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Associative Fine-Tuning of Biologically Inspired Active Neuro-Associative Knowledge Graphs

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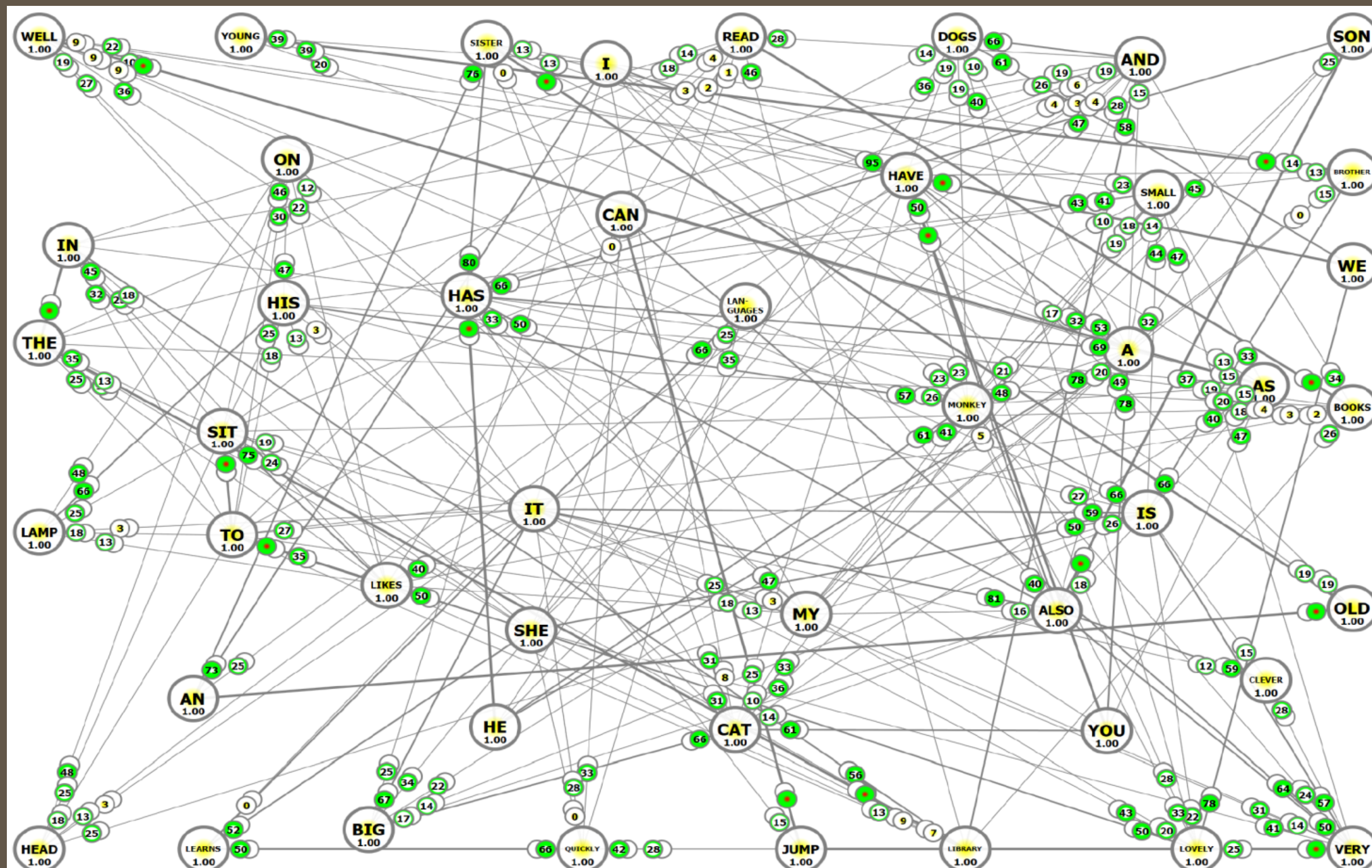
Research inspired by brains and biological neurons

- ✓ Work in parallel and asynchronously
- ✓ Associate stimuli context-sensitively
- ✓ Use time approach for computations
- ✓ Represent various data and their relations
- ✓ Self-organize neurons developing a very complex structure
- ✓ Aggregate representation of similar data
- ✓ Integrate memory and the procedures
- ✓ Provide plasticity to develop a structure to represent data and object relations

ACTIVE NEURO-ASSOCIATIVE KNOWLEDGE GRAPHS (ANAKG)



- ✓ ANAKG produces a complex graph structure of dynamic and reactive neurons and connections to represent a set of training sequences.
- ✓ Neurons aggregate all instances of the same elements that occur in all sequences.

Objectives and Contribution

- ✓ Construction of the fine-tuning algorithm for synaptic weights to achieve better recalling of associatively stored training sequences and better generalization.
- ✓ Avoid unintended activations to stop possible false-recalling of sequences.
- ✓ Construct a well-aggregative model for storing correlated training sequences.
- ✓ Reproduce functionality of the biological neural substance.

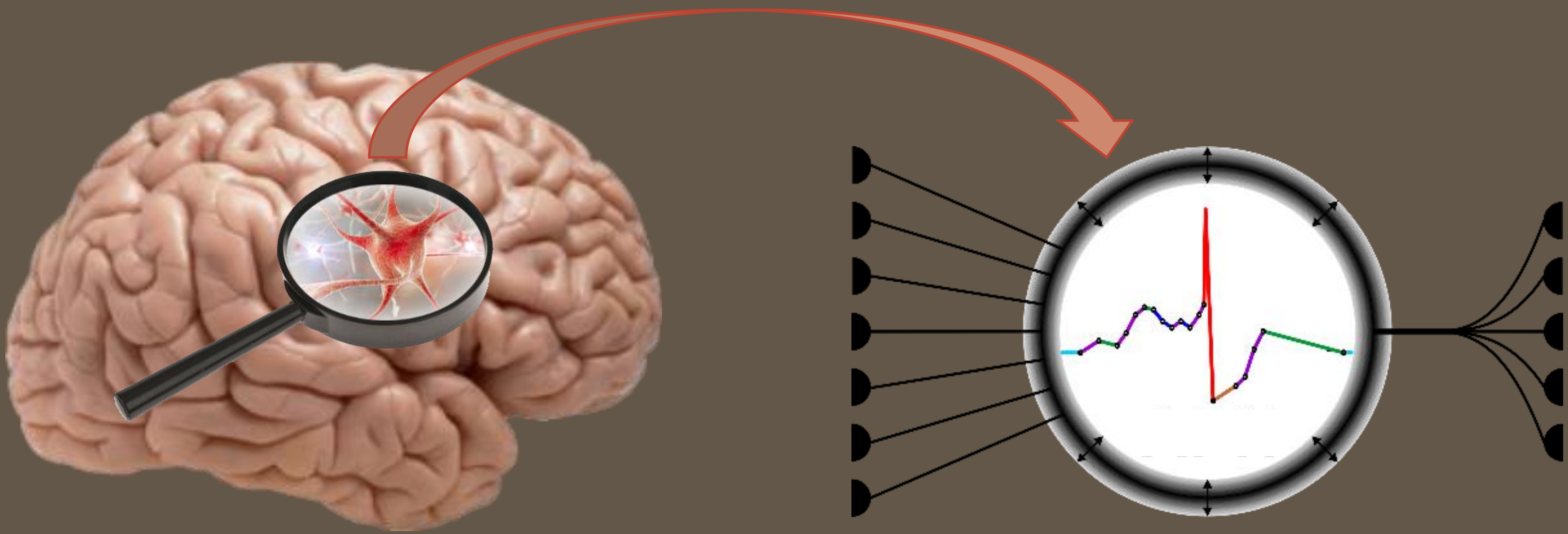
ASN Neurons

- ✓ Connect context-sensitively to emphasize training sequences and automatically develop an ANAKG network structure.
- ✓ Aggregate representations of the same elements of the training sentences - no duplicates!
- ✓ Work asynchronously in parallel because time influences the results of the ANAKG network.
- ✓ Integrate memory and associative processes

GOAL: Reproduce functionality of the biological neural substance!

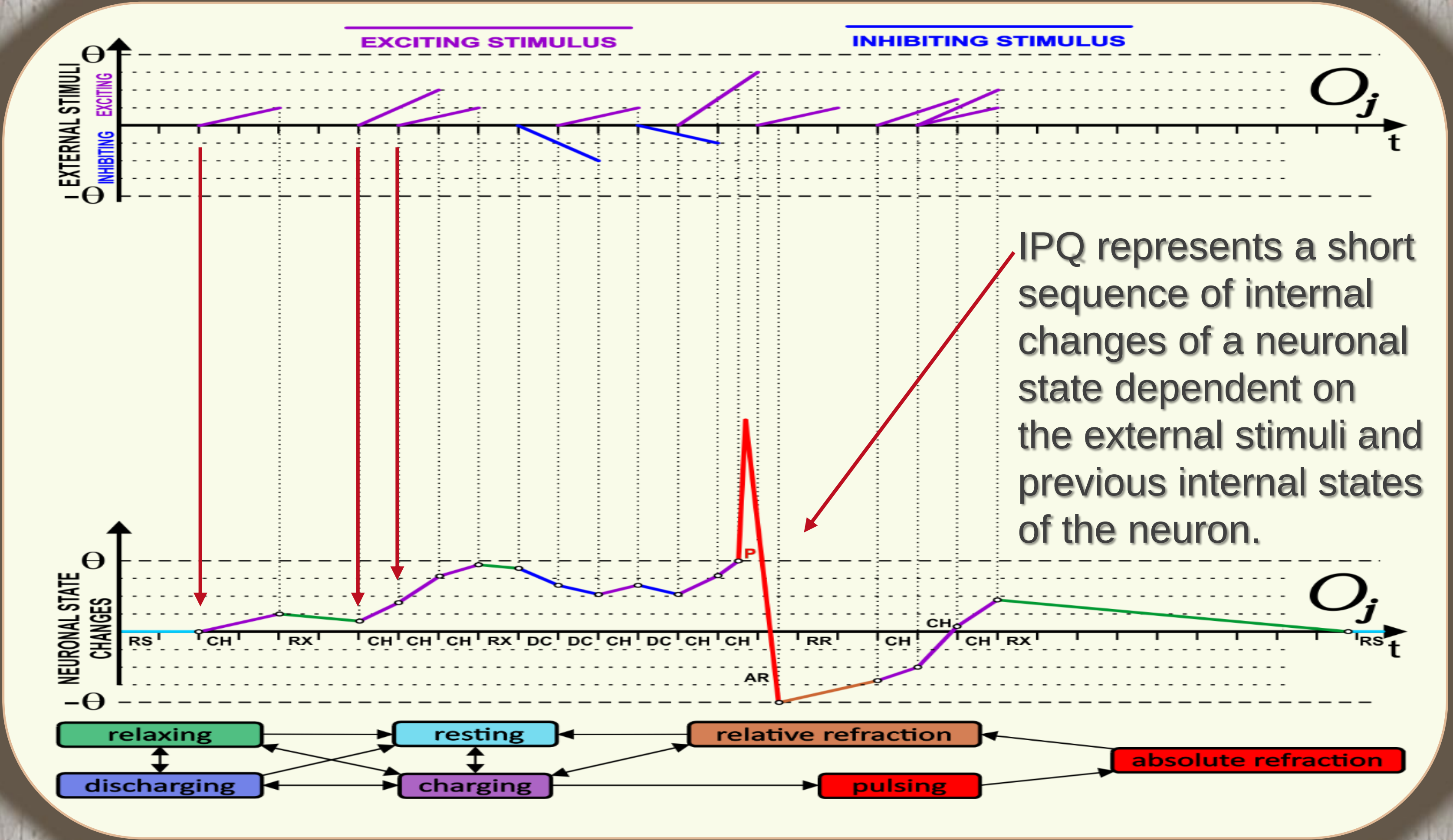
Associative Spiking Neurons ASN

- ✓ Were developed to reproduce plasticity and associative properties of real neurons that work in time.



- ✓ They implement internal neuronal processes (IP) and efficiently manage their processing using internal process queues (IPQ) and a global event queue (GEQ).
- ✓ ASN neurons are updated only at the end of the internal processes (not continuously) to provide efficiency of data processing!

How ASN neurons work and how they are modeled?



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

Model and Adaptation of Associative Spiking Neurons

Synaptic efficacy defines the efficiency of the synapsis of the stimulations and spiking reactions of the postsynaptic neurons:

$$\delta_{N_m,N_{m+r}} = \sum_{\{(S_m,S_{m+r}) \in S^n \in \mathbb{S}\}} 1/\left(1+\frac{\Delta t^A - \Delta t^C}{\theta_{N_{m+r}} \cdot \Delta t^R}\right)^{\tau}$$

It depends on:

Δt^A - the period of time that lapsed between the stimulation of the synapse between the N_m and N_{m+r} neurons and the activation of the postsynaptic neuron N_{m+r} during training of the training sequence set $\mathbb{S} = \{S^1, \dots, S^N\}$;
Δt^C - the period of time necessary to charge and activate the postsynaptic neuron N_{m+r} after stimulating the synapse between the N_m and N_{m+r} neurons (here Δt^C);
$\Delta t^R = 200\mathrm{ms}$ - the maximum period of time during which the postsynaptic neuron N_{m+r} recovers and returns to its resting state after its charging that was not strong enough to activate this neuron;
$\theta_{N^n_{m+r}} = 1$ - the activation threshold of the postsynaptic neuron N_{m+r};
$\tau = 4$ - the context influence factor changing the influence of the previously activated and connected neurons on the postsynaptic neuron N_{m+r}.

Model and Adaptation of Associative Spiking Neurons

Synaptic efficacy δ and the number η of activations of the presynaptic neuron N_m during training of the training sequence set $\mathbb{S}$ is used to define synaptic permeability p:

$$p = \theta \cdot \frac{2 \cdot \delta}{\eta + \delta}$$

OR

$$p = \theta \cdot \frac{\eta \cdot \delta}{\eta \cdot \delta + \eta^2 - \delta^2}$$

Which is finally used to compute synaptic weights:

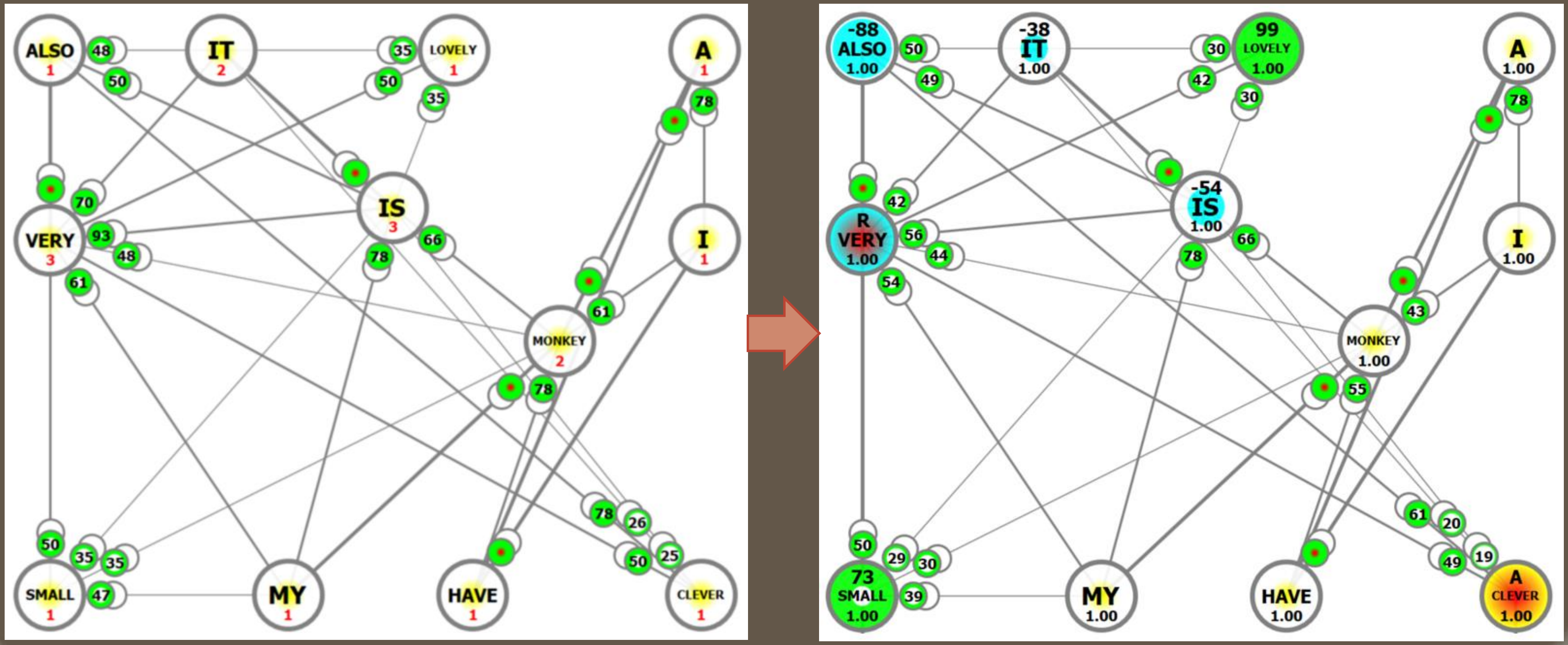
$$w = c \cdot p \cdot m$$

where c is the synaptic influence: excitatory (c = 1) or inhibitory (c = −1), and m is the multiplication factor modeling the number of synapses connecting the presynaptic and postsynaptic neurons.

Adaptation and Tuning of Associative Spiking Neurons

The weights computed in a presented way are good enough for the primary set of weights in the complex graph neural networks:

I have a monkey. My monkey is very small. It is very lovely. It is also very clever.



The introduced tuning process allows for the achievement of better recalling results thanks to the slight modification of the multiplication factors of the synapses.

Tuning Process of ANAKG

Two repetitive steps of the **tuning process**:

1. All undesired and premature activations of neurons are avoided for all training sequences by using **weakening operations.**
2. Conflicts between correlated training sequences are fine-tuned using **strengthening operations**.

We define: s_{last}^{charge} - the strength of the last stimulus,

x – charge level at the moment when the last stimulus came

x_{all}^{max} - the maximum dynamic charge level of each stimulated neuron

$$x_{all}^{max} = \begin{cases} x + s_{last}^{charge} & if\ x + s_{last}^{charge} > x_{all}^{max} \\ x_{all}^{max} & otherwise \end{cases}$$

$x_{context}^{max}$ - the previous maximum charge level establishing the context of the last stimulus that should activate the neuron:

$$x_{context}^{max} = x_{all}^{max} - s_{last}^{charge}$$

The correct activation of the neuron assumes that

$$x_{context}^{max} < \theta \leq x_{context}^{max} + s_{last}^{charge}$$

On this basis we can define **strengthening and weakening operations** for the tuning process.

Weakening Operation

The weakening operation defines how the multiplication factor *m* decreases when a neuron is activated in the incorrect context or prematurely in the reduced context:

$$\gamma = \begin{cases} \dfrac{\theta}{(x_{all}^{max} + \varepsilon)} & for\ the\ undesired\ activations \\ \dfrac{\theta}{(x_{context}^{max} + \varepsilon)} & for\ the\ premature\ activations \end{cases}$$

$$m = m \cdot \gamma$$

$$w = c \cdot p \cdot m$$

The multiplication factors of the incorrect activations must be deceased to operate on the right stimulation context of the next neurons of the recalled training sequence.

Weakening operations always start and finish the tuning process of the ANAKG network.

Strengthening Operation

The strengthening operation defines how the multiplication factor *m* increases when a neuron is not activated in the right context of all predecessor of the training sequence or too late:

$$\gamma = \frac{\theta}{x_{all}^{max} - \varepsilon}$$

$$m = m \cdot \gamma$$

$$w = c \cdot p \cdot m$$

The strengthening operation always tries to achieve stimulation of the next sequence element. However, sometimes it is not beneficial if the initial context is not unique, e.g. there are few training sequences which start from the same subsequences of elements.

Strengthening operations allows for recalling of the following elements of the training sequences when the stimulation context is unique.

Experimental Results

The achieved results confirm that the proposed tuning process is beneficial and produce better-adapted weights allowing to achieved better recalls from the ANAGK network.

Input Stimulations	ANAKG Responses	Tuned ANAKG Responses
I also	I also have a	I also have a monkey
I have	I have a	I have a
I have an	I have a an old sister	I have an old sister
I have a young	I have a young brother	I have a young brother
I also have a big	I also have a big cat	I also have a big cat
You	You have a cat	You have a cat as well
My son	My son also has a monkey	My son also has a monkey
My brother	My brother	My brother is small
My monkey	My monkey	My monkey is
My monkey is very	My monkey is very small	My monkey is very small
It can	It can jump very quickly	It can jump very quickly
It is also	It is also very	It is also very clever
It is very	It is very	It is very lovely
It learns	It learns	It learns quickly
It likes to	It likes to sit on my his lamp monkey is small	It likes to sit on his lamp
She is very	She is very	She is very lovely
She likes to	She likes to sit on my his lamp monkey is small	She likes to sit in the library and read books
He	He has a monkey	He has a monkey
He has	He has a monkey	He has a monkey and dogs
His monkey is	His monkey is	His monkey is small
His monkey is small	His monkey is small	His monkey is small as well
We have lovely	We have lovely	We have lovely dogs

TRAINING DATA SET:
I have a monkey.
My monkey is very small.
It is very lovely.
It likes to sit on my head.
It can jump very quickly.
It is also very clever.
It learns quickly.
My monkey is lovely.
I also have a big cat.
My son also has a monkey.
It likes to sit on his lamp.
I have an old sister.
She is very lovely.
My sister has a small cat.
She likes to sit in the library and read books.
She quickly learns languages.
My sister has a cat.
It is very small.
You have a cat as well.
It is big.
I have a young brother.
My brother is small.
He has a monkey and dogs.
His monkey is small as well.
We have lovely dogs.

Conclusions

- ✓ **The presented fine-tuning algorithm adapts weights of the associative pulsing neurons of the ANAKG neural network more accurately and allows to achieve better recalling of training sequences.**

ANAKG:	UNTUNED	FINE-TUNED
Evaluation Results	correctly recalled	correctly recalled
4 sequences	85%	100%
25 sequences	76%	95%
hundreds of very correlated sequences	54%	91%

Questions or Remarks?

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