Multi-Class and Multi-Label Classification Using Associative Pulsing Neural Networks

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Brains and Neurons

How do they really work?

Real Neurons

- ✓ Work in parallel and asynchronously
- ✓ Associate stimuli context-sensitively
- ✓ Use time approach for computations
- ✓ Use temporal internal states and context
- ✓ Represent various data and their relations
- ✓ Use a context of other neuronal stimulations
- ✓ Self-organize neurons developing a structure
- ✓ Aggregate representation of similar data
- ✓ Store and recall data in the same manner
- ✓ Integrate memory and the procedures
- ✓ Provide plasticity to develop a structure to represent data and object relations

How do neurons work?

Brains

- ✓ Process various kind of data efficiently
- ✓ Combine memory and data processing
- ✓ Form, represent and provide knowledge
- ✓ Allow forming complex neuronal structures
- ✓ Self-organize representation of related data
- ✓ Have natural ability to aggregate and classify
- ✓ Can plastically change their neuronal structure to adapt to represent new data relations and their processing!
- ✓ Are the seat of intelligence

How do brains work?

Fundamental
Question of Neuroscience

How is information encoded and decoded by a series of pulses forwarded by neurons after action potentials?

- by a number of pulses (quantitative coding)?
- by a rate of pulses (rate coding)?
- by temporal differences between pulses (temporal coding)?

How information is coded?

Objectives and Contribution

Implementation of associative mechanisms inspired by real neurons to develop and self-organize associative pulsing neurons (APN) in order to:

- ✓ **represent any training data without supervised learning,**
- ✓ **allow APN neurons to classify input data to one or many classes of the same (multi-class classification) or different attribute (multi-label classification).**

using quantitative and rate coding for interpretation of achieved results.

Classification Types

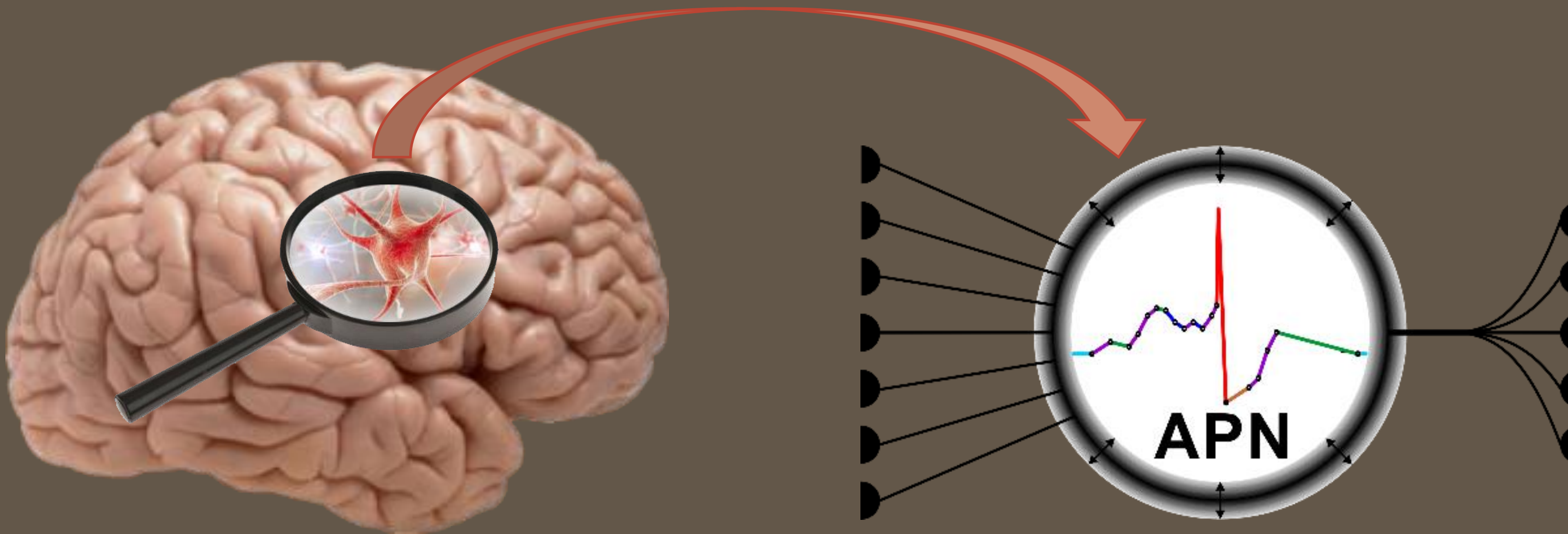
Multi-class classification tasks occur when there are multiple categories (classes), but each pattern is assigned only to one of them.

Multi-label classification tasks occur when each pattern can be associated with multiple categories (classes), i.e. when we have a set of target labels.

Multi-classification tasks are very common in our world and everyday life! People choose between various labels and classes flexibly and quickly.

Associative Pulsing Neurons APN

- ✓ Were developed to reproduce plastic and associative functionalities of real neurons.



- ✓ They implement internal neuronal processes and efficiently manage their processing.

Reproduction of functionalities,
not a biological substance!

Differences of APN and Spiking Models

Spiking Neurons:

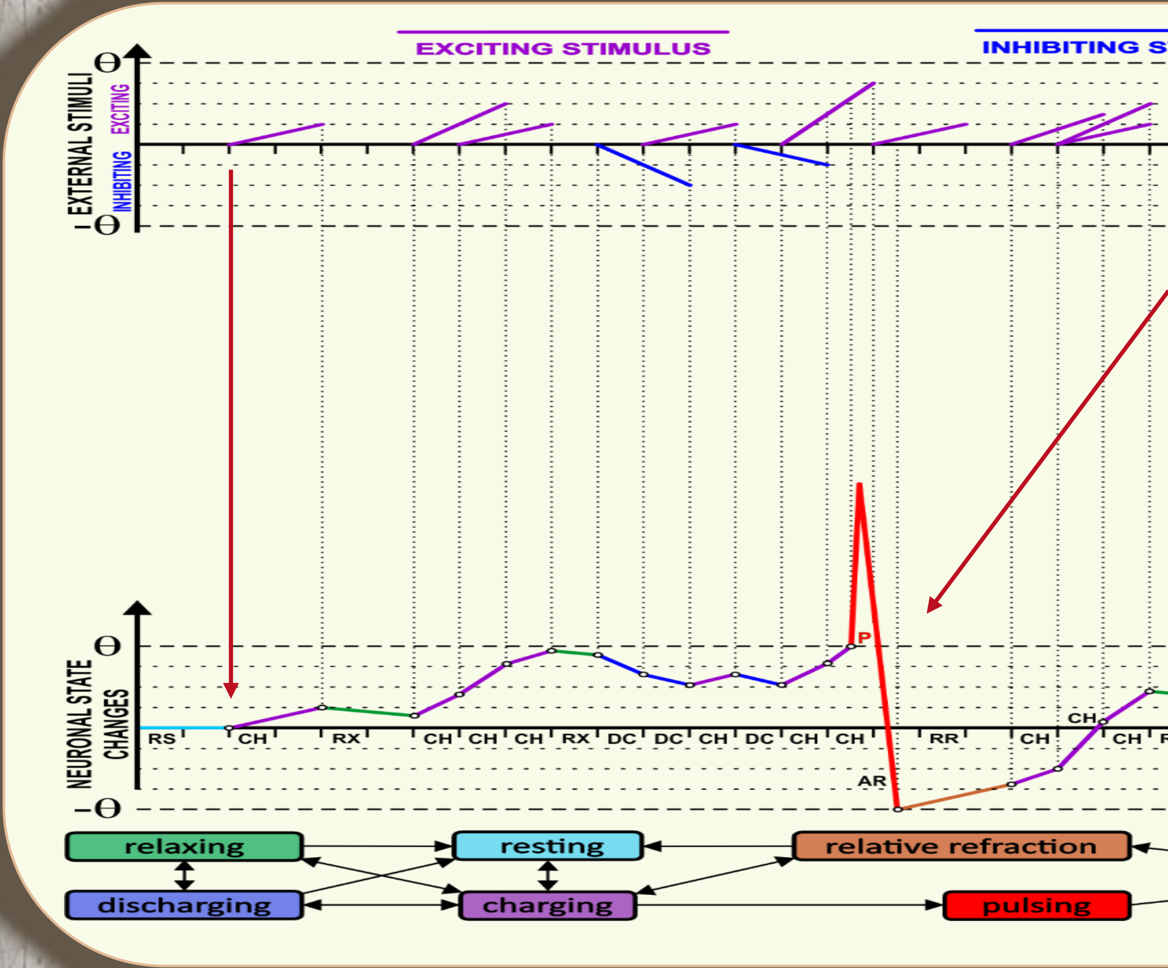
- ✓ Focus on the reliable and accurate reproduction of a biological platform and processes in membranes (e.g. electrical potentials).
- ✓ Do not define neurogenesis and plasticity processes which let spiking neurons connect automatically and develop their structure.
- ✓ The internal processes are defined by complex mathematical functions which take a lot of processing time.

Associative Pulsing Neurons:

- ✓ Focus on the reproduction of functional aspects of real neurons, especially on associative processes that take place in real brains.
- ✓ Define conditional plasticity and neurogenesis processes which allow to develop and adapt a neuronal structure from scratch.
- ✓ The internal processes are efficiently managed and processed using Internal Process Queues and a Global Event Queue.

APNs reproduce functionality of real neurons, not a platform!

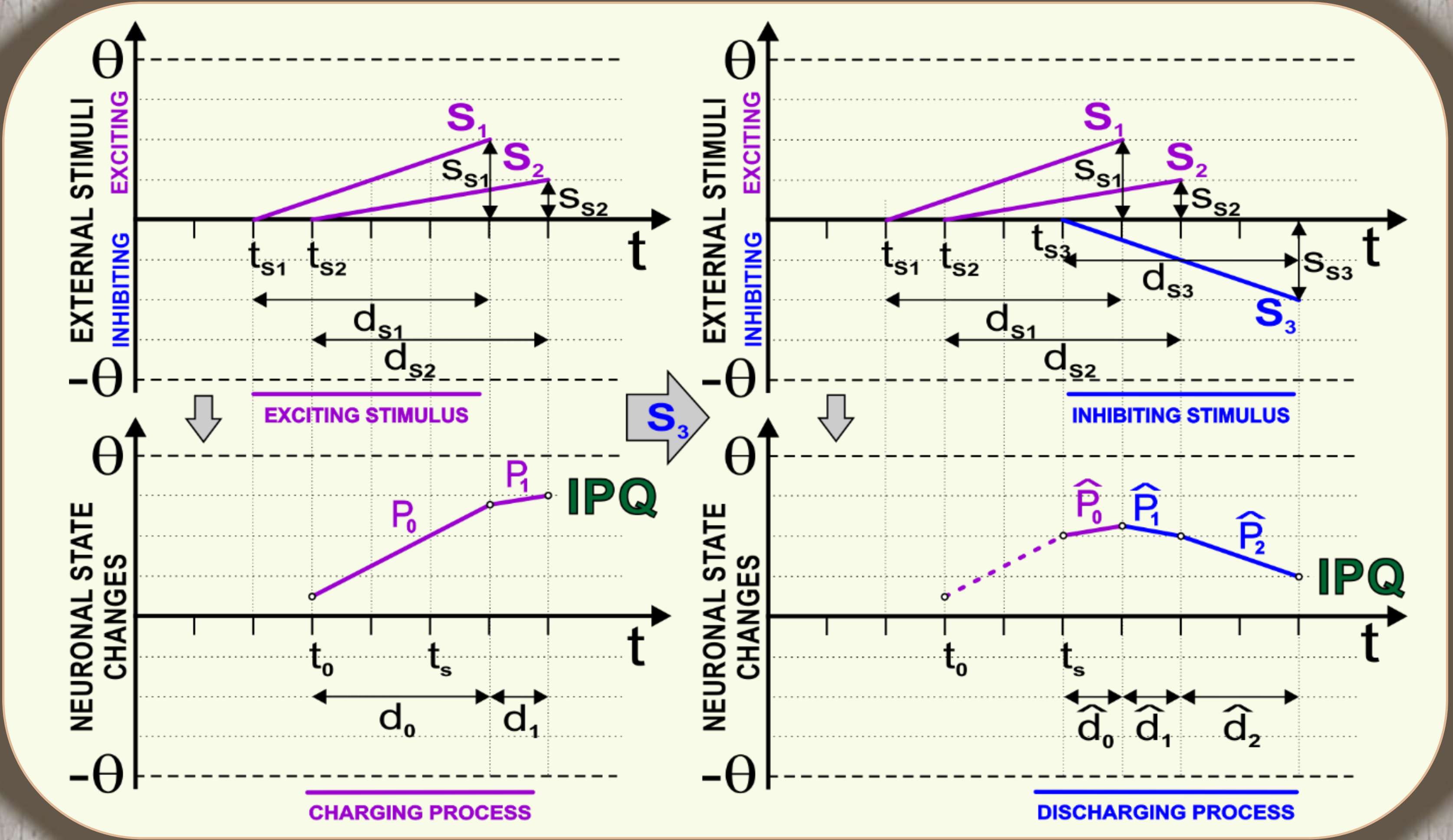
Each APN uses an IPQ Internal Process Queue



IPQ represents a short sequence of internal changes of a neuronal state dependent on the external stimuli and previous internal states of the neuron.

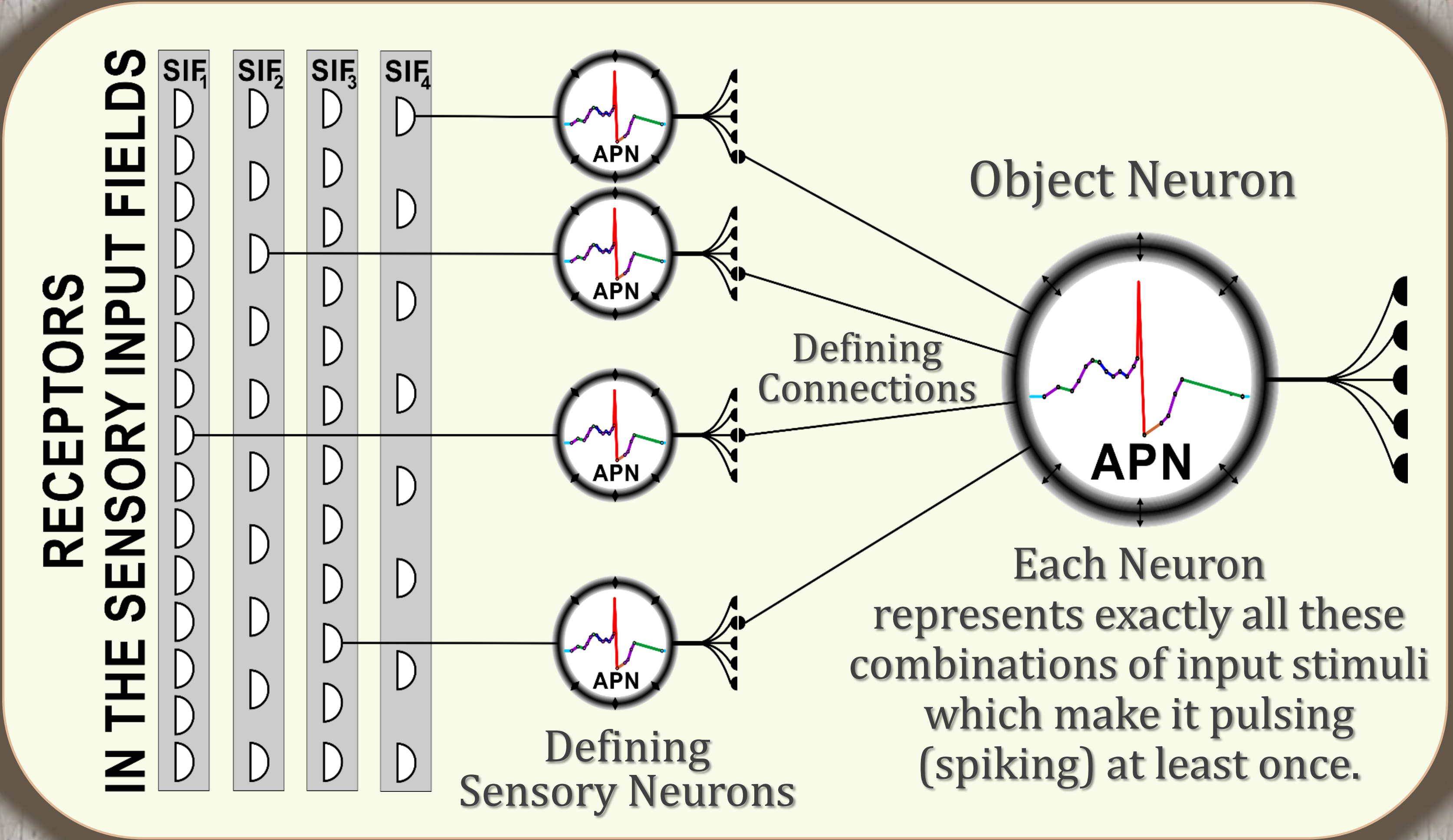
Internal states of APN neurons are updated only at the end of internal processes (IP) that are supervised by the Global Event Queue.

Internal Integration of
External Stimuli and Internal Processes



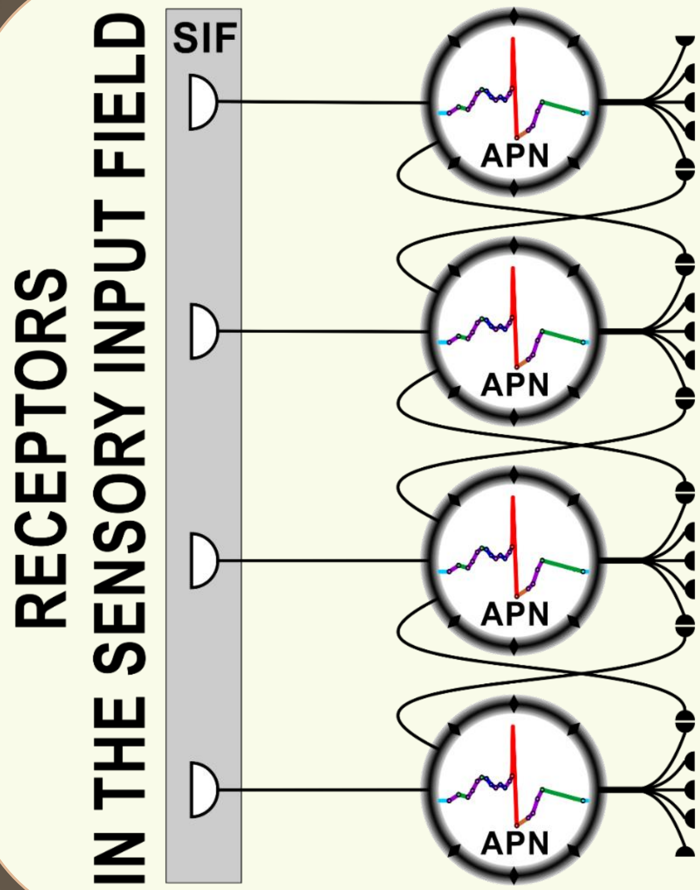
Upcoming new stimuli are integrated with the IPQ making changes in the overlapping IPs.

Objects are defined by the combinations of connected neurons



Any combination of neurons stimulating another neuron can define its content when they make it pulsing.

Neighbor connections allow for representation of similarities

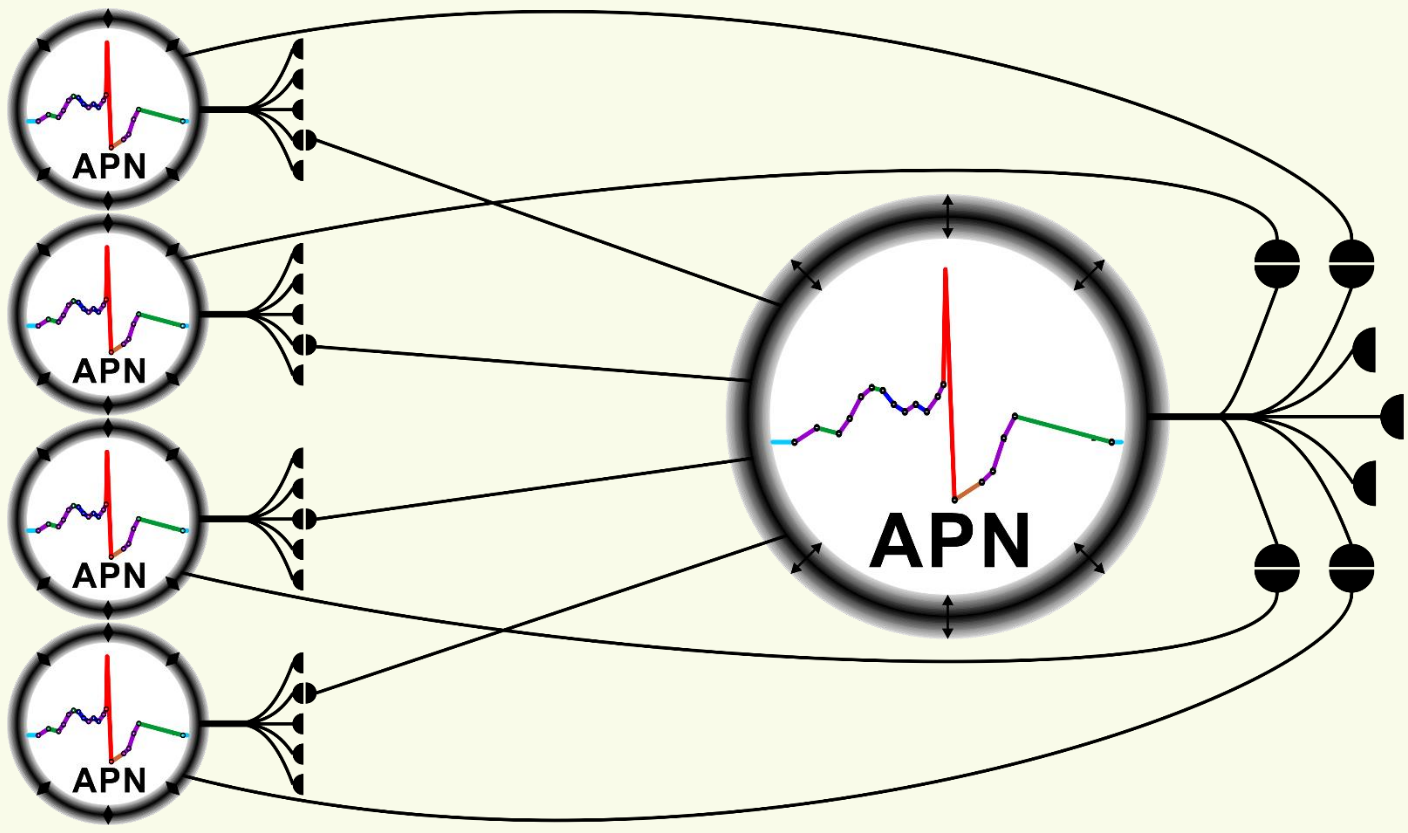


Neighbor connections between APN neurons allow representing associations of similarity between neurons representing similar values.

In result, such neurons take part in the creation of similarity associations between object neurons indirectly and allow for reasoning about similarities and classes.

Aggregated representation of the same features and connections to similar values allow for inferences about classes.

Double-sided connections allow two-sided inference

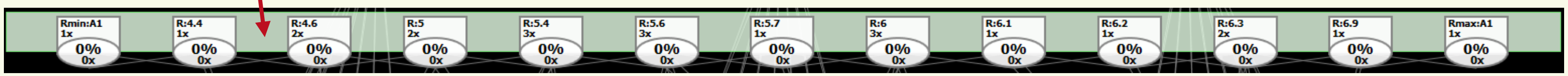


In the APN networks, neuronal connections can allow stimulating neurons in both directions to recall various associations.

APNN Basic Elements

Sensory Fields, Receptors, Sensory and Object Neurons

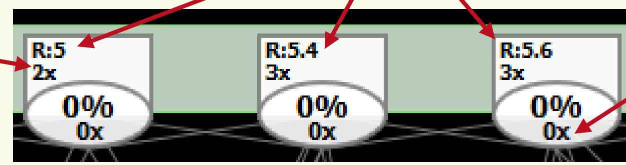
Each Sensory Field is sensitive for values of a given attribute (feature):



Receptors (rectangles) are sensitive for given values, their subsets or ranges:

Number of Aggregated Duplicates

Charging Level
(in percentage)

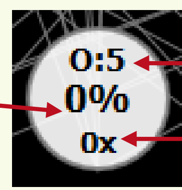


Number of Pulses
(activity status)

Sensory Neurons (ellipses) are stimulated and charged by the connected Receptors. They can also be connected to other Sensory Neurons representing similar values.

Object Neurons (circles) are defined by various combinations of pulses coming from Sensory Neurons (ellipses) and represent training samples:

Charging Level
(in percentage)



Object or Training Sample ID

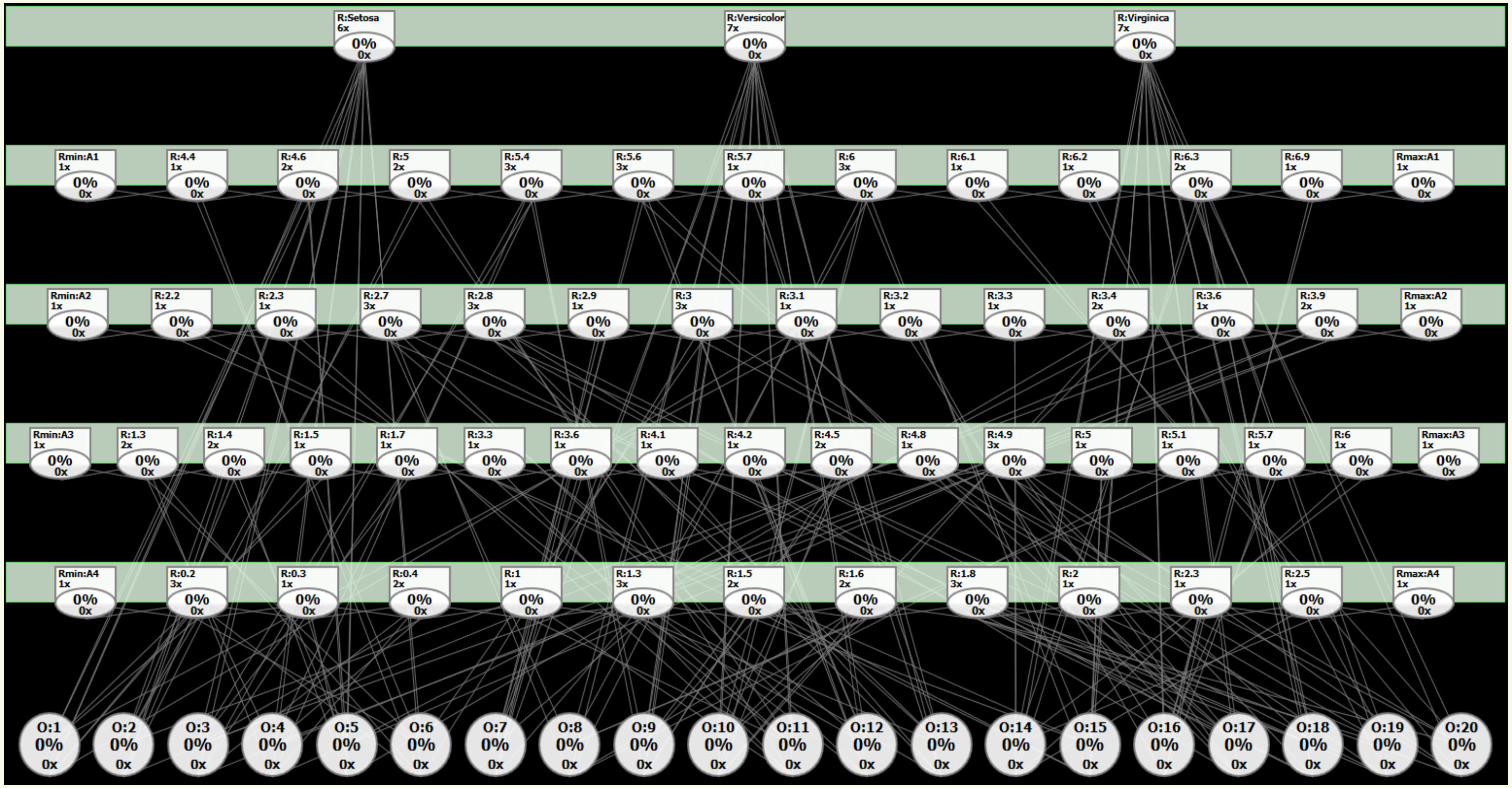
Number of Pulses (activity status)

Object Neurons represent combinations of input stimuli (values).

Receptors are sensitive for some input values.
Sensory Neurons transform these values
into pulses of appropriate rates.

Double-sided connections allow two-sided inference

Receptors and Sensory Neurons transforming input values.



Object Neurons representing combinations of input stimuli (values).

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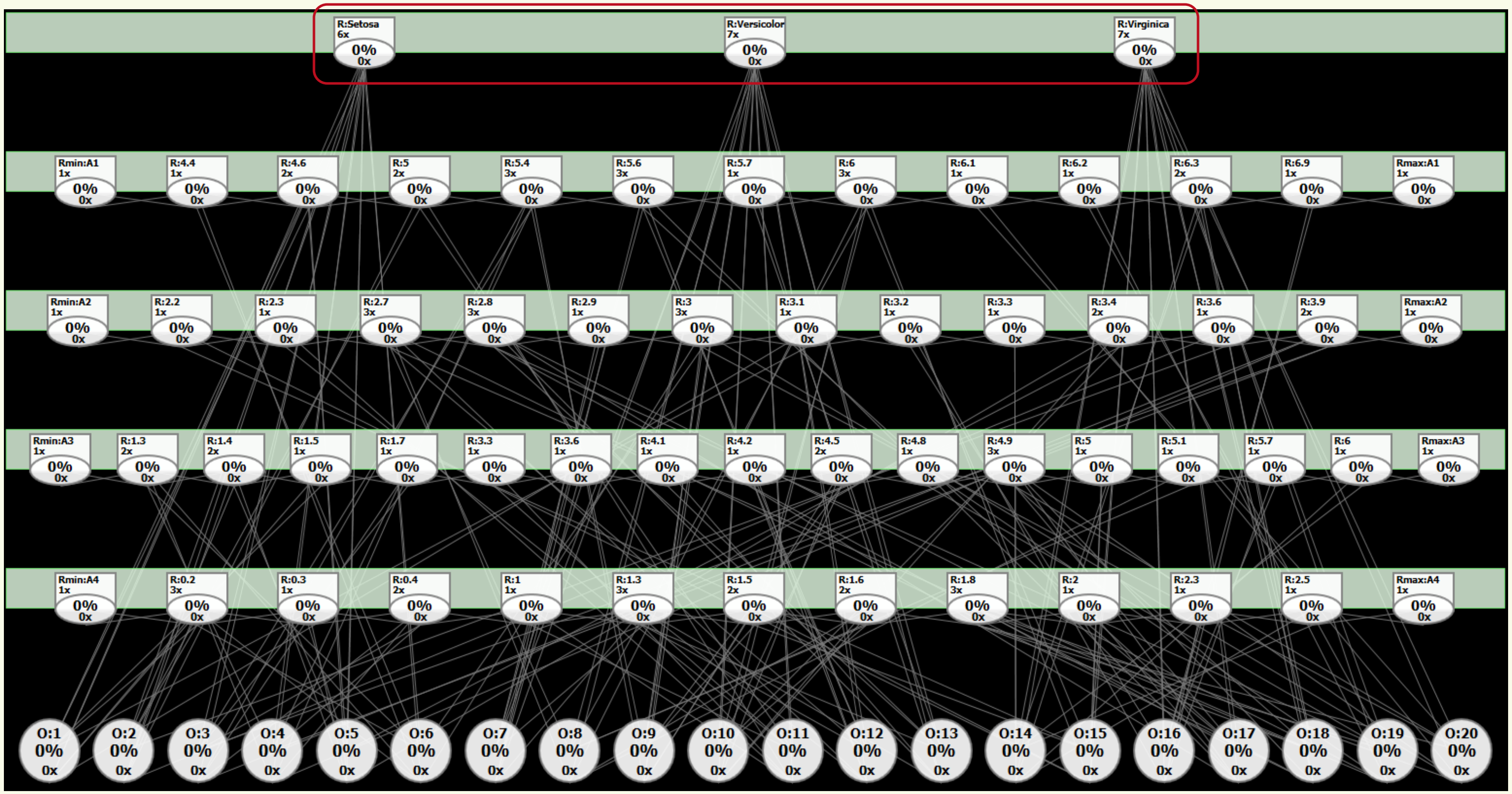
Class Labels and Attributes are treated in the same way!

Class Labels are treated and connected in the same way as other Attribute Values.



Object Neurons can be defined by any Attributes and Labels combinations.

We do not need to specify which Attribute defines Class Labels before the creation of the network. Every Attribute can be a Class!

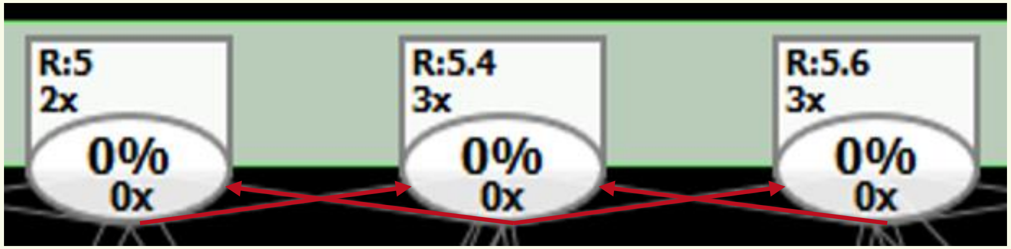
Connection Weights of Neighbor Sensory Neurons

Connection Weights between Sensory Neurons representing similar values are computed (not trained) on the basis of the similarities between the values represented by the connected Sensory Neurons:

$$w_{S_{v_i}^{a_k}, S_{v_j}^{a_k}} = \left(1 - \frac{\left|v_i^{a_k} - v_j^{a_k}\right|}{r^{a_k}}\right)^p$$

where r^{a_k} is the current range of values for the attribute a_k represented by the Sensory Field

p controls the influence on Sensory Neurons representing similar values



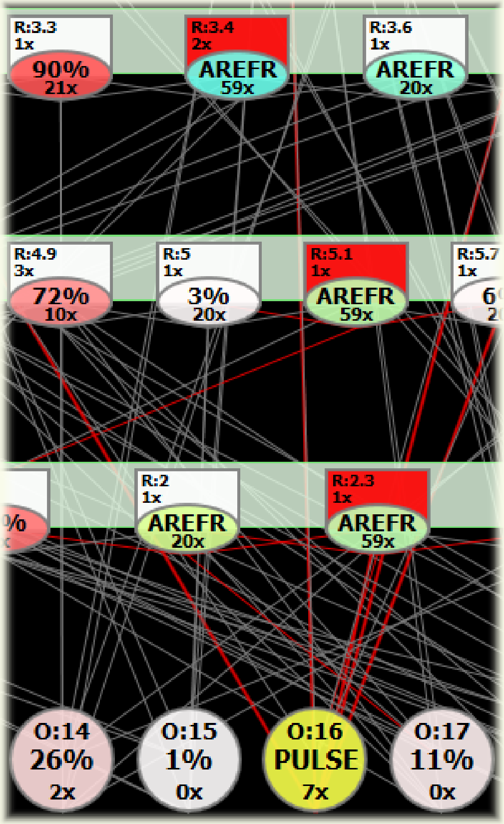
Connections between Sensory Neurons representing neighbor values represent associative similarity relations!

Connection Weights between Sensory and Object Neurons

Connection Weights between Sensory and Object Neurons represent associative defining relations. A few or many associative defining relations coming from Sensory Neurons define an Object Neuron, so the weights are computed in this way to activate the Object Neuron (make it pulsing) when the defining Sensory Neurons are fired:

$$w_{S_{v_i}^{a_k},O_j} = \frac{1}{K} \qquad w_{O_j,S_{v_i}^{a_k}} = \theta = 1$$

where θ is the activation threshold of APN neurons which is always equal to one here.
K is the number of attributes defining each Object Neuron in this dataset.



This APNN used for multi-classification tasks uses only associations of similarity and defining associations.

Receptor Reactions to the Stimulation of a Sensory Field

Receptors are sensitive for given values, ranges or subsets of values.
In the presented solution, the receptor sensitiveness was defined as:

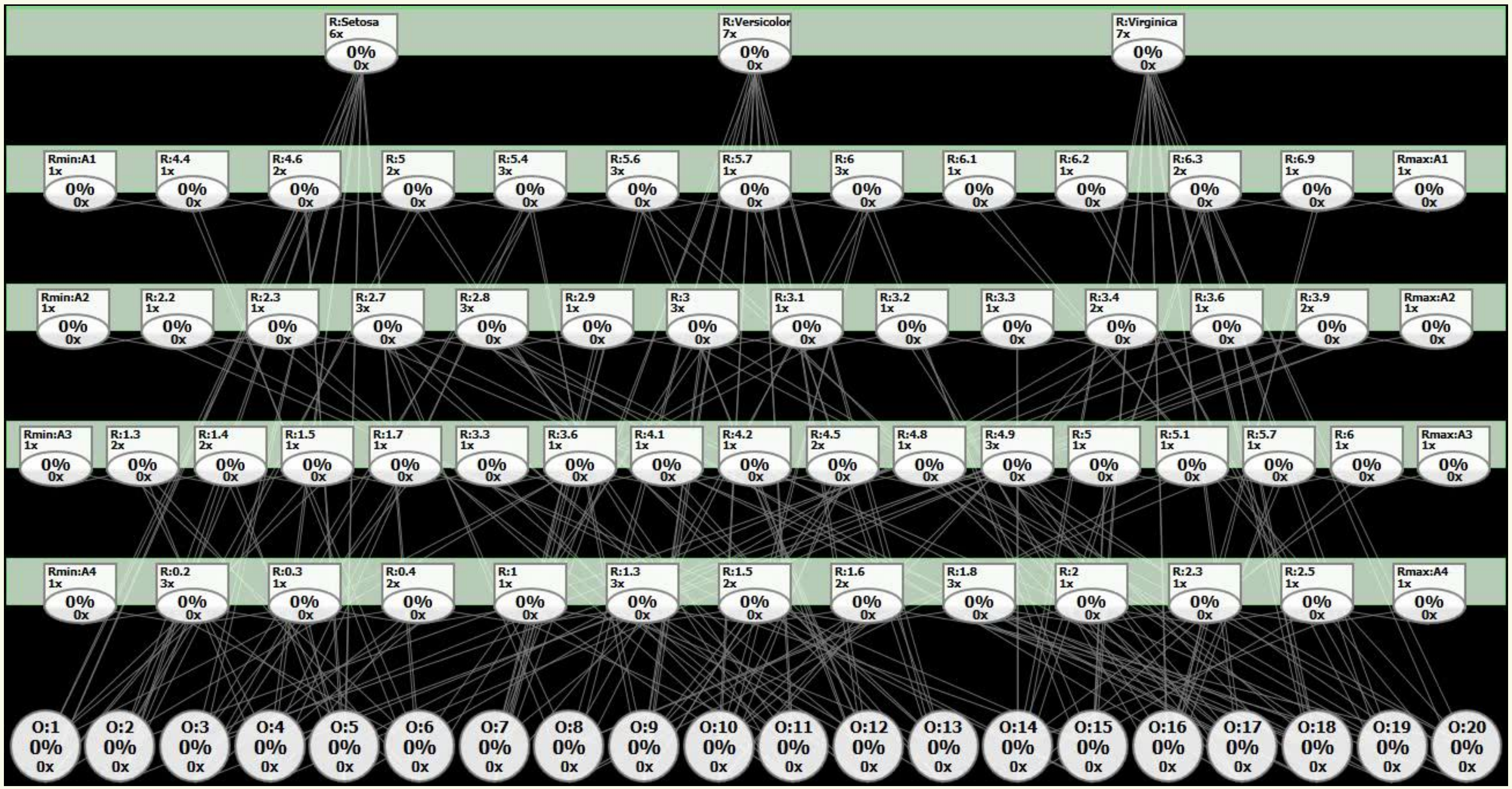
$$x_{v_i}^{a_k} = \begin{cases} \left(1 - \dfrac{\left|v_i^{a_k} - v^{a_k}\right|}{r^{a_k}}\right)^q & if\ r^{a_k} > 0 \\ \left(\dfrac{\left|v_i^{a_k}\right|}{\left|v_i^{a_k}\right| + \left|v_i^{a_k} - v^{a_k}\right|}\right)^q & if\ r^{a_k} = 0 \end{cases}$$

q controls the input influence on Sensory Neurons representing less similar values.

Receptors play a very important role in the APNN networks, allowing their adequate configuration and correct work!

The number and rate of pulses define the answer of the network

The most frequently pulsing Sensory Neurons represent the strongest association.



The most frequently pulsing Object Neuron represents the recognized pattern.

This network recognized training pattern No. 16,
The missing value 6.9 of the leaf-length attribute, and
classified inputs [?, 3.4, 5.1, 2.3] as Virginica!

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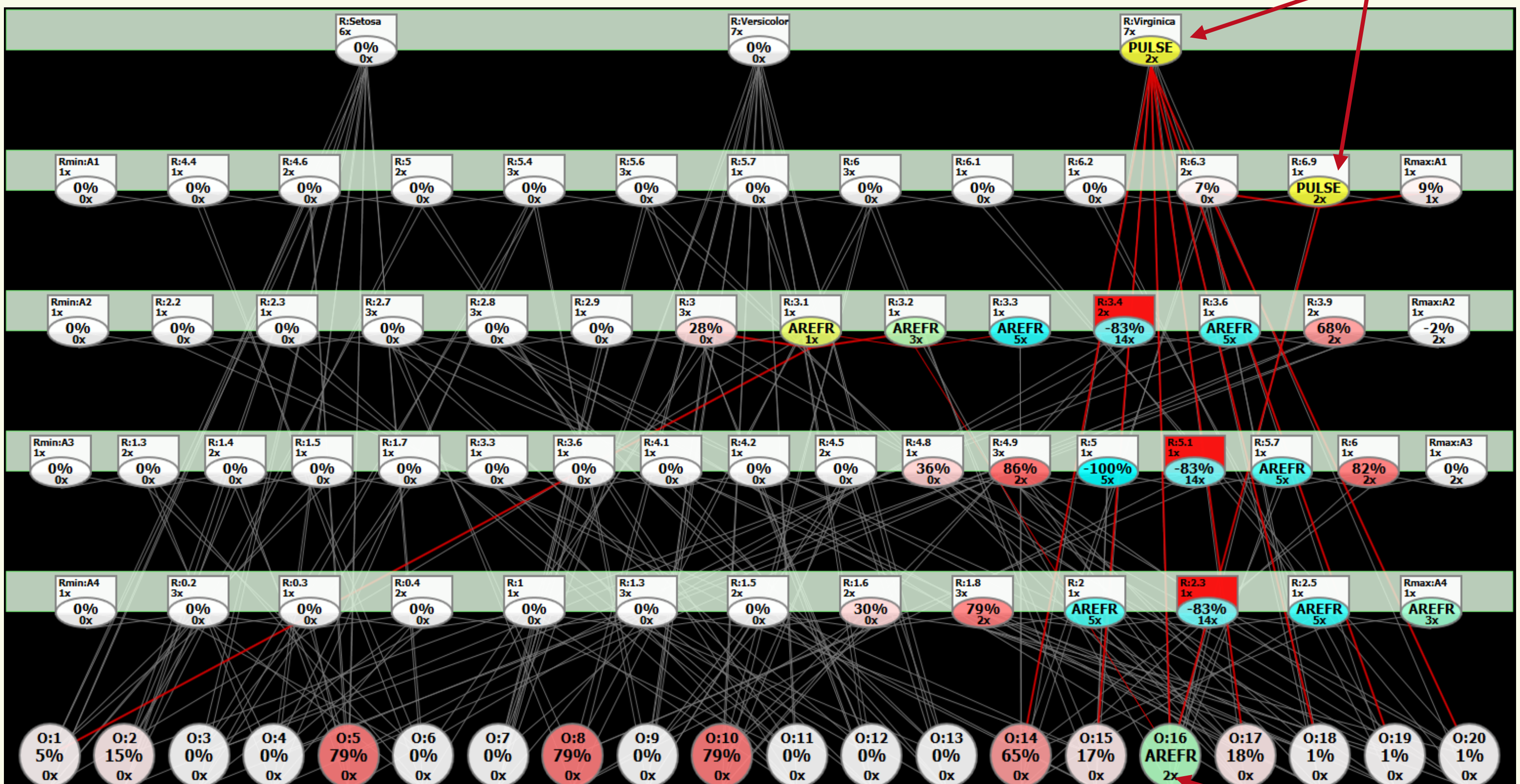

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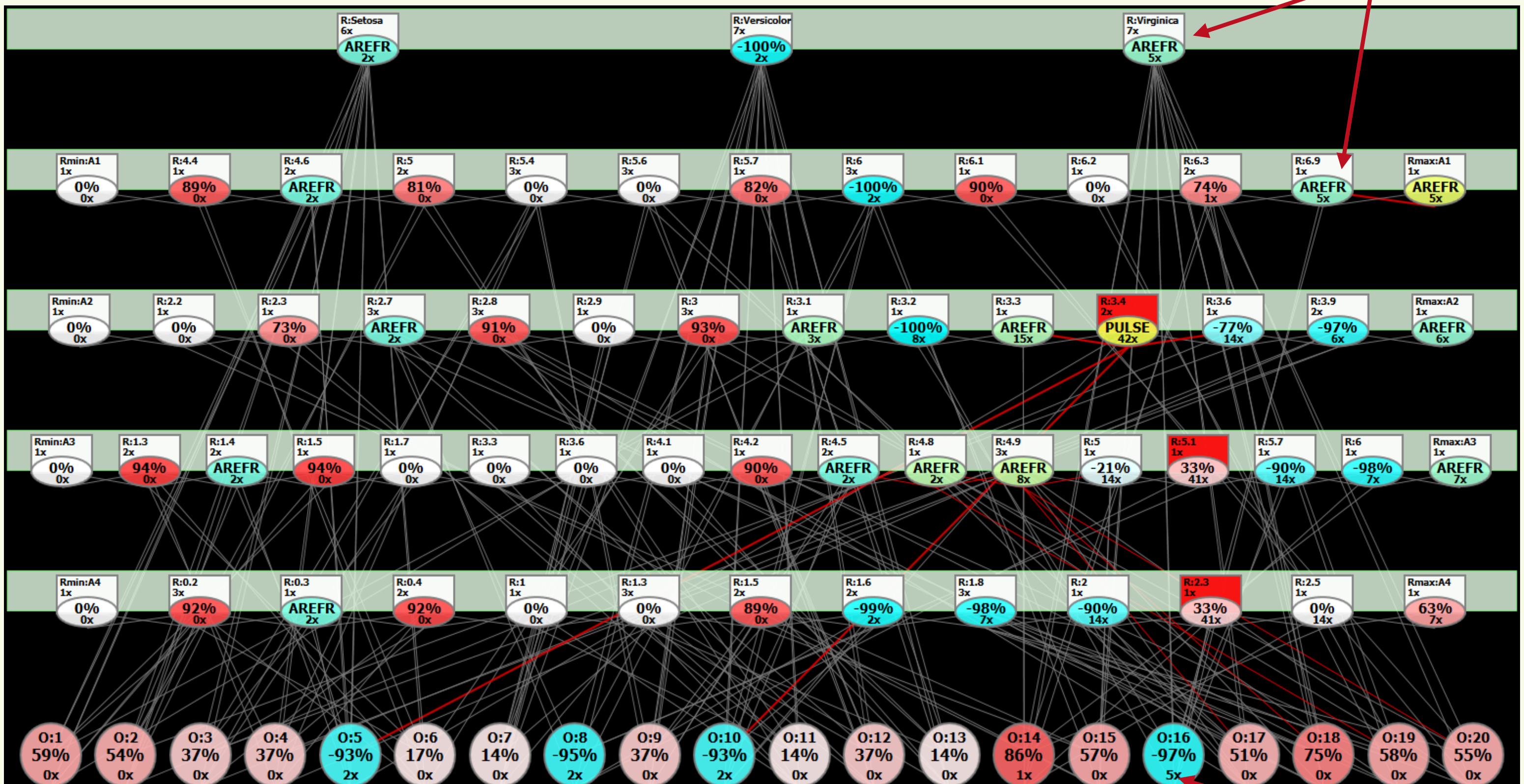

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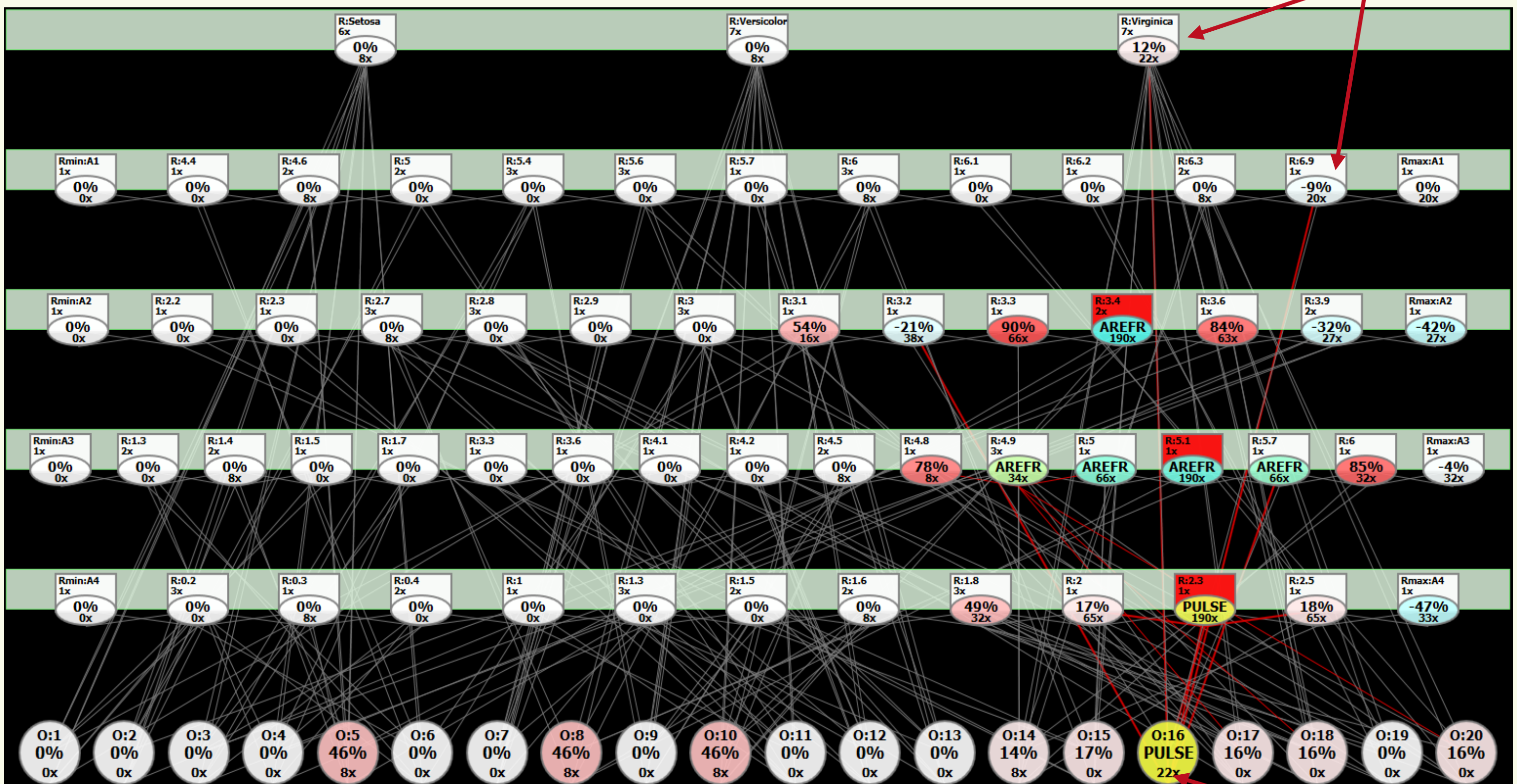

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Results of Classification for Various Datasets

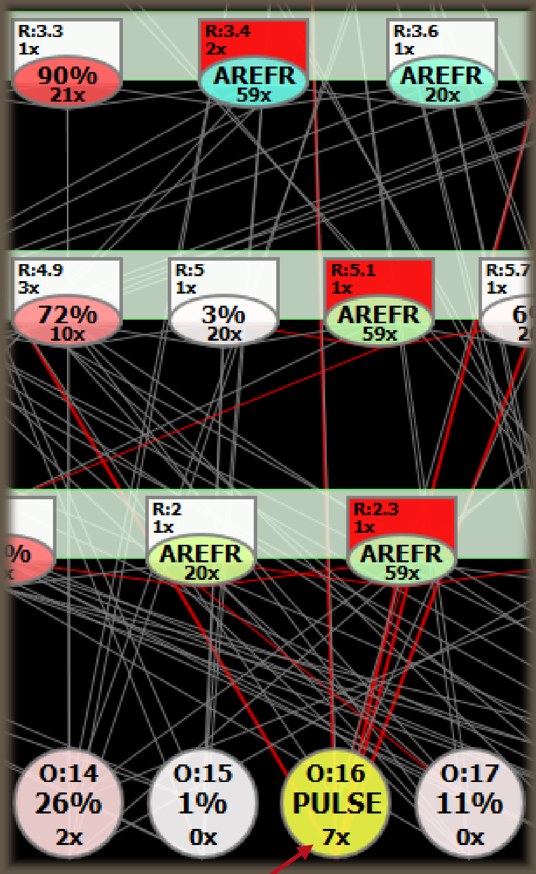
Datasets	APNN	The Best Classifiers	Time *
Iris (p=1, q=1)	99.47%	98,45% = 99,8% (MLP; RBFN; PNN; NaiveBayes; ROC Area) [29]	6.02 s
Wine (p=1, q=1)	98.48%	97,8% - 98,9% (kNN, Manhattan, auto k=1-10; IncNet, Gauss; SSV opt prune) [28]	6.33 s
Cars Evaluation (p=1, q=1)	97.24%	93,22% - 93,51% (Decision Trees; NaiveBayesian; MLP [30]	41:12.76 s
Breast Cancer Wisconsin (p=1, q=1)	95.58%	97,0% - 97,5% (Naïve MFT; SVM Gauss, C=1, s=0.1; NB + kernel est) [27][28]	10:21.01 s

* The total time of the creation, adaptation, and 10-folds CV of APNNs

The achieved classification results are comparable to the best classifiers used in Computational Intelligence!

Answer to the Fundamental Question of Neuroscience

The presented APNN neural network showed that the APN neurons use the quantitative and rate coding to represent answers – the strength of associations between outputs and input stimuli which strength is based on the transformations made by Receptors.



Numbers of pulses code answers!

Conclusions

- ✓ APNN networks are based on the conditionally created associative connections.
- ✓ Weights are computed on the basis of similarity, location, types of connections, a number of activations, the time passed between activations or other approaches.
- ✓ APNN networks consist of various kinds of differently specialized neurons.
- ✓ The presented approach used Sensory Neurons charged by Receptors represented aggregated attribute values and Object Neurons defining training objects.
- ✓ Associative Pulsing Neural Networks (APNNs) constructed from Associative Pulsing Neurons (APNs) thanks to the similarity and defining connections allow for successful single-class, multi-class, and multi-label classification, pattern recognition, finding missing values or similar training patterns simultaneously.

Questions or Remarks?

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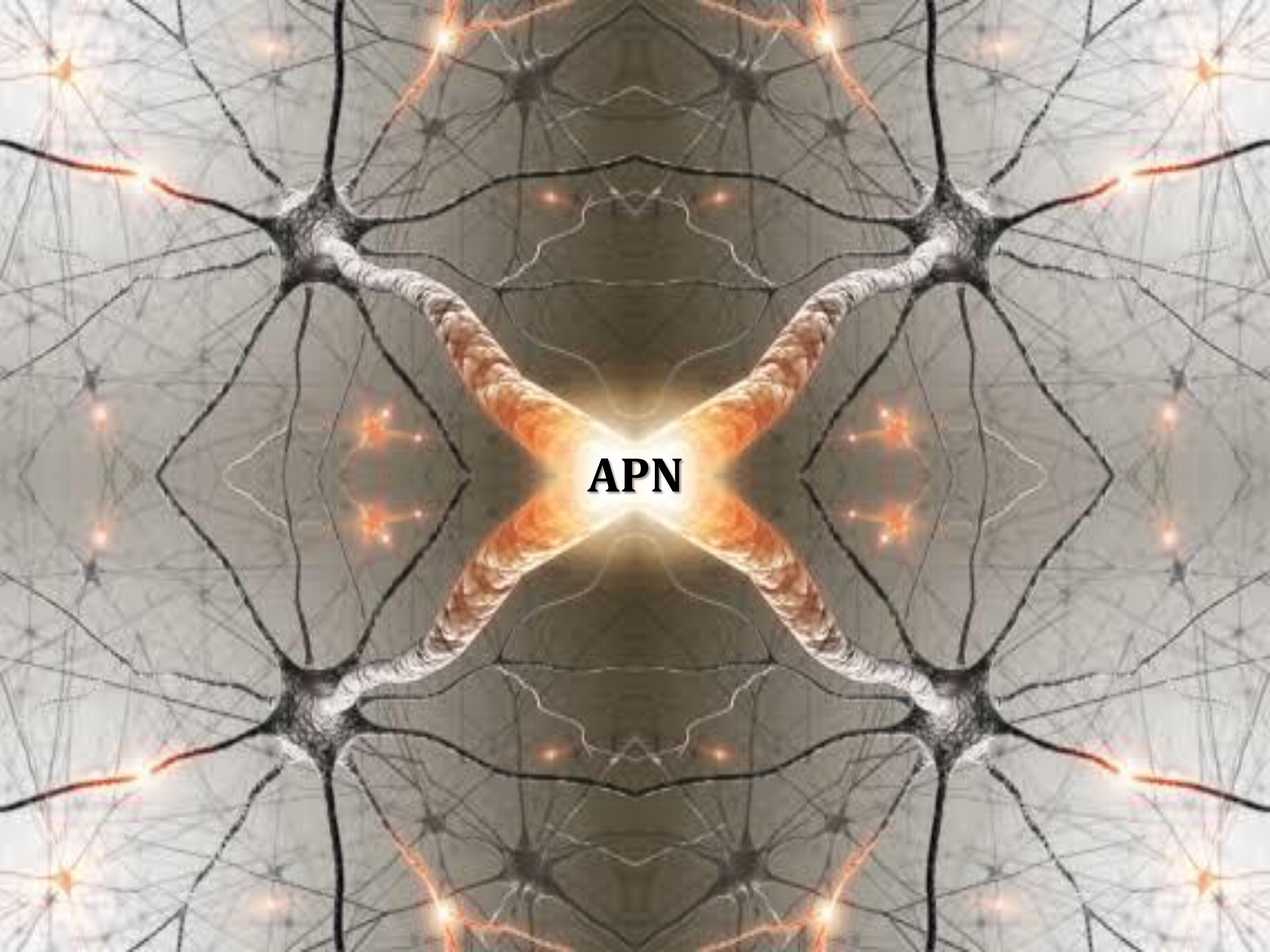
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