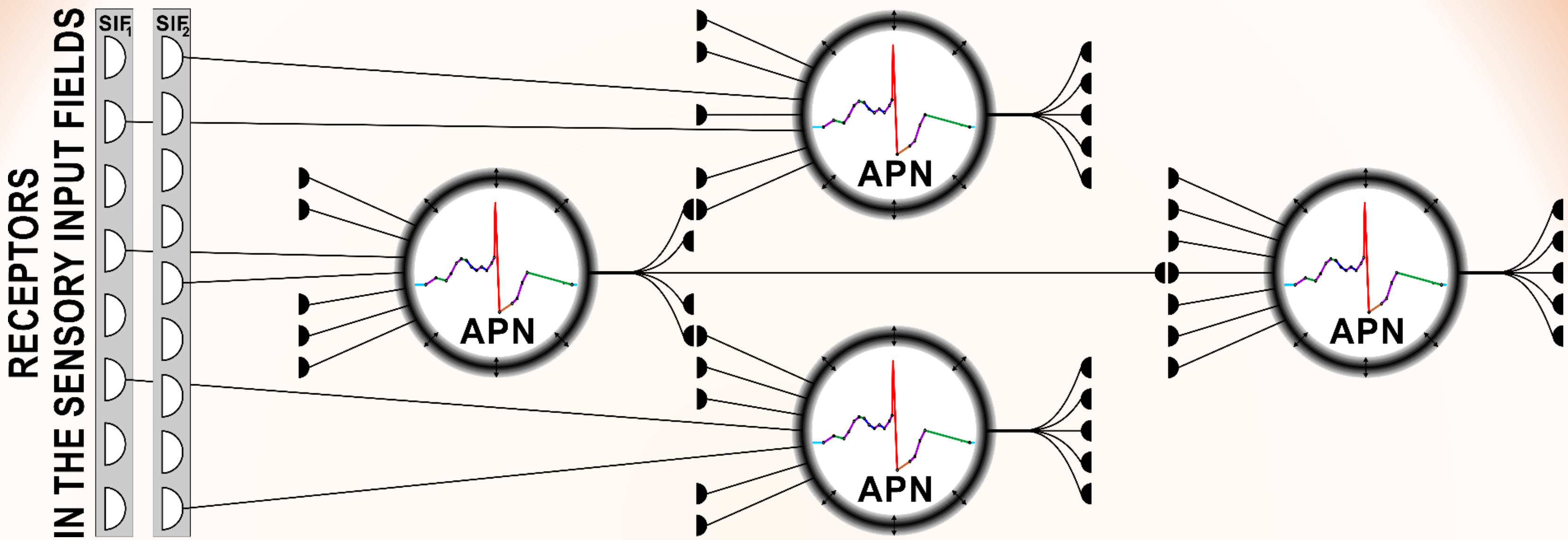
It allows for recalling of associated information.

When APNs are created?

- They are automatically created for receptors placed in the sensory input fields (SIFs) if no existing neuron reacts to their stimulation.
- They can connect to one or many receptors according to the passage of time between the receptor stimulations.
- They connect to other neurons if they fire in the close succession of time to reproduce the sequence of object occurrences.
- They are not created if any of the existing neurons fires because it means that such a class of objects (combination of input stimuli) is already known and represented in the neural network.

Conditional creation and connection of neurons.

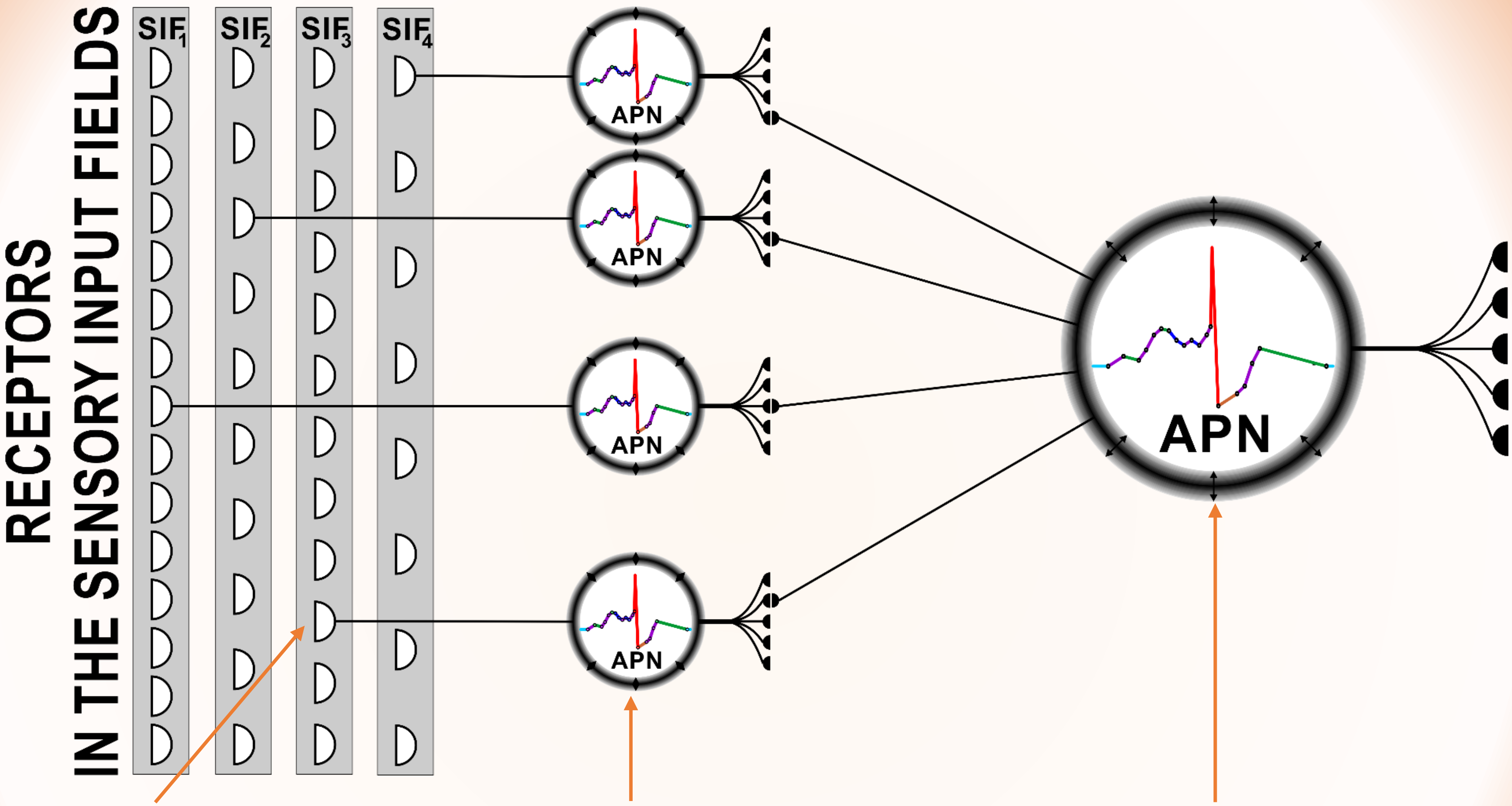
Connections and Synapses



- Receptors of the SIFs are directly connected to APNs (no synapses).
- Each receptor continuously stimulates the connected APN until the input stimulus influence on the SIF but the APN is updated in the discrete moments of time when the stimulus vanishes or charges the APN.
- APNs are connected via synapses which have their weights coming from different synaptic permeability computed as a result of the synaptic efficiency of firing the postsynaptic neuron.

Plastic conditional connections.

Receptor Stimulation

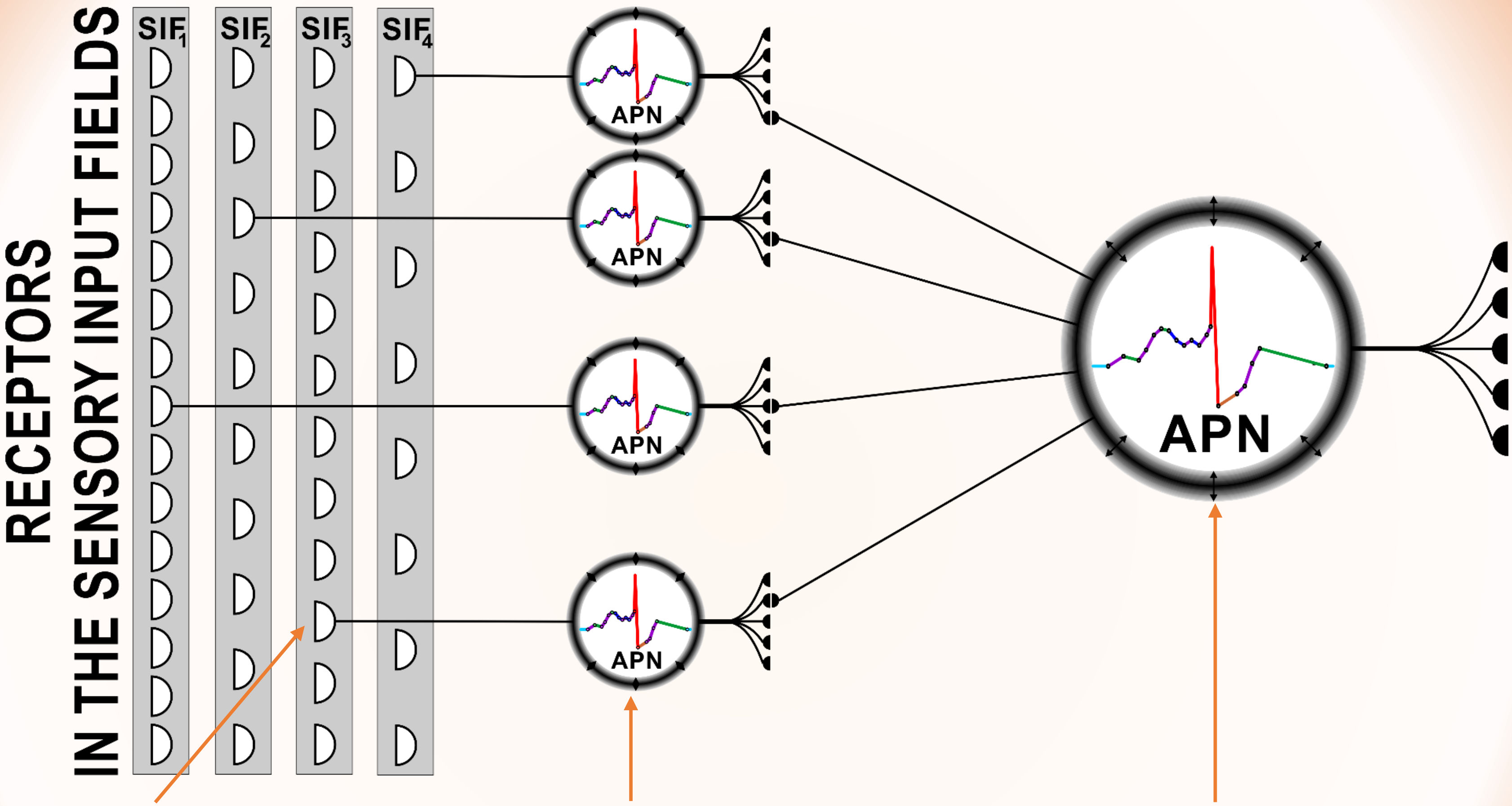


Receptors stimulate **Sensory Neurons** which stimulate **Object Neurons**.

Sensory Neurons react to the stimulations of the connected **Receptors** and **code the stimulation strength** in a form of **pulse frequencies**.

Variety of APN neurons in the network.

Receptor Stimulation

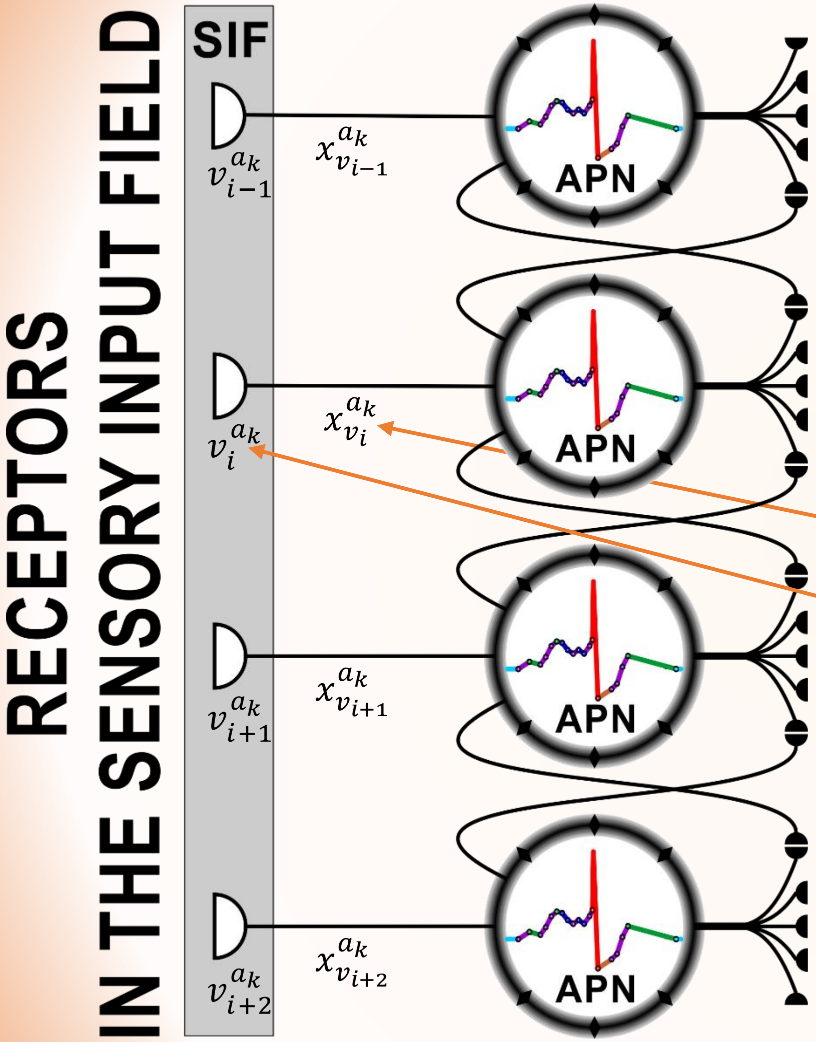


Receptors stimulate Sensory Neurons which stimulate Object Neurons.

The connected Object Neurons sum stimuli coming from Sensory Neurons and pulse when their pulsing thresholds are achieved.

Variety of APN neurons in the network.

Receptor Stimulation Strength



Receptors stimulate Sensory Neurons with a strength coming from the similarity of the input stimulus v^{a_k} to the value $v_i^{a_k}$ represented by the Receptor:

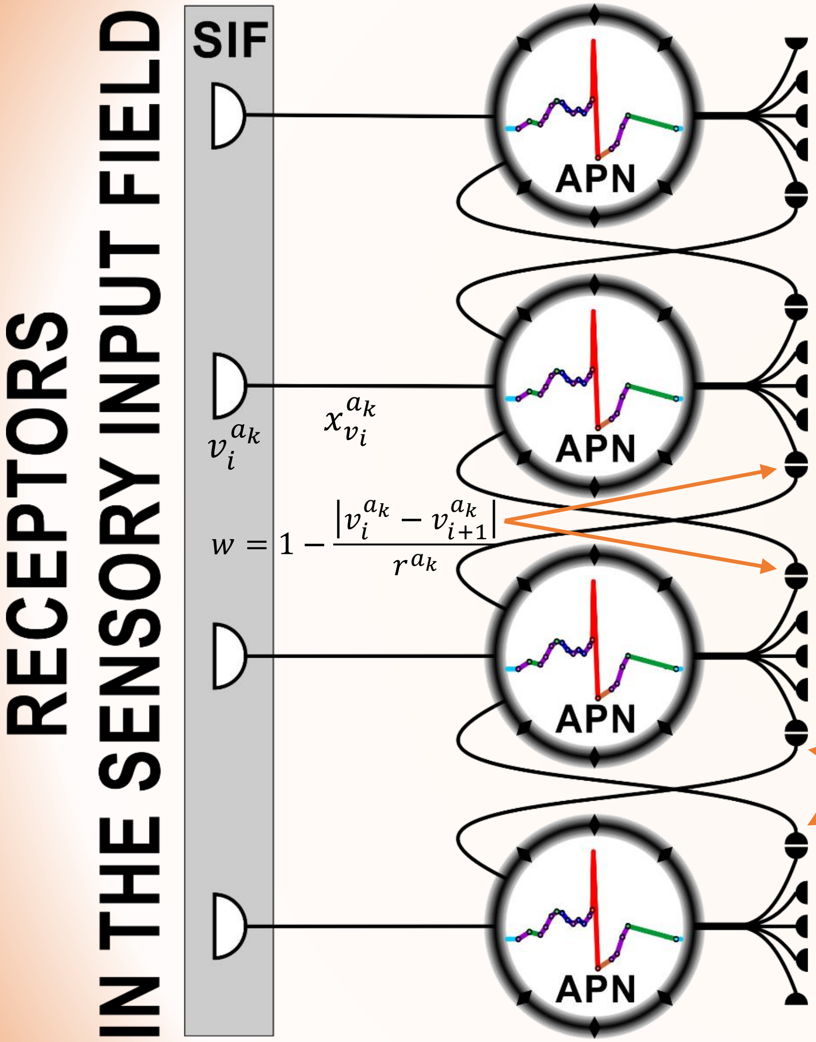
$$x_{v_i}^{a_k} = \begin{cases} 1 - \dfrac{\left|v_i^{a_k} - v^{a_k}\right|}{r^{a_k}} & if\ r^{a_k} > 0 \\ \dfrac{\left|v_i^{a_k}\right|}{\left|v_i^{a_k}\right| + \left|v_i^{a_k} - v^{a_k}\right|} & if\ r^{a_k} = 0 \end{cases}$$

Where $r^{a_k} = v_{max}^{a_k} - v_{min}^{a_k}$ is a range of values represented by the SIF, i.e.:

$v_{min}^{a_k} = min\{v_i^{a_k}\}$ and $v_{max}^{a_k} = max\{v_i^{a_k}\}$

Charging the APNs takes different time.

Sensory Neuron Activation Time



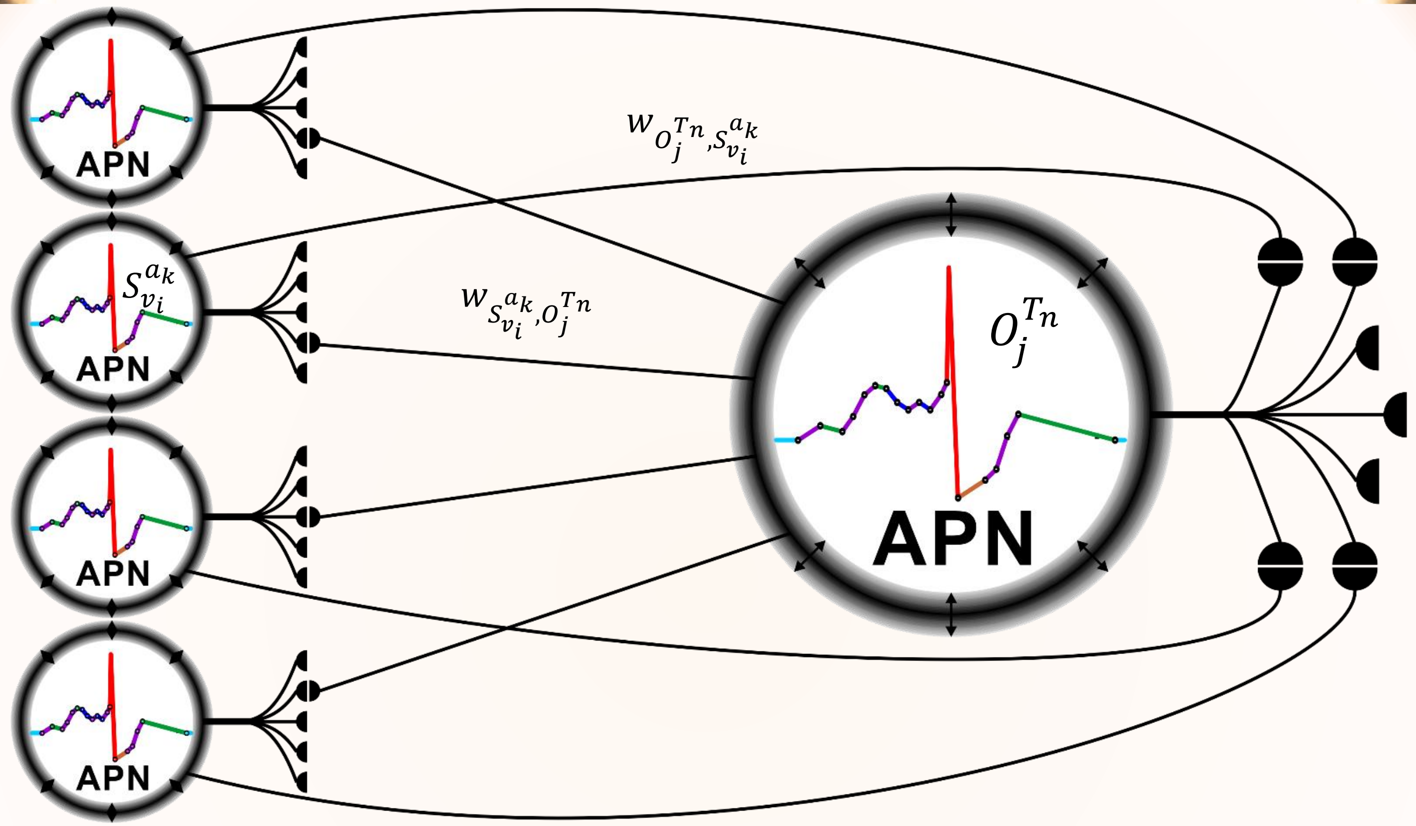
Sensory Neurons charge over time and according to the strength of the continuous stimulus of the Receptor it starts pulsing (activates) after the following period of time $t_{v_i}^{a_k}$ when it is solely stimulated by this Receptor:

$$t_{v_i}^{a_k} = \begin{cases} \dfrac{r^{a_k}}{\left(r^{a_k} - \left|v_i^{a_k} - v^{a_k}\right|\right)} & if\ r^{a_k} > \left|v_i^{a_k} - v^{a_k}\right| \\ \infty & if\ r^{a_k} = \left|v_i^{a_k} - v^{a_k}\right| \\ 1 + \left|\dfrac{v_i^{a_k} - v^{a_k}}{v_i^{a_k}}\right| & if\ r^{a_k} = 0 \end{cases}$$

Sensory Neurons are connected to each other when they represent similar (neighbor) values represented by the Receptors because they pulse one after another as a result of the presentation of input data.

Implementation of the time approach in APNs.

Stimulation of Object Neurons

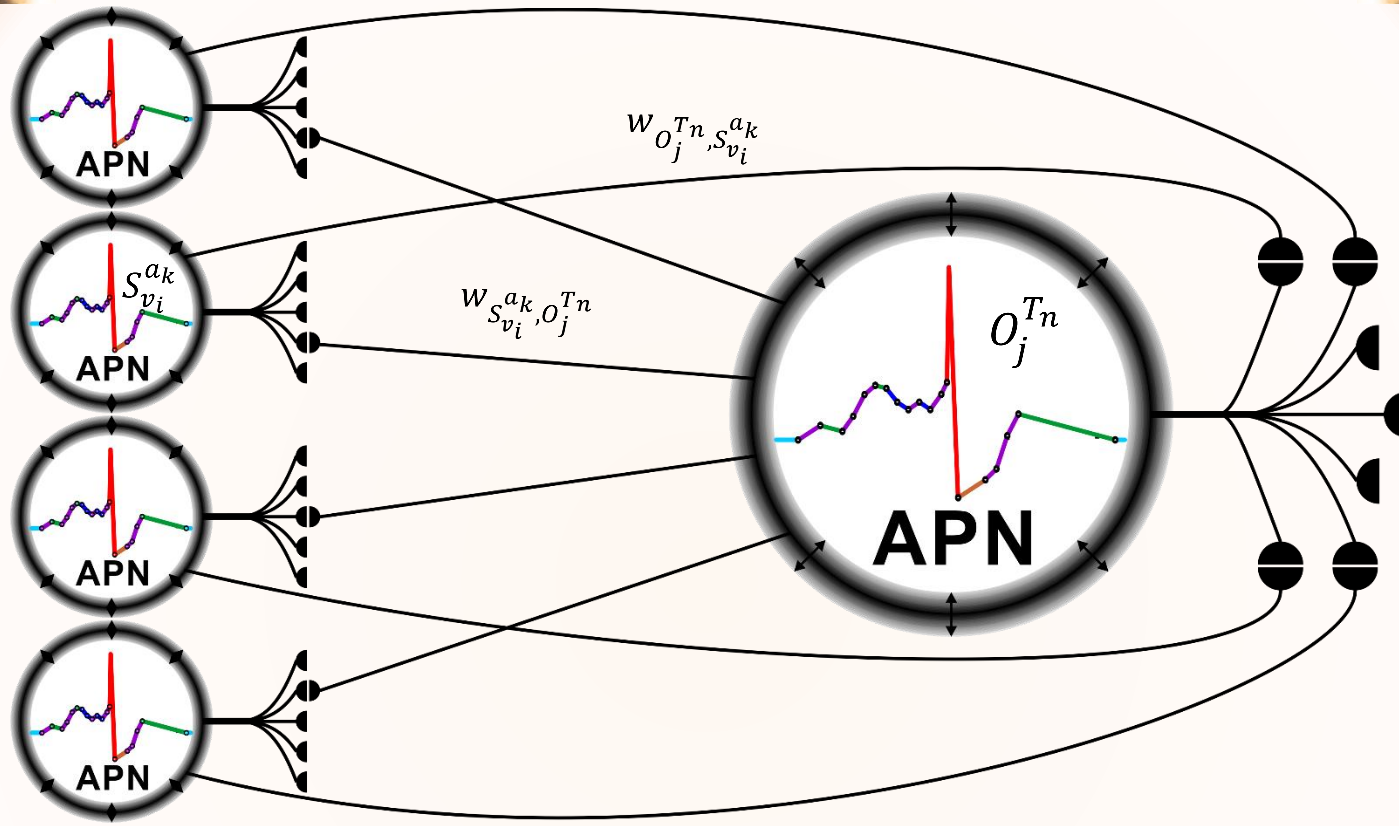


The number of outgoing connection is taken into account when calculating the weights of the connections from the Sensory Neurons to the Object Neurons:

$w_{S_{v_i}^{a_k},O_j^{Tn}} = \frac{1}{N_{v_i}^{a_k}}$ **and for the defining connections:** $w_{O_j^{Tn},S_{v_i}^{a_k}} = 1$

The connection rarity determines the certainty.

Thresholds of Object Neurons



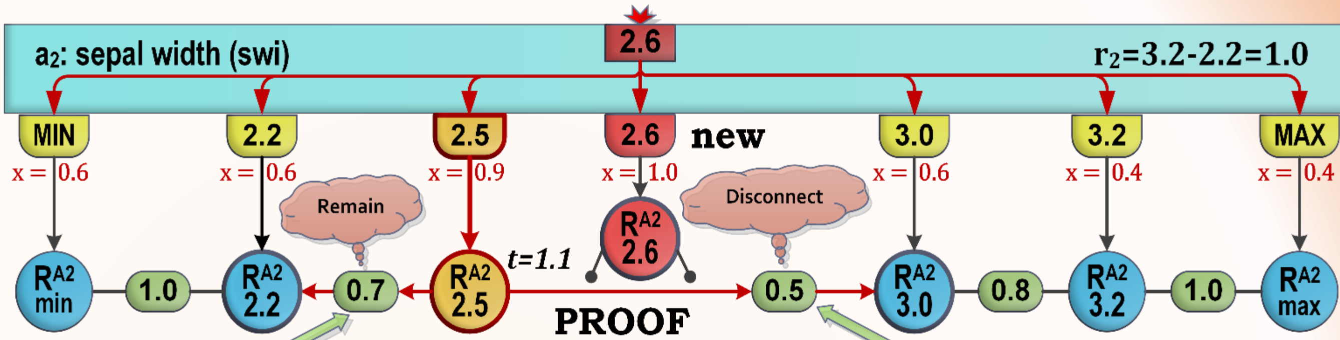
The threshold of object neurons is usually equal one but in some cases it should be smaller to satisfy the necessity to activate the Object Neuron by the defining combination of input stimuli:

$$\theta_{O_j} = \begin{cases} 1 & if\ W_{O_j} \geq 1 \\ W_{O_j} & if\ W_{O_j} < 1 \end{cases} \quad \textbf{where} \quad W_{O_j} = \sum_{S_{v_i}^{a_k}} w_{S_{v_i}^{a_k}, O_j}$$

The connection rarity determines the certainty.

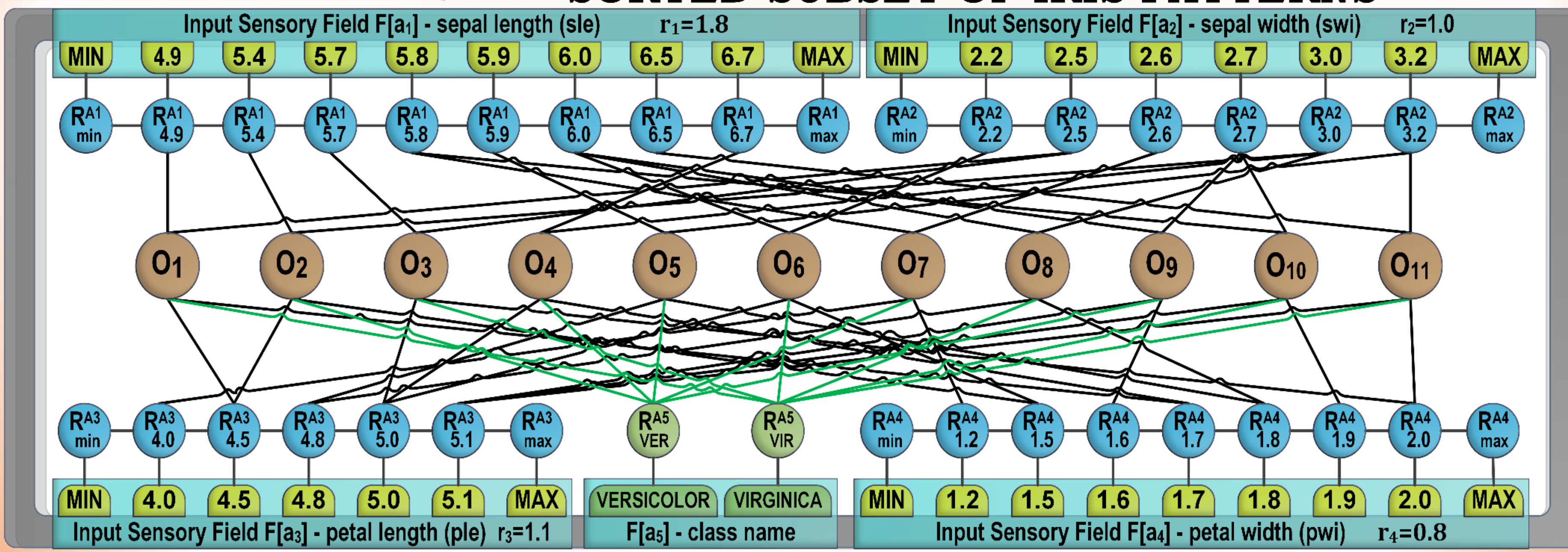
CONNECTION PLASTICITY

	Attributes $a_1,\dots,a_5$				
	sle	swi	ple	pwi	class name
O_1	4.9	2.5	4.5	1.7	VIRGINICA
O_2	5.4	3.0	4.5	1.5	VERSICOLOR
O_3	5.7	2.5	5.0	2.0	VIRGINICA
O_4	6.7	3.0	5.0	1.7	VERSICOLOR
O_5	5.9	3.2	4.8	1.8	VERSICOLOR
O_6	6.0	2.2	5.0	1.5	VIRGINICA
O_7	5.8	2.6	4.0	1.2	VERSICOLOR
O_8	6.0	3.0	4.8	1.8	VIRGINICA
O_9	5.8	2.7	5.1	1.9	VIRGINICA
O_{10}	6.0	2.7	5.1	1.6	VERSICOLOR
O_{11}	6.5	3.2	5.1	2.0	VIRGINICA



$$1-\frac{|2.2-2.6|}{1.0}=0.6 \not> 0.7 = 1\cdot\left(1-\frac{|2.5-2.2|}{1.0}\right)>0 \quad 0<1\cdot\left(1-\frac{|2.5-3.0|}{1.0}\right)=0.5<0.6=1-\frac{|3.0-2.6|}{1.0} \tag{10}$$

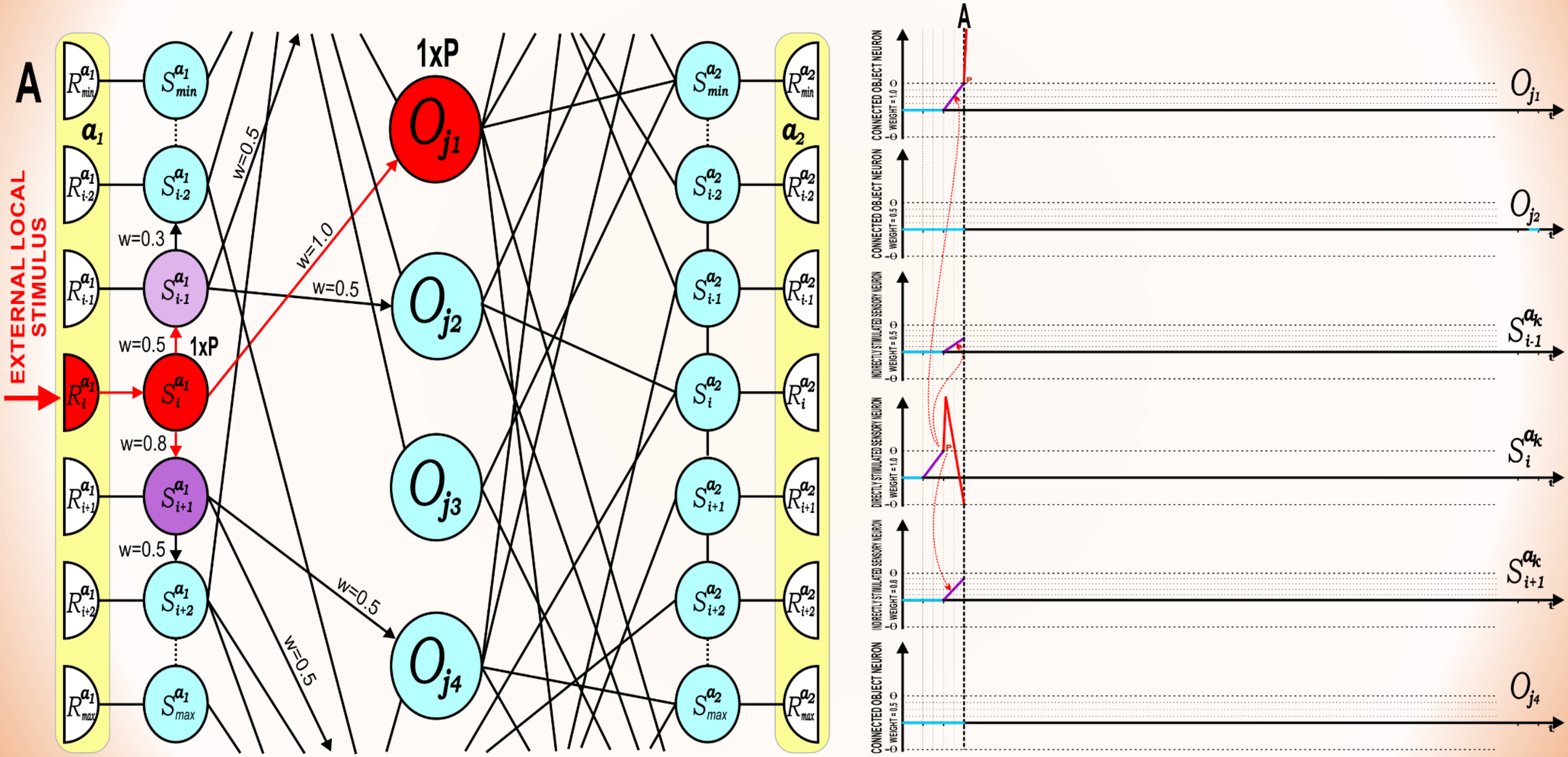
SORTED SUBSET OF IRIS PATTERNS



ASSORT-2 algorithm defines the conditions which must be met to create or update the connections between sensory neurons.

EVENT DRIVEN SIMULATION

- Neural state changes according to the continuous input stimulus of the receptor $R_i^{a_k}$ and the forwarded pulses after activation of neurons.

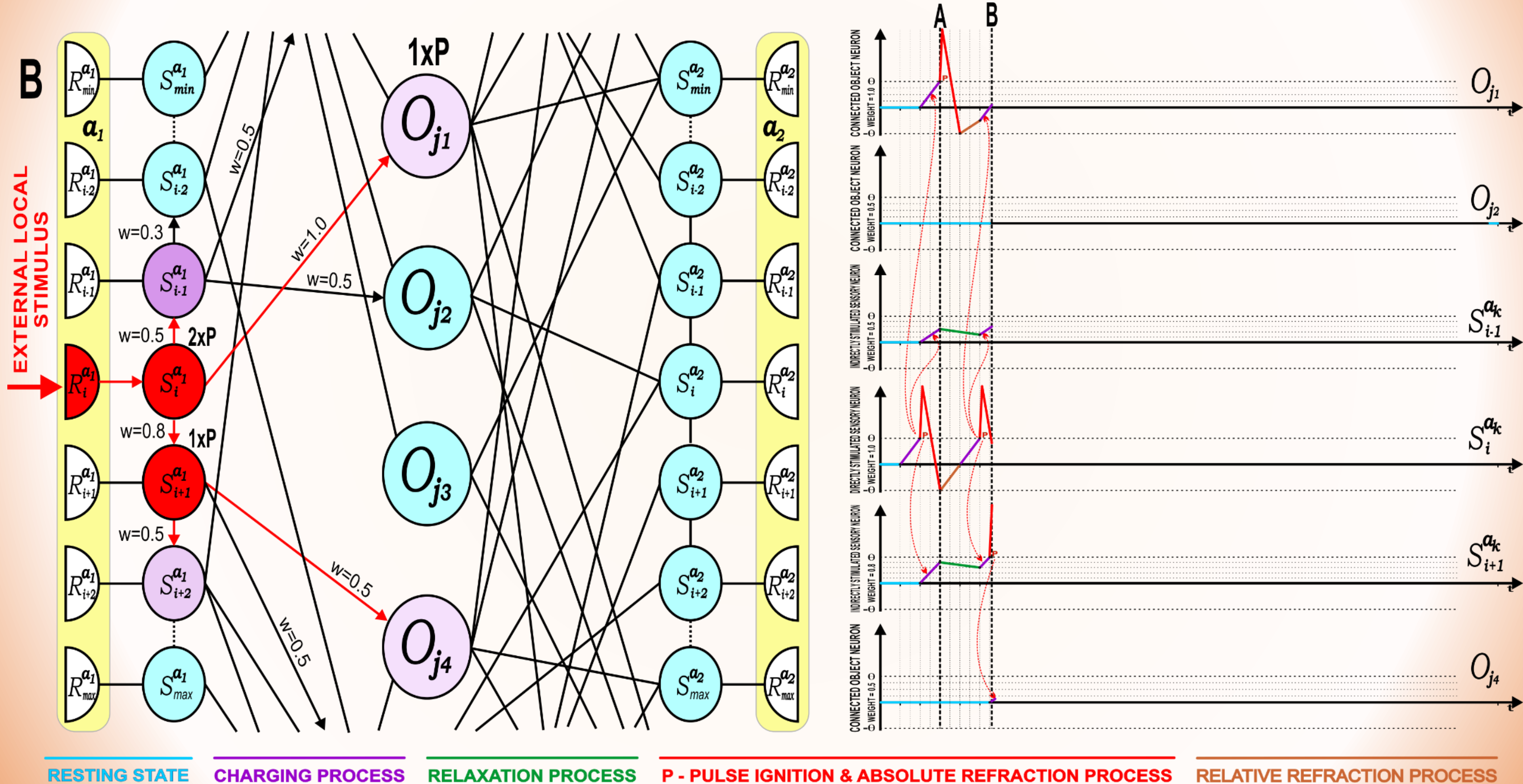


RESTING STATE | CHARGING PROCESS | RELAXATION PROCESS | P - PULSE IGNITION & ABSOLUTE REFRACTION PROCESS | RELATIVE REFRACTION PROCESS

Synaptic dependencies between receptors, sensory and object neurons.

EVENT DRIVEN SIMULATION

- Neural state changes according to the continuous input stimulus of the receptor $R_i^{a_k}$ and the forwarded pulses after activation of neurons.



Synaptic dependencies between receptors, sensory and object neurons.

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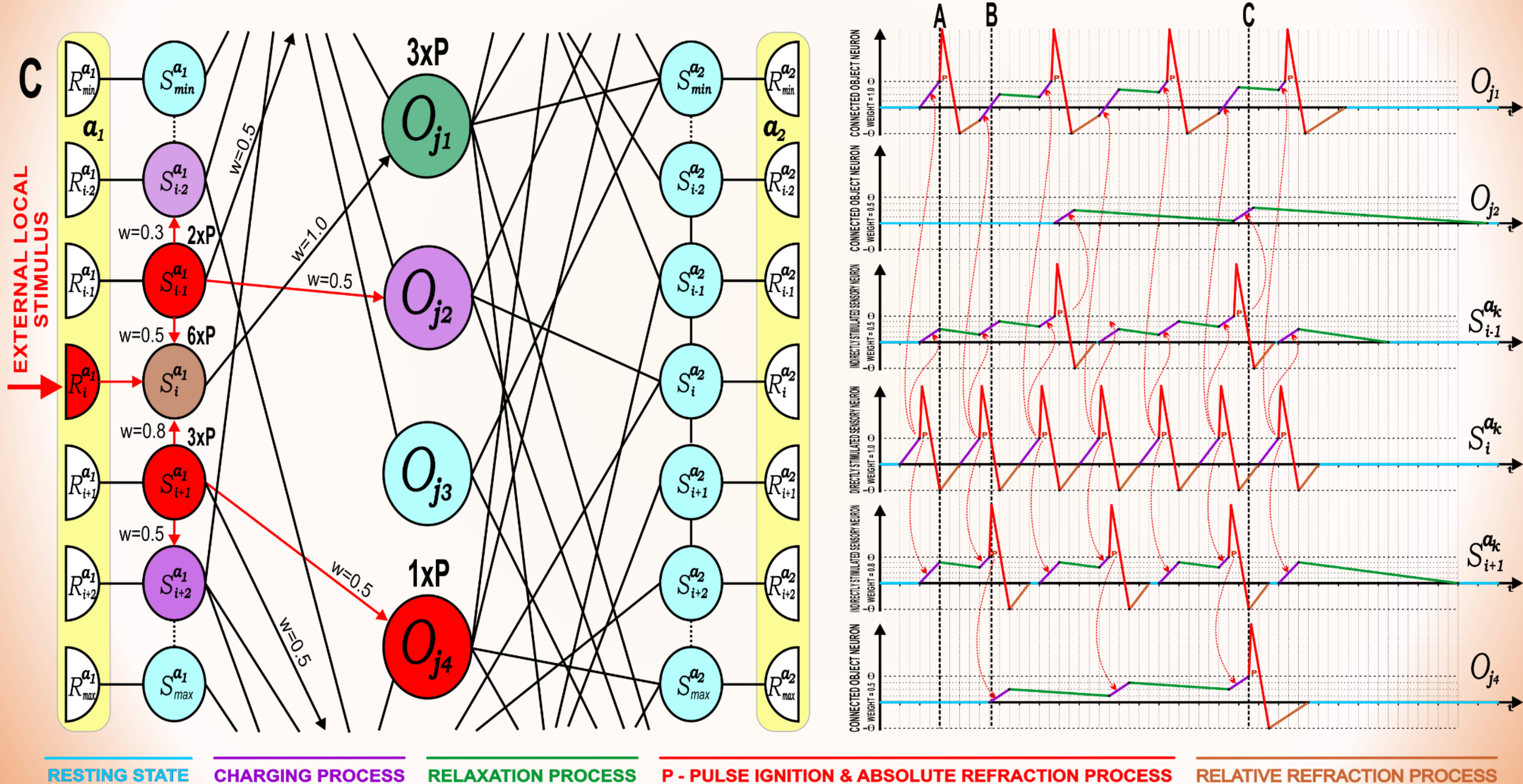
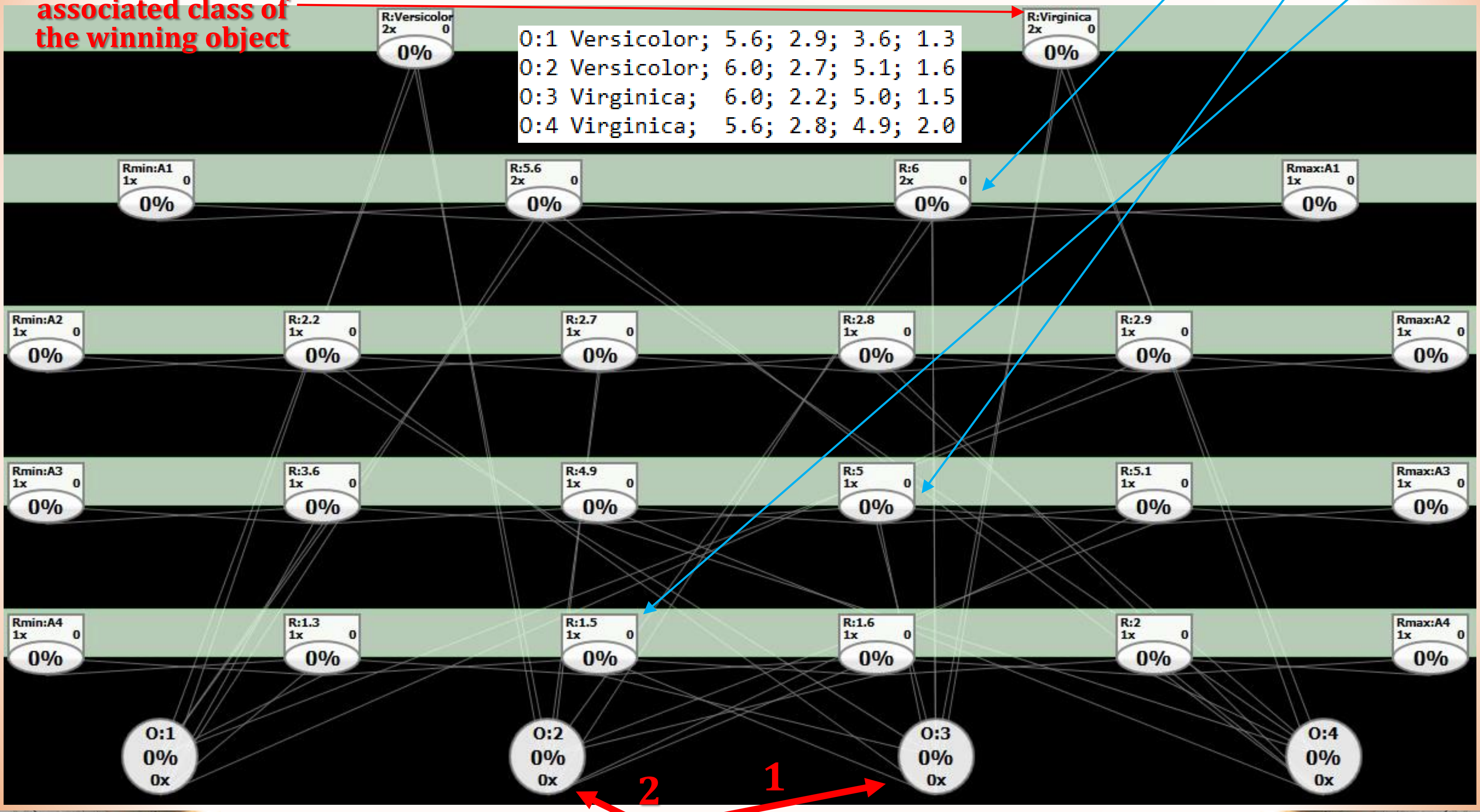


Synaptic dependencies between receptors, sensory and object neurons.

EXPERIMENTS & ANIMATION with APN Neural Network

Let's stimulate receptors with the following input vector [?, 6.0, ?, 5.0, 1.5]. What is the most similar objects to the presented inputs?

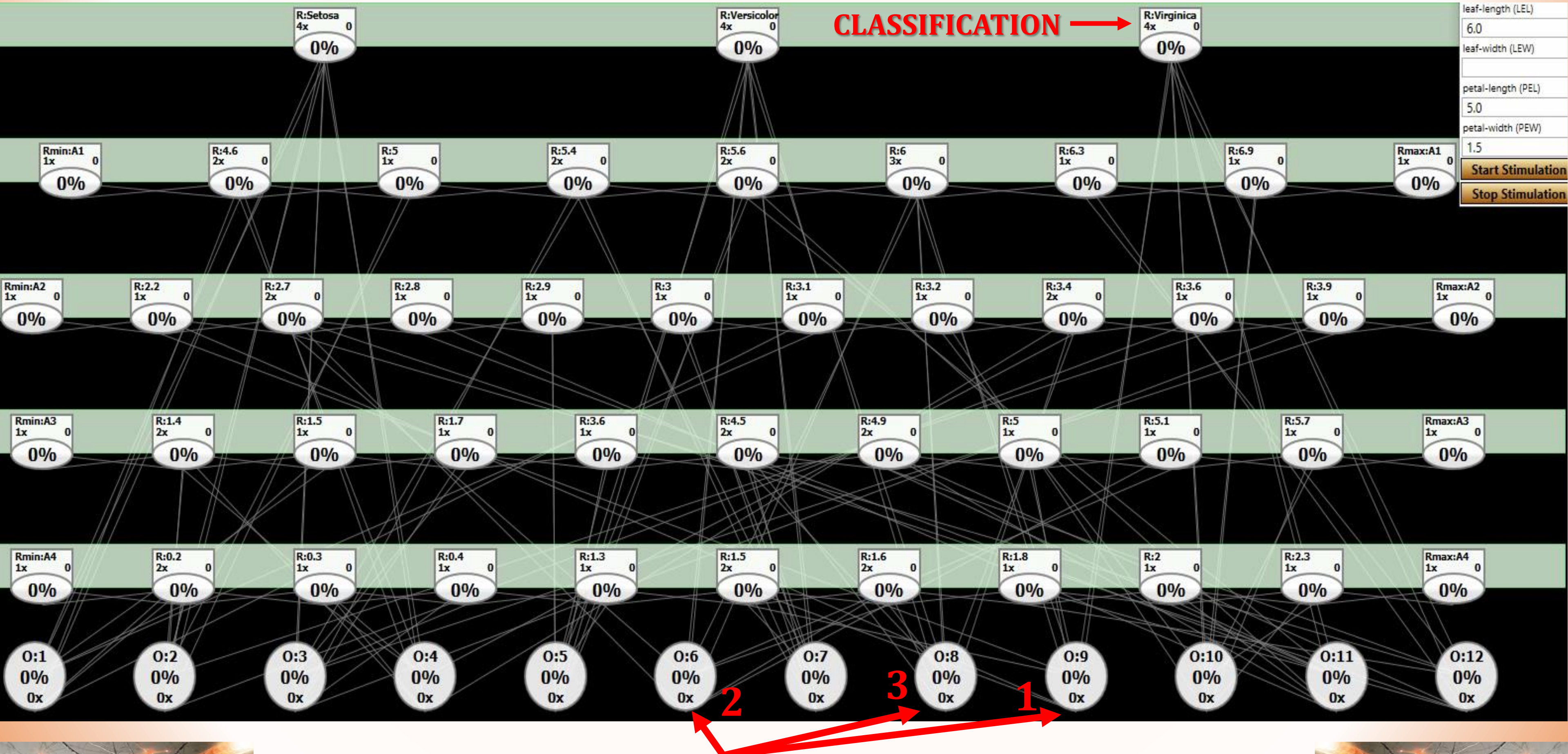


The most associated APNs representing the most similar training patterns will pulse first and the most frequently!

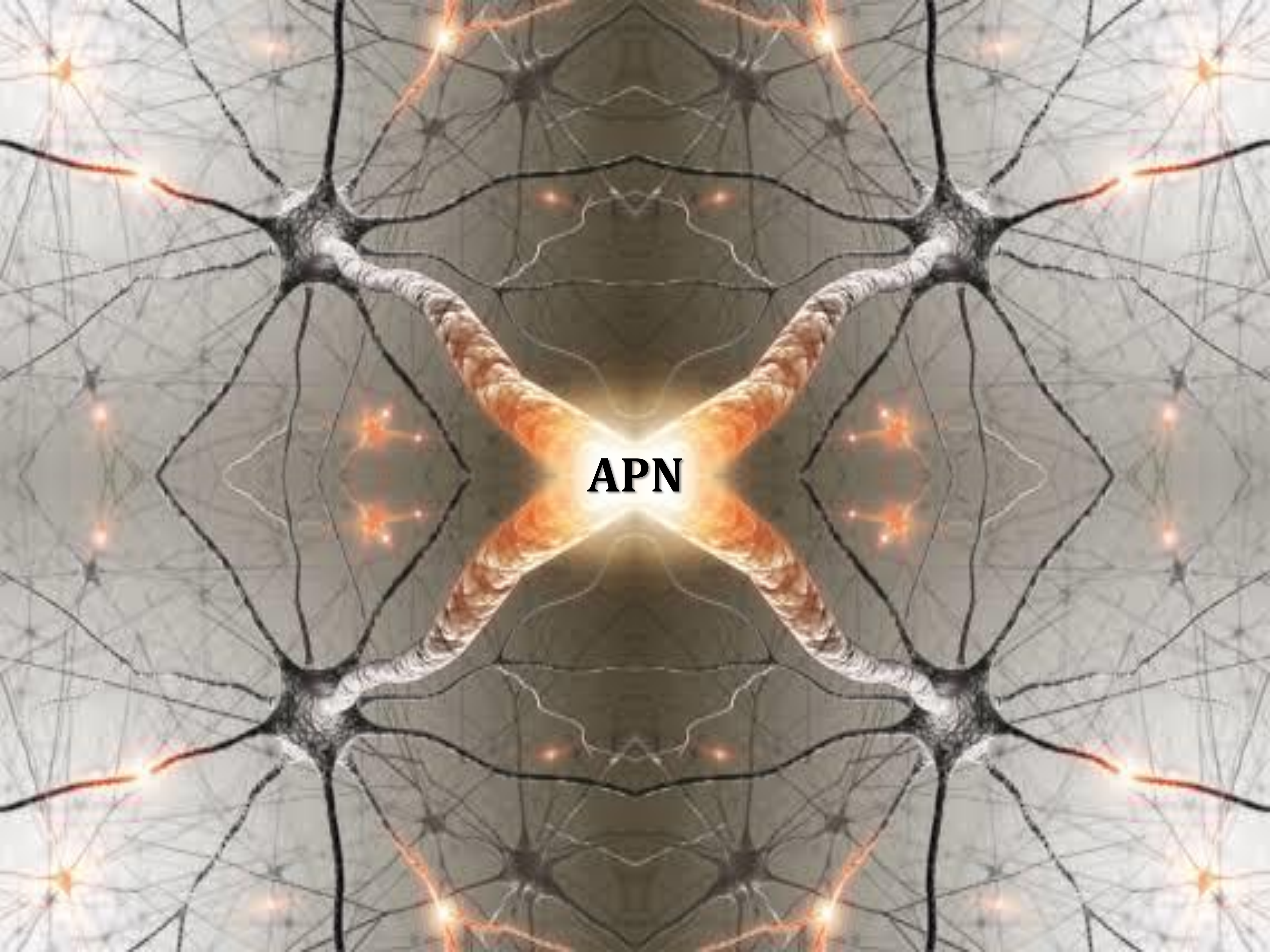
EXPERIMENTS & ANIMATION with APN Neural Network

Let's use a bigger data set and stimulate receptors with the same vector [?, 6.0, ?, 5.0, 1.5].

O:1	Setosa;	4.6;	3.1;	1.5;	0.2
O:2	Setosa;	5.0;	3.6;	1.4;	0.2
O:3	Setosa;	5.4;	3.9;	1.7;	0.4
O:4	Setosa;	4.6;	3.4;	1.4;	0.3
O:5	Versicolor;	5.6;	2.9;	3.6;	1.3
O:6	Versicolor;	6.0;	2.7;	5.1;	1.6
O:7	Versicolor;	5.4;	3.0;	4.5;	1.5
O:8	Versicolor;	6.0;	3.4;	4.5;	1.6
O:9	Virginica;	6.0;	2.2;	5.0;	1.5
O:10	Virginica;	6.9;	3.2;	5.7;	2.3
O:11	Virginica;	5.6;	2.8;	4.9;	2.0
O:12	Virginica;	6.3;	2.7;	4.9;	1.8



The most associated APNs representing the most similar training patterns will pulse first and the most frequently!


APN

Conclusions

The fundamental question from neuroscience about the way the information is encoded and decoded after the action potentials has been answered:

- **The frequencies of series of pulses of neurons represent adequate strengths of associations of various pieces of information and the similarity of objects.**
- **Temporal differences between pulses have no direct meaning, however the time is crucial for all internal neuronal processes and sequences of pulses.**

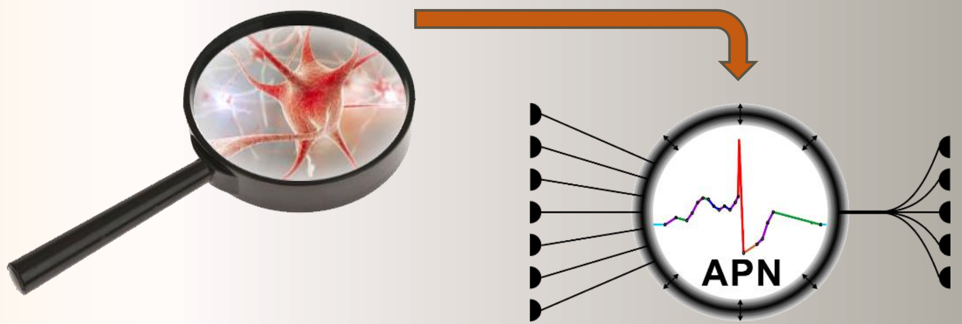
Conclusions

- Associative Pulsing Neurons (APNs) represent these time-spread combinations of input stimuli which make them pulsing.
- The Associative Pulsing Neurons which pulse first and most frequently represent the most associated values, objects, or pieces of information with an input context, and represent the answer of the neural network that is distributed in time according to the time of the pulses.

Conclusions

Associations represented by APN connections can represent various relations:

- **Similarity** of values or objects
- **Proximity** of objects in space
- **Succession** of objects in time
- **Context** for further stimulations



Conclusions

APN neurons are updated in discrete moments of time:

- **when a new external stimulus comes,**
- **when the internal process is finished.**

These features of the APN model determine the high speed of simulation together with the smart implementation of short IPQs and the GEQ.

Conclusions

APN internal processes are efficiently managed, updated, and ordered by:

- **IPQ – Internal Process Queue** which transforms all stimulations to the form of subsequent and not overlapping in time processes in each neuron.
- **GEQ – Global Event Queue** which sorts and watches out all the order and moments in time when each neuron should be updated.

Conclusions

- APN neurons **create a dedicated network structure** for given training data automatically and very fast in comparison to other ontogenic algorithms.
- APN neural networks also **learn and work a few times faster** than many contemporary spiking models of neurons, e.g. Izhikevich spiking neurons, according to fast linear approximation and combinations of internal neural processes.

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