Innovative Types and Abilities of Neural Networks Based on Associative Mechanisms and a New Associative Model of Neurons

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Abstract. This paper presents a new concept of representation of data and their relations in neural networks which allows to automatically associate, reproduce them, and generalize about them. It demonstrates an innovative way of developing emergent neural representation of knowledge using a new kind of neural networks whose structure is automatically constructed and parameters are automatically computed on the basis of plastic mechanisms implemented in a new associative model of neurons - called as-neurons. Inspired by the plastic mechanisms commonly occurring in a human brain, this model allows to quickly create associations and establish weighted connections between neural representations of data, their classes, and sequences. As-neurons are able to automatically interconnect representing similar or sequential data. This contribution describes generalized formulas for quick analytical computation of the structure and parameters of ANAKG neural graphs for representing and recalling of training sequences of objects.

Keywords: Associative mechanisms · As-neurons · ANAKG neural graphs · Knowledge engineering · Knowledge representation · Artificial neural associative systems · Associative neural networks · Emergent cognitive systems

1 Introduction

Brains are well-developed biological machines that efficiently represent and process big-data. The principle of operation of the human mind is not based on numerical computational processes, but on active associative context-sensitive consolidation of many pieces of information which forms knowledge and allows generalization and creativity [14] [31]. Generalization is indispensable for modelling and operation of knowledge and intelligence [8]. In the current stage of development of neural networks, we have many structures, models of neurons, and training methods that enable approximation, association, prediction, regression, recognition, and classification [3] [21] [29]. The majority of artificial neuron models represents weighted sums which are used to compute output values using various activation functions [21] [29]. Artificial neural networks (ANNs) are trained using external algorithms [17] [21] [29] which usually do not exist in real

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brains [16] [19]. Biological neurons use internal, plastic, and local adaptation mechanisms which enable them to represent frequently repeated combinations of similar input stimuli and connect these representations to reproduce their sequence. Current investigations in neurobiology [15] [16] [19] [20] provide insight into universal plastic mechanisms which enable neurons to automatically change their connections and parameters to consolidate and represent frequent and similar combinations of object features and their sequences.

The essence of intelligence is the ability to memorize, reproduce, and generalize about frequent and similar patterns which define objects, actions, and their sequences, which allows to predict and control future events. As brains have insufficient resources to memorize every pattern [7] [16] [19] [25] [26], they prefer to represent and memorize only classes of patterns representing subgroups of similar objects. Classes are represented in neurons as combinations of their most frequent and representative features. Such connected neurons can represent statements, rules, and algorithms based on the most frequent and similar sequences of training objects. This unified, simplified, and consolidated representation of objects and their sequences is fundamental for knowledge representation, generalization, creativeness, and managing big-data on the fly [14] [22] [23] [24]. This kind of representation allows to quickly recognize similar objects and their sequences as well as recall other corresponding pieces of information. Thus, neural representations of classes of objects can be activated by various pieces of the objects defining these classes. The previously activated neurons can temporarily influence potential future activity of other connected neurons (Fig. 2-3) and thus control them and represent a context for their subsequent possible activations. This control can not only strengthen the influence of other inputs - in effect enabling or accelerating their activity - but also inhibit their influence and decelerate or even stop their activity due to inhibitory connections. This feature defines the possibility to control neuronal activity within the context of previous objects, events, and thoughts in brains [12] [16] [19].

Human languages help to share important information, define rules, methods, and algorithms, as well as allow to describe things and actions precisely to avoid misunderstandings. They make way for human cooperation which relies strongly on communication, knowledge, and intelligence. They allow people to solve problems on the basis of previously solved tasks which were somehow similar to the currently solved problems. Solutions are usually described by algorithms in the form of a sequence of steps [9] [11] [12]. Such steps are performed under the conditions of given contexts defined by various circumstances. Our brains can consolidate sequential relations, dependencies, rules, conditions, and develop complex algorithms using consolidated neural representations of objects defined by their subsets of features. This paper informs about neural associative processes and describes a generalized universal model for associative context-sensitive consolidation of training sequences of objects which can represent things and procedures in general.

A neuron represents an object or its part when it activates as a result of a time-spread combination of input stimuli triggered by the object. Thus, each

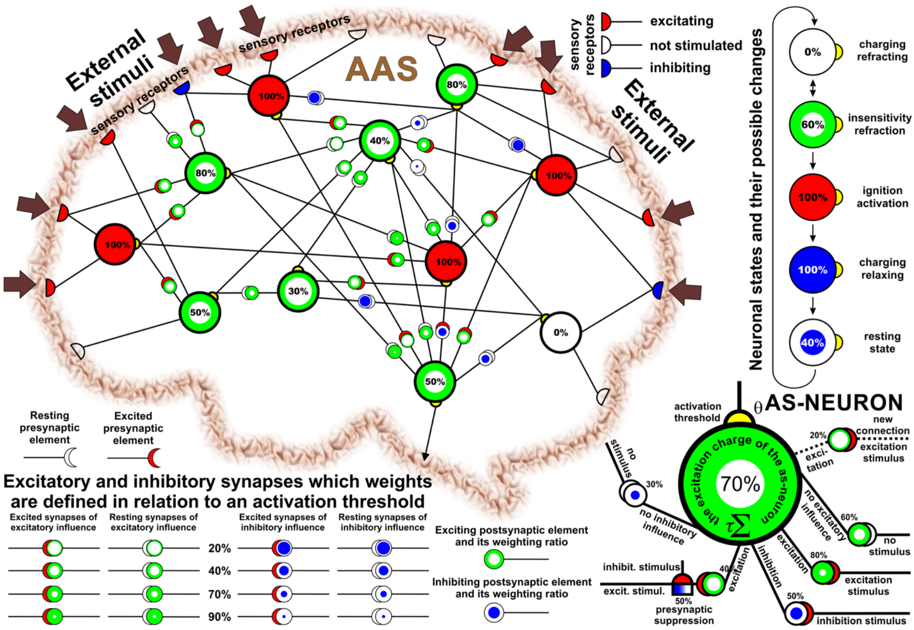

Fig. 1. As-neurons capable of representation of most frequent and repeatable combinations of input stimuli and their sequences

neuron represents an infinite set of time-spread combinations of input stimuli that can activate it. This set can contain similar as well as differing combinations, which allows neurons to automatically generalize about objects and create representations of their classes. As a result, similar objects produce similar neural reactions, and similarly affect other connected neurons. Connections between neurons also enable to represent various time-spread sequences of objects (e.g. sentences, rules, or algorithms). The preceding objects in each sequence - that are represented in a neural network and have triggered activity of other neurons - create an activity context for subsequent objects represented by other neurons only if these neurons are connected together and can influence their states as a result of their activity. Connections between as-neurons described in this paper are automatically created if their activity occurs in short intervals [12], e.g. for as-neurons representing objects of each training sequence. This feature of as-neurons enables their network automatic, consolidated, and context-sensitive representation of time-spread sequences of classes of objects that as-neurons already represent. Synaptic weights are presented as a percentage of threshold values (Fig. 1) because it is important to notice how much each weight influences the activation of a postsynaptic as-neuron. Connections and synaptic weights between as-neurons enable to differentiate various influences of the context formed by the activity of other presynaptic neurons. This allows to produce different context-sensitive reactions of a neural network constructed from as-neurons. Furthermore, associative consolidation of representations of various sequences in a single neural graph sometimes triggers generalized reactions that have not been trained (Fig. 3). This kind of generalization can be sometimes intuitively interpreted as creativity [11] [12].

This paper describes a generalized associative model of neurons (as-neurons) (Fig. 1) for an upgraded fast automatic construction of ANAKG neural graphs - introduced in [11] and [12] - capable of representing and consolidating training sequences of objects. An introduced associative method for automatic development of ANAKG neural graphs constructed from as-neurons is very fast because it demands only a single browse through a training sequence set ($\mathbb{S}$). All parameters and connections are automatically computed locally by as-neurons and synapses. This is possible if the training sequence set is fully defined and available before starting the adaptation process [11] [13]. In nature, due to emotions, needs, and other circumstances, the thinking processes favour and many times rehearse specific training patterns, which are trained at various moments and contexts. In machine learning, we lack such redundant information, treat data in the same way, and build a computational model quickly for a precise number of training patterns [5] [6] [21] [29]. These circumstances can force adaptation methods to work differently. In order to use the time-dependent mechanisms of biological neurons for efficient machine learning, we have to intelligently speed up or slow down the simulation time of as-neurons to automatically produce appropriate connections between them. We also need to substitute the initial structure and connections of biological neurons - inherited and naturally developed - with fast plastic mechanisms which let as-neurons quickly develop an artificial structure representing classes of training objects, their relations and sequences.

2 Active Associative Mechanisms in Neural Networks

Association is usually defined as a connection or relation between two or more objects [2] [3] [18] [30] [32]. Brains contain reactive neurons [16], which allow us to consider a special kind of associations - active associations - which automatically trigger relationships between neural representations of object classes via automatic reactivity of neurons and their ability to stimulate neurons representing other object classes in diverse ways. Stimulated neurons can be activated, which automatically triggers recalling of sequences of associated neural representations of other object classes through weighted neural connections. Such active associations are modelled in a new kind of systems - called artificial neural associative systems (aas-systems) - defined in [11] and [12]. Among other elements, the aas-systems are built from reactive as-neurons that enable to automatically create active associations between neural representations of object classes reproducing their context-sensitive relationships with other classes. In aas-systems, the capabilities observed in brains can be adapted to tasks of machine learning and cooperation with contemporary computers by introducing new kinds of sensory receptors not occurring in nature [12].

Associative systems exhibit a few important features that determine and define active associations in neural graphs: similarity, sequence, frequency, uniqueness, parallelism, and time-dependency of associative processes. These processes are controlled by local dependencies transmitted through connections and by the flow of time. They can also activate plastic mechanisms reconstructing associations. Similar neurons, which are often connected together and can stimulate each other, usually represent similar objects defined by similar feature values. Representation of object sequences is very important because it allows to associate even totally different objects which are somehow related. In an aas-system representing sequences of objects, the as-neurons representing them form new connections or strengthen the existing ones to reproduce these sequences. It is sometimes impossible to unambiguously represent all correlated sequences of objects in aas-systems. Varying frequencies of presenting individual sequences during training of the aas-systems play an important role in the adaptation process: frequently occurring training sequences of objects will be more strongly represented and more easily recalled than those that occur more rarely. Moreover, this enables to forget less frequent and correlated sequences. This mechanism automatically manages knowledge of aas-systems. On the other hand, unique objects and unique combinations of common objects create unique contexts for easy recalling of sequences. To demonstrate how it works in your brain, you can try to put together two or three common objects in a unique (untypical) configuration and place them on your desk when you leave thinking about something you would like to remember when you come back. When you come back you will immediately remember what you wanted when you see this unique (untypical) object configuration you left on your desk. ANAKG neural graphs - parts of aas-systems - adequately connect neural representations of objects and strengthen the connections reproducing their frequencies, sequences, and uniqueness. Additional connections are used to reproduce the contexts of recently presented objects that activated the as-neurons which represent them. This allows for automatic sequential context-sensitive recalling of associated objects (Fig. 2-3) [11].

$$\delta_{S,\widehat{S}} = \sum_{\{S \rightsquigarrow \widehat{S} \;:\; (\dots \rightsquigarrow S \rightsquigarrow \dots \rightsquigarrow \widehat{S} \rightsquigarrow \dots) \in \mathbb{S}\}} \left(\frac{1}{1 + \frac{\Delta t - t_a^{\widehat{S}}}{\omega}} \right)^{\gamma} \tag{1}$$

$$w_{S,\widehat{S}} = \frac{\eta_S \cdot \delta_{S,\widehat{S}} \cdot \theta_{\widehat{S}}}{\eta_S + (\eta_S - 1) \cdot \delta_{S,\widehat{S}}} \tag{2}$$

$$f_{\widehat{S}}(t) = \pm \theta_{\widehat{S}} \cdot \left(\frac{t}{\omega} - 1 \right)^{\gamma} \tag{3}$$

$$\begin{aligned} \widehat{X}_{\widehat{S}}^{t_2} = R_{\widehat{S}}^{\Delta t}\left(X_{\widehat{S}}^{t_1}\right) = \operatorname{sgn}\left(X_{\widehat{S}}^{t_1}\right) \cdot f_{\widehat{S}}\left(f_{\widehat{S}}^{-1}\left(\left| X_{\widehat{S}}^{t_1} \right| \right) + \Delta t \right) = \\ = \operatorname{sgn}\left(X_{\widehat{S}}^{t_1}\right) \cdot \theta_{\widehat{S}} \cdot \left(\sqrt[\gamma]{\frac{\left| X_{\widehat{S}}^{t_1} \right|}{\theta_{\widehat{S}}}} - \frac{\Delta t}{\omega} \right)^{\gamma} \end{aligned} \tag{4}$$

$$X_{\widehat{S}}^{t_2} = g\left(X_{\widehat{S}}^{t_1}\right) = \begin{cases} \sum_{S \rightsquigarrow \widehat{S}} w_{S,\widehat{S}} \cdot x_S^{t_2} + R_{\widehat{S}}^{t_2-t_1}\left(X_{\widehat{S}}^{t_1}\right) & \text{if } \left|X_{\widehat{S}}^{t_1}\right| < \theta_{\widehat{S}} \\ \sum_{S \rightsquigarrow \widehat{S}} w_{S,\widehat{S}} \cdot x_S^{t_2} + R_{\widehat{S}}^{t_2-(t_1+t_r)}\left(-\theta_{\widehat{S}}\right) & \text{if } X_{\widehat{S}}^{t_1} \geq \theta_{\widehat{S}} \wedge t_2 > t_1 + t_r \\ -\theta_{\widehat{S}} & \text{if } X_{\widehat{S}}^{t_1} \geq \theta_{\widehat{S}} \wedge t_2 \leq t_1 + t_r \end{cases} \tag{5}$$

$$x_S^{t_2} = h\left(X_S^{t_2-t_a^S-t_s}\right) = \begin{cases} 1 \text{ if } X_S^{t_2-t_a^S-t_s} \geq \theta_{\widehat{S}} \\ 0 \text{ if } X_S^{t_2-t_a^S-t_s} < \theta_{\widehat{S}} \end{cases} \tag{6}$$

$$t_a^S = T(X_S, \theta_S) = \left\lceil \frac{t_a^{MAX}}{1 + \frac{X_S - \theta_S}{\theta_S}} \right\rceil \tag{7}$$

where

- $S \rightsquigarrow \widehat{S}$ - a synaptic weighted connection between as-neurons S and $\widehat{S}$,
- $\delta_{S,\widehat{S}}$ - efficiency of synaptic connection at activating postsynaptic as-neuron $\widehat{S}$ through presynaptic as-neuron S accordingly to the time interval of their activations,
- θ_S - an activation threshold of as-neuron S,
- η_S - a number of activations of presynaptic as-neuron S,
- ω - maximum time necessary to gradually relax each as-neuron from its most excited state to its resting state,
- t_s - time necessary to propagate a stimulus along a connection and through a synapse from a presynaptic as-neuron S to a postsynaptic as-neuron $\widehat{S}$,
- t_r - absolute refraction time in which as-neurons are unsusceptible for any stimulations,
- t_a^S - computed relative activation time of as-neuron S according to its above-threshold excitation level determined by its activation threshold θ_S $(0 < t_a \leq t_a^{MAX})$,
- t_a^{MAX} - maximum activation time of as-neurons when $X_S = \theta_S$,
- t_1 - the moment of the last update of a neuronal state,
- t_2 - the current moment of a neuronal state update,
- $f_{\widehat{S}}(t)$ - concave continuously decreasing functions used to define relaxation function R of as-neurons,
- $R_{\widehat{S}}^{\Delta t}$ - a relaxation function that gradually turns the as-neuron $\widehat{S}$ to its resting state, where Δt is the relaxation period from its last update during which no external stimuli occurred,
- $x_S^{t_2}$ - an input stimulus distributed from as-neuron S to synapses, where t_2 is a moment of its influence on postsynaptic as-neurons via these synapses,
- $h(X_S^t)$ - a function that determines the presynaptic influence of as-neuron S accordingly to the activation threshold of this as-neuron.

The context of past events should not last infinitely, their influence on recalling of following objects has to be gradually reduced and stopped (4). Consequently, the neurons need a built-in mechanism which will gradually reduce their excitation (3). In biological neurons, such a mechanism is called relaxation [16] [19], during which neurons return back to their resting states after the stimulations have failed in activating them or after the activations precede the refraction period. An associative model of neurons (as-neurons) (Fig. 1) augments the models of artificial neurons [21] [29] and spiking neurons [15] by additional features and functions that enable as-neurons to automatically connect and represent classes of objects and their sequences allowing for context-sensitive recalling, generalization, and creativeness [14]. The as-neurons weigh and add input stimuli (2), use activation thresholds $\theta_{\widehat{S}}$, relax, refract (5), start plastic processes to change weights (2), and automatically connect to other as-neurons, whose activities often occur in similar periods [11] [12]. The synchronisation of firing of as-neurons usually suggests that object classes represented by these as-neurons are semantically related (e.g. they are similar, define the same class, or follow one another), so they should be connected or their connections should be strengthened. In this way, related object classes represented by as-neurons can be conditionally recalled according to the strength of synaptic connections between them.

As-neurons work in parallel in time, but their activations are often not synchronized, so they need a special simulation environment. Due to the limitations of today's computers, some simplified models have also been proposed [11] [12] to enable and accelerate an adaptation process of aas-systems. These models assume updating in discrete moments of simulation time and accomplish the main associative goals which allow to automatically influence representation and relationships of other data. Thus, aas-systems are automatically internally programmed by training data relationships - not by external training algorithms. They use plastic mechanisms that can automatically react to input data and represent these relationships in synaptic weights, connections, and thresholds. External stimulations of any time-spread combination of as-neurons (directly or via sensory receptors) recall an active associative reaction of the aas-system according to the relationships in the represented training data. This results in stimulation of other connected as-neurons as well. Upon activation, they produce an answer built from the represented classes of objects in a sequence arising from the moments of their activations (Fig. 3). Frequently activated as-neurons can newly interconnect or strengthen their existing connections in order to remember the result of associative recalling and make it available for the future. In this way, aas-systems - a kind of emergent cognitive systems - can develop new internal associations according to external and internal stimuli. This process resembles the ability to recall self-developed conclusions during thinking in people.

Brains have the built-in ability to develop initial neural structures. Aas-systems lack genetically inherited structures, so we have to use some extra rules to quickly develop these structures for various training data. This often proves advantageous, because the structures can be created according to a given task without the limitations introduced by e.g. inherited types of receptors or an imposed initial structure. The aas-system structures can be automatically optimized and specialized in associating given training data. New as-neurons are created as a consequence of external input stimuli which have not produced activation of any existing as-neuron. The axon of as-neuron S connects to as-neuron $\widehat{S}$ if as-neuron $\widehat{S}$ is activated in short period ($\leq \omega$) after as-neuron S has been activated and this connection is reinforced when this sequence of activations is repeated in the future. In the ANAKG neural graphs only $\delta_{S,\widehat{S}}$ (1) and η_S have to be computed during a single browse through a training sequence set. Weights (2) can be computed at the end of this fast adaptation process. The construction process of ANAKGs has been precisely described in [11], [12], and [14].

3 Generalization of Training Sequences

This section describes an experiment in which a training sequence set called 'Monkey': "*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.*" was used to develop an ANAKG graph shown in Fig. 2. New as-neurons represented each new word. Words from each sentence were presented with an interval of 20 units of simulation time. Connections were established between all as-neurons in each sequence of words (sentence) so that each as-neuron representing a word in a sequence was connected to all as-neurons representing all following words in this sequence. If the same word occurred in many sequences, the same neuron represented it. This process naturally combined and interlaced all training sequences taking into account contexts of previous words in each sentence. This also aggregated representations of all the same words in all training sequences. The amount of activations of all presynaptic as-neuron η_S was computed according to the number of repetitions of words of all training sequences (Tab. 1). They served to compute the efficiencies of all synaptic connections $\delta_{S,\widehat{S}}$ (1) at activating postsynaptic as-neurons $\widehat{S}$ by stimulations of presynaptic as-neurons S according to the time interval of their activations (Tab. 1). Weights were computed according to formula (2) introduced in the previous section (Tab. 2). Other constants were set according to the average times described by Kalat in [16], assuming that each unit of simulation time conforms to approximately 1 ms of biological neuron operation in the following way: maximal relaxation time $\omega = 100$, maximal charge time of excited as-neurons that achieved their activation thresholds $t_a^{MAX} = 15$, connection and synaptic transmission time $t_s = 5$, absolute refraction time $t_r = 3$, and activation thresholds of all as-neurons $\theta = 1$. Gamma constant $\gamma = 4$ allowed to achieve appropriate concave shape of function (3) used for relaxation (4).

The constructed ANAKG neural graph allowed for external stimulation of any as-neuron, as-neuron combination, or sequence to elicit an ANAKG reaction. Depending on the breadth of a context of initializing external stimulations of as-neurons, we could obtain various behaviours and answers. The ANAKG neural graph answers were constructed from sequences of objects represented by activated as-neurons. In the constructed ANAKG graph (Fig. 2), as-neuron MONKEY was stimulated and activated two times in $t = 0$ and $t = 20$. The first activation of as-neuron MONKEY has stimulated connected as-neurons

Table 1. $\delta_{S,\widehat{S}}$ (1) and η_S values computed for training sequence set 'Monkey'

			POSTSYNAPTIC AS-NEURON																					
	η	Σδ	A	ALSO	CAN	CLEVER	DOG	HAVE	HEAD	I	IS	IT	JUMP	LEARNS	LIKES	LOVELY	MONKEY	MY	ON	QUICKLY	SIT	SMALL	TO	VERY
PRESYNAPTIC AS-NEURON	2	A					0,534										1,000					1,000		
	2	ALSO	1,000			0,534	0,310															0,534		1,000
	1	CAN											1,000							0,310				0,534
	1	CLEVER																						
	1	DOG																						
	2	HAVE	1,534	1,000			0,192										0,534					0,310		
	1	HEAD																						
	2	I	0,844	0,534			0,126	2,000									0,310					0,192		
	4	IS		1,000		0,310										1,534						0,534		2,534
	5	IT		0,534	1,000	0,192			0,085		2,000		0,534	1,000	1,000	0,310		0,126	0,192	0,726	0,310		0,534	1,154
	1	JUMP																		0,534				1,000
	1	LEARNS																		1,000				
	1	LIKES							0,126									0,192	0,310		0,534		1,000	
	2	LOVELY																						
	3	MONKEY									2,000					0,534						0,310		0,534
	3	MY							1,000		1,067					0,310	2,000					0,192		0,310
	1	ON							0,534									1,000						
	2	QUICKLY																						
	1	SIT							0,310									0,534	1,000					
	2	SMALL					1,000																	
	1	TO							0,192									0,310	0,534		1,000			
	4	VERY				1,000										1,000				1,000		1,000		

Table 2. $w_{S,\widehat{S}}$ (2) values computed for training sequence set 'Monkey'

			POSTSYNAPTIC AS-NEURON																					
	θ	w	A	ALSO	CAN	CLEVER	DOG	HAVE	HEAD	I	IS	IT	JUMP	LEARNS	LIKES	LOVELY	MONKEY	MY	ON	QUICKLY	SIT	SMALL	TO	VERY
PRESYNAPTIC AS-NEURON	1	A					0,421										0,667					0,667		
	1	ALSO	0,667			0,421	0,269															0,421		0,667
	1	CAN											1,000							0,310				0,534
	1	CLEVER																						
	1	DOG																						
	1	HAVE	0,868	0,667			0,175										0,421					0,269		
	1	HEAD																						
	1	I	0,593	0,421			0,118	1,000									0,269					0,175		
	1	IS		0,571		0,252										0,713						0,381		0,874
	1	IT		0,374	0,556	0,167			0,080		0,769		0,374	0,556	0,556	0,248		0,114	0,167	0,459	0,248		0,374	0,600
	1	JUMP																		0,534				1,000
	1	LEARNS																		1,000				
	1	LIKES							0,126									0,192	0,310		0,534		1,000	
	1	LOVELY																						
	1	MONKEY									0,857					0,394						0,257		0,394
	1	MY							0,600		0,624					0,257	0,857					0,170		0,257
	1	ON							0,534									1,000						
	1	QUICKLY																						
	1	SIT							0,310									0,534	1,000					
	1	SMALL					0,667																	
	1	TO							0,192									0,310	0,534		1,000			
	1	VERY				0,571										0,571				0,571		0,571		

IS, VERY, SMALL, and LOVELY but did not result in further activations of other as-neurons. The second activation of as-neuron MONKEY triggered a sequence of activations of the as-neurons representing words: MONKEY IS VERY LOVELY (Fig. 2-3). Notice, that this sequence of words had not been used during construction and adaptation of this ANAKG graph, so it came into being as a result of generalization of all training sequences. The ANAKG neural graphs are universal and can consolidate and generalize sequences representing anything.

This example shows a new kind of generalization and highlights the importance of neuron relaxation common in biological neural networks. Without the relaxation of as-neurons, this result and a similar kind of network answers would be impossible. Moreover, these as-neurons produced this sequence of activations automatically as an answer to external stimulations of single as-neuron MONKEY. Stimulating an initial sub-sequence of any training sequence in almost all cases causes recalling of the remainder of this training sequence. Given a context, the differing length of the initial sub-sequence depends on the training frequency and uniqueness of the recalled sequence. Rare and more correlated sequences demand

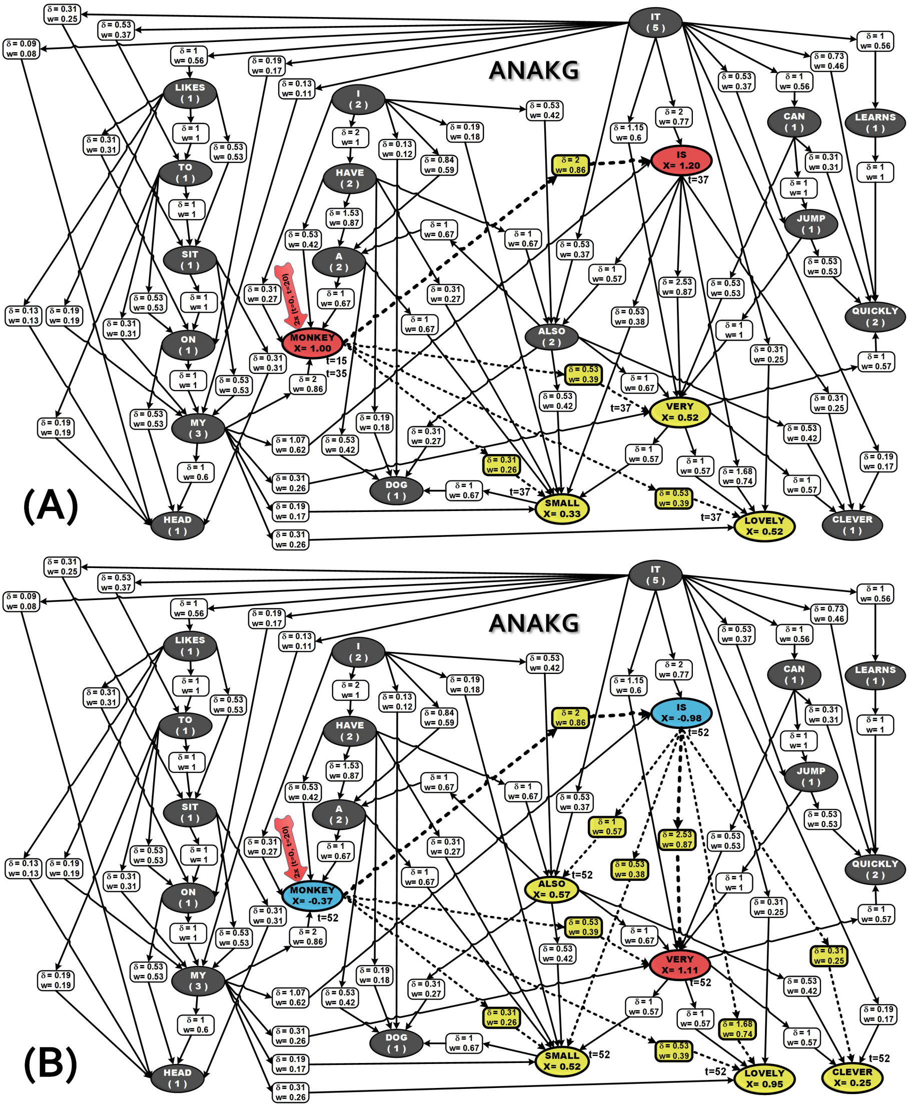

Fig. 2. A developed ANAKG graph for the presented training sequence set: (A) two sequential external stimulations of as-neuron MONKEY in simulation time: t=0 and t=20 result in activation of as-neuron IS, (B) as-neuron IS together with the previous contextual excitation coming from as-neuron MONKEY activates as-neuron VERY

a wider context for initial recalling than sequences that have a more unique initial sequence or have been trained more frequently than the others. The context for recalling of subsequent as-neurons in a sequence is formed based on below-threshold excitations that enable as-neurons activations in the immediate future (Fig. 2-3).

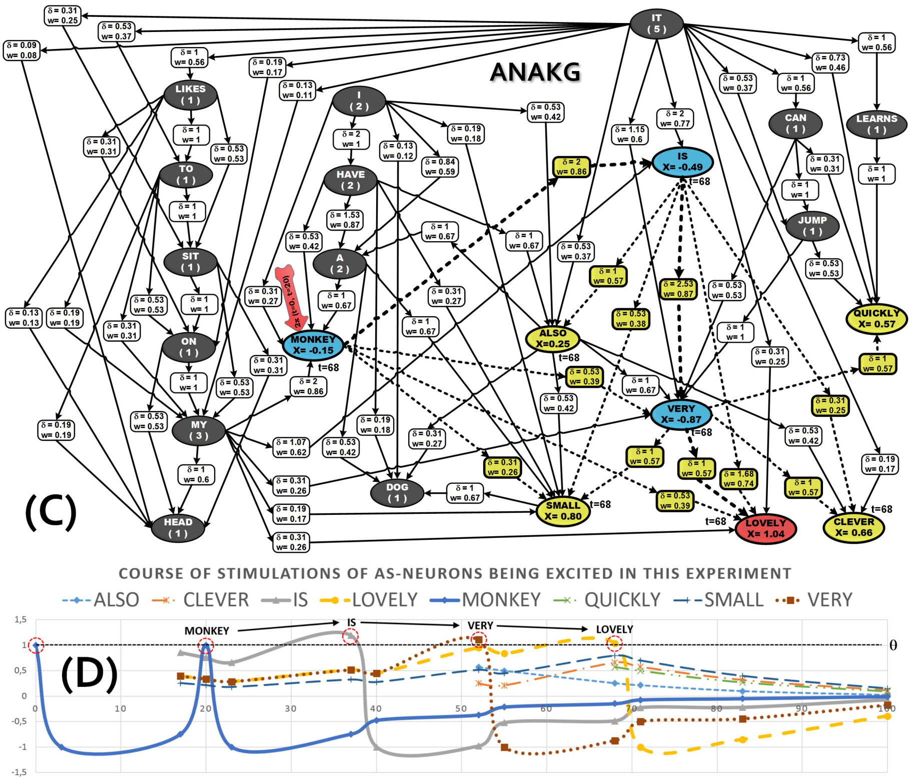

Fig. 3. The automatically stimulated and activated as-neurons: (C) as-neuron VERY together with the previous contextual excitations coming from as-neurons MONKEY and IS activates as-neuron LOVELY (Fig. 2), (D) time chart of the as-neuron excitations, activities, and refractions, presenting an ANAKG answer to the external stimulations of as-neuron MONKEY represented by sequentially activated as-neurons

4 Summary and Conclusions

This paper extends the abilities of commonly used neural networks in the field of artificial intelligence. It introduces a new kind of neurons and adaptation strategies. The presented adaptation strategy uses novelty parameters regarding the numbers of activations of as-neurons and time-dependent delta parameters that measure the efficiency of synaptic connection between presynaptic and postsynaptic as-neurons accordingly to the time interval of their activations. This paper also presents generalized formulas to quickly construct and adapt ANAKG neural networks to represent training sequence sets. A single browse through a training sequence set allows to construct a structure and compute all parameters of this network. This work shows that this kind of neural networks can not only remember a great part of training sequences but also generalize about them. The ANAKG neural networks as well as aas-systems are not intended to precisely remember training data but rather to represent the knowledge about trained objects, generalize about them, and even get creative answers. Knowledge is always the generalization of trained objects, facts, and rules. Our brains also do not precisely remember all the trained objects, facts, and rules, but represent classes of objects and only the most important or frequent facts and rules. This limitation is necessary if we want to process big-data and form knowledge on their basis. The precision of representation of classes of objects and represented facts and rules depends on the number and kind of perception elements (receptors) as well as the number of neurons that can be used to represent them. However, knowledge more capable of generalizing comes into being when objects are well aggregated and their sequences are appropriately consolidated. Such knowledge makes an indispensable background for intelligent processing and intelligence.

The experiments confirmed the adaptive and generalizing abilities of the presented ANAKG neural graphs. The obtained results demonstrate the associative capabilities that can be modelled and used in the field of artificial intelligence. These investigations have shown new possible directions of investigation that can spark the creation of new neural associative models of knowledge representation and extend the capabilities of artificial intelligence, knowledge mining, and emergent cognitive systems. This research was supported by AGH 11.11.120.612.

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