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Theme: Smart Manufacturing, Smart Future

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Module 6: Neural Network and Learning Machines for Robots

Contextual Generalizing of Robot Control Step Sequences Using Associative Neural Graphs

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What do we need in Robotics?

Brainlike Efficiency & Intelligence

that will manage and generalize data & sequential operations

Brainlike efficiency?

Contemporary computers are based on John von Neumann architecture and use Turing machine as a computational model.

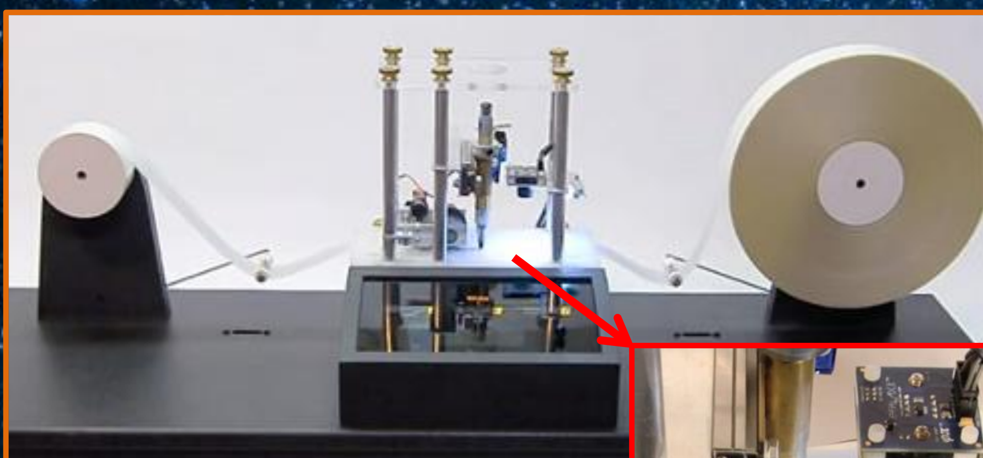
X

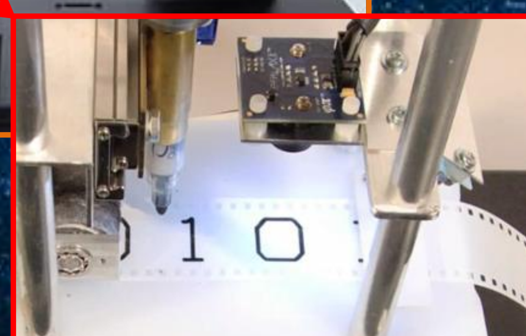
Brains do not use Turing machine and thanks this they can be computationally more efficient!

Efficiency of computers

Efficiency of contemporary computers is limited by Turing machine which demands many looping operations:

FOR, FOREACH, WHILE, REPEAT, DO…





Intelligence?

Intelligence is the ability to gain and use knowledge appropriately and efficiently to achieve goals or satisfy needs.

It enables us to:

- ✓ **Form knowledge and contextually associate data**
- ✓ **Contextually bring back (recall) memories**
- ✓ **Generalize about known or similar facts and rules**
- ✓ **Make summaries**
- ✓ **Draw conclusions**
- ✓ **Behave creatively taking into account new contexts**

Robots?

- ➢ Use plenty of sophisticated algorithms that can intelligently process various tasks
- ➢ Can even learn and adapt to similar tasks

BUT

- Do not perceive undefined events and objects
- Do not gain and form knowledge about them
- Do not think (in the human sense)
- Do not generalize rules or be creative
- Do not summarize or draw conclusions

Question?

How to automaticially combine facts and rules to form knowledge that will be able to contextually recall facts, rules or their generalization, draw conclusions or making summaries?

We need to use associative mechanisms that successfully work in our brains!

Associative Neural Graphs
Artificial Associative Systems

This presentation?

It introduces a new universal approache to interpret biological signals in neurons and neural networks to model them in order to automatically associate data, facts and rules to form knowledge to use it contextually.

This universal approach can be used to:

- ✓ Control robot step sequences or movements
- ✓ Adequatelly associate various points in maps
- ✓ Natural description of objects and images
- ✓ Various linguistic problems … etc.

to automatically conclude about their interactions.


Brain
?
How does it work?

B R A I N

- efficient big data processing machine
- not remember all data but their classes
- associates important or frequent data
- forms knowledge on their basis
- is automatically programmed by the external data via various senses and receptors that affect it in time

B R A I N

- ✓ A usuall reaction for sensorial stimuli of a human brain is produced in about 300 – 1100 ms on average.
- ✓ Biological neurons are usually activated 12 – 30 times per second, so they are activated again after 33 – 83 ms.
- ✓ In result, such neurons can be sequentially activated only about 4 – 25 times when producing an inteligent output reaction on initial stimuli.
- ✓ Our brains have no time to loop huge amouts of stored data or search for information in data tables in the way that is often and usually used in computer science: ~~FOR, FOREACH, WHILE, REPEAT, DO…WHILE~~

B R A I N

CONCLUSION

Our brains should use another computational model to be able to achieve goals and process information so fast!

There is no time for looping or searching for whatever!

~~TURING MACHINE?~~

ALTERNATIVE

Automatic and contextual

ASSOCIATION

of data, facts and rules

using reactive neurons, their connections in an active interneuronal space and biologically plausible mechanisms that are successfully working in our brains.

ASSOCIATION?

An active contextual connection that:

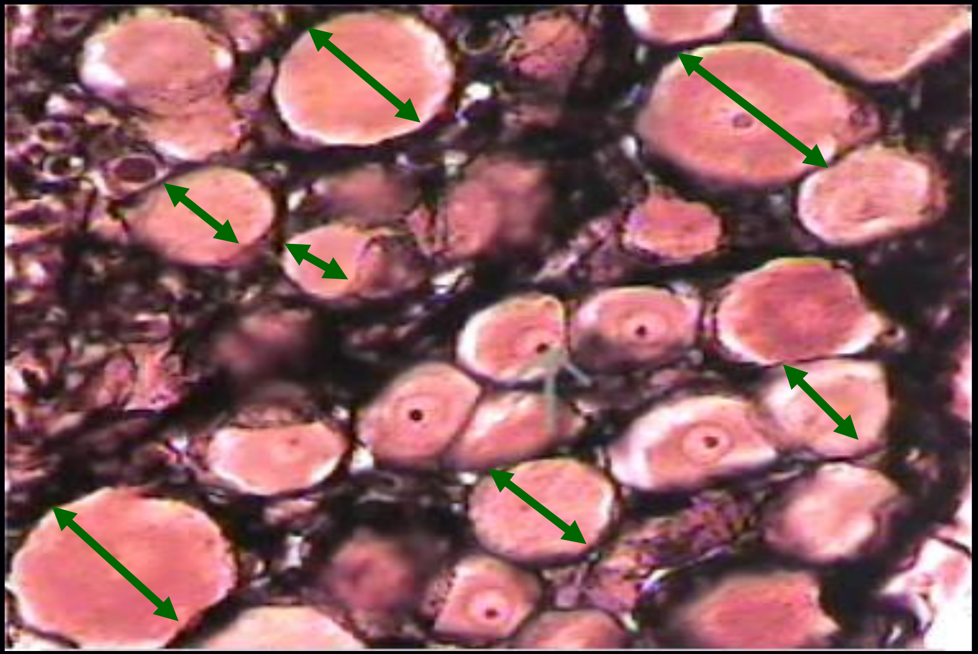
- ✓ **Aggregates similar data and their groups**
- ✓ **Contextually consolidates data sequences**
- ✓ **Automatically forms knowledge about them**
- ✓ **Very fast (constant computational time)**

Can be modeled using
Associative Neural Graphs
in Artificial Associative Systems

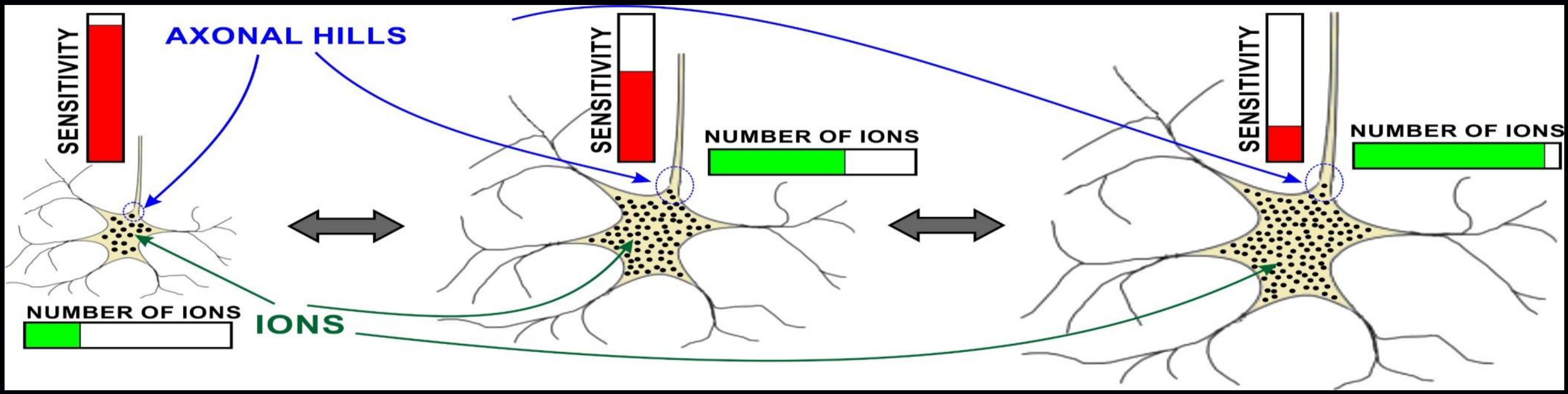
Where is the difference?

- ✓ Represented groups of data are actively and contextually connected
- ✓ Associative processes do not browse through huge amounts of data because important data are connected and immediatelly available
- ✓ Associative processes have always constant computational complexity

Plasticity and growth of neurons



- ✓ Biological neurons differ in:
- ✓ size and internal capacity
- ✓ sensitivity and reactivity for input stimuli
- ✓ represented subsets of input stimuli that activate them
- ✓ connections and weights…

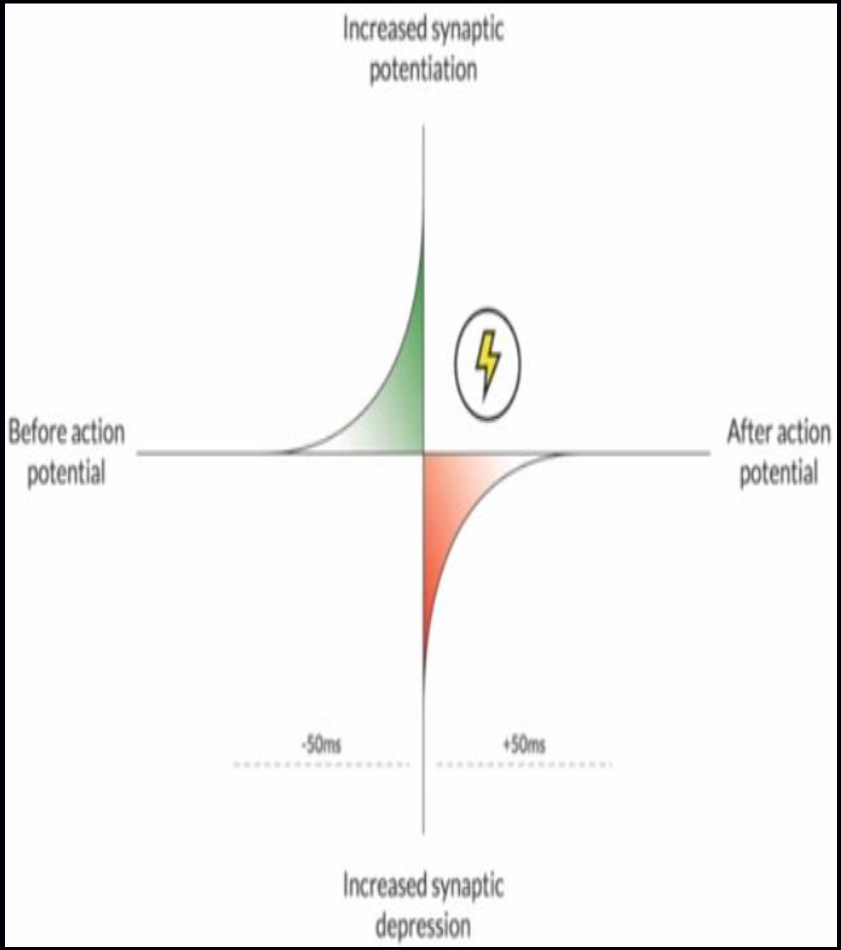


Frequency of active reactions

- ✓ Neurons can be activated when **attain an activation threshold** during charging.
- ✓ **Not every combination** of input stimuli activate neurons.
- ✓ Active reaction of a neuron gives it a possibility to quickly **influence other connected neurons.**
- ✓ Active reactions of neurons **activate plasticity** and reinforcement processes in synapses.
- ✓ The lack of active reaction of neurons can **degrade and weaken** input synapses and connections.
- ✓ Frequency of active reactions of neurons can influe their **growth** and change their **sensitivity** for next input stimuli.

Observations from neurobiology

- ✓ Connections between neurons are automatically created and strengthen if their activity often occurs in short intervals (the synaptic potentiation is increased).
- ✓ Connections between neurons are automatically weaken if presynaptic activity of neurons often do not bring on activity of postsynaptic neurons (the synaptic depression is increased).



Efficiency of synaptic connections

- ✓ Neurons can usually create many new synaptic connections.
- ✓ The creation process of connections is conditional.
- ✓ We observe that often activated neurons in close interval connect, multi-connect, or reinforce synaptic weights.
- ✓ The reinforcement of a synaptic connection depends on how fast a postsynaptic neuron is activated after synapsis stimulation.

Efficiency of synaptic connections depends on:

- ✓ Frequency of successful activation of a postsynaptic neuron after synapsis stimulation.
- ✓ Depends on intervals between stimulation of synapsis and a moment of a postsynaptic neuron activation.

MODELING OF SYNAPTIC EFFICIENCY IN ANAKG-3

Synaptic efficiency between two connected and sequentially activated neurons is computed in accordance with each interval between a synaptic stimulus and a moment of postsynaptic neuron activation:

$$\delta_{S,\widehat{S}} = \sum_{\{S \rightsquigarrow \widehat{S} \,:\, (\cdots \rightsquigarrow S \rightsquigarrow \cdots \rightsquigarrow \widehat{S} \rightsquigarrow \dots) \in \mathbb{S}\}} \left(\frac{1}{1 + \frac{\Delta t^{ACT} - \Delta t^{CHARGE}}{\theta_{\widehat{S}} \cdot \Delta t^{RECOVER}}} \right)^{\gamma}$$

$\delta_{S,\widehat{S}}$	- efficiency of synaptic connection at activating postsynaptic as-neuron $\widehat{S}$ through presynaptic as-neuron S accordingly to the time interval of their activations
$S \rightsquigarrow \widehat{S}$	- a synaptic weighted connection between as-neurons S and $\widehat{S}$
$\mathbb{S}$	- a set of training sequences
$\theta_{\widehat{S}}$	- an activation threshold of postsynaptic as-neuron $\widehat{S}$
Δt^{ACT}	- duration of time between activation of the synapse between as-neurons S and $\widehat{S}$ and activation of postsynaptic as-neuron $\widehat{S}$
Δt^{CHARGE}	- duration of time necessary for charging the postsynaptic as-neuron $\widehat{S}$ as a result of synaptic activity of synapse between as-neurons S and $\widehat{S}$
$\Delta t^{RECOVER}$	- maksimum duration of time in which as-neurons with $\theta = 1$ recover their resting state (relaxation)

WEIGHT COMPUTATION IN ANAKG-3

Synaptic efficiencies and frequencies of activations of presynaptic neurons are used to compute weights (synaptic conductance):

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

$w_{S,\widehat{S}}$ - synaptic weight (conductance) for synaptic connection $S \rightsquigarrow \widehat{S}$

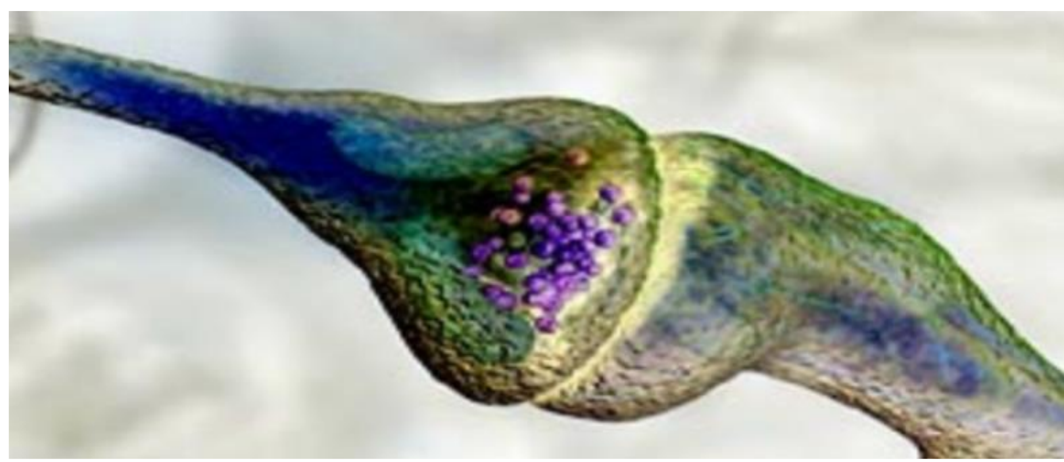
$\delta_{S,\widehat{S}}$ - efficiency of synaptic connection at activating postsynaptic as-neuron $\widehat{S}$ through presynaptic as-neuron S accordingly to the time interval of their activations

$S \rightsquigarrow \widehat{S}$ - a synaptic weighted connection between as-neurons S and $\widehat{S}$

η_S - a number of activations of presynaptic as-neuron S

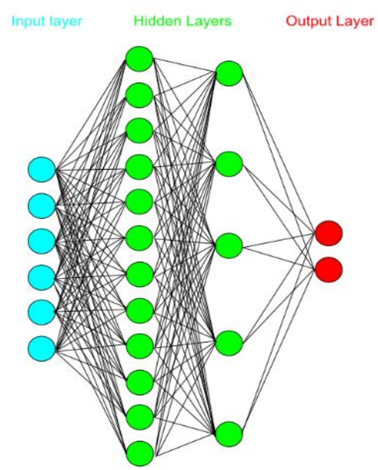
$\theta_{\widehat{S}}$ - an activation threshold of postsynaptic as-neuron $\widehat{S}$

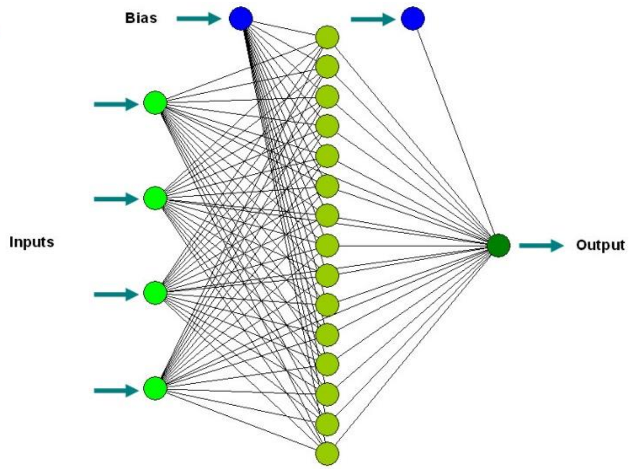
All weights in ANAKG-3 can be computed after a <u>single browse through</u> a training sequence set!



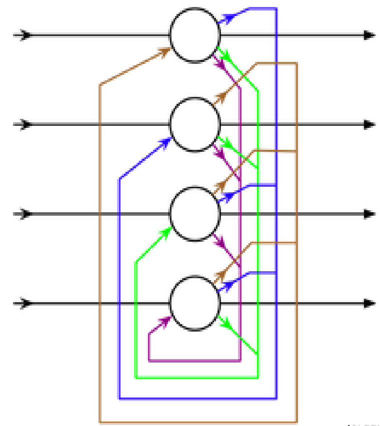
What kinds of neural networks we can already train?

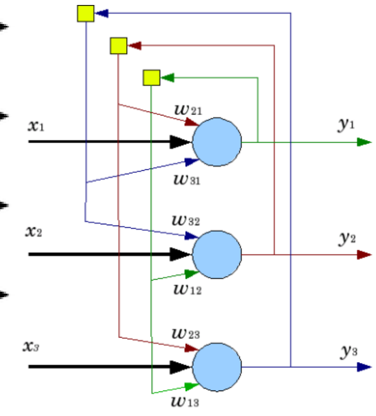
Multilayer Feedforward Neural Networks



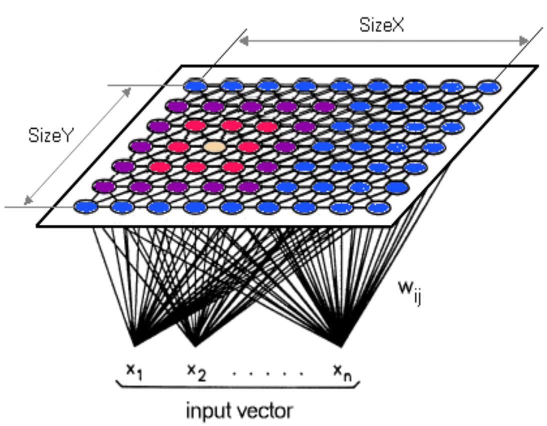


Recurrent Neural Networks

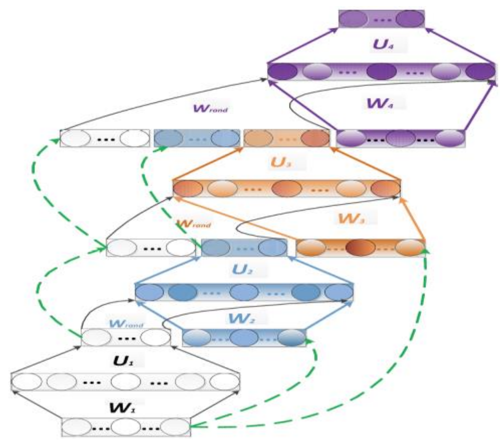




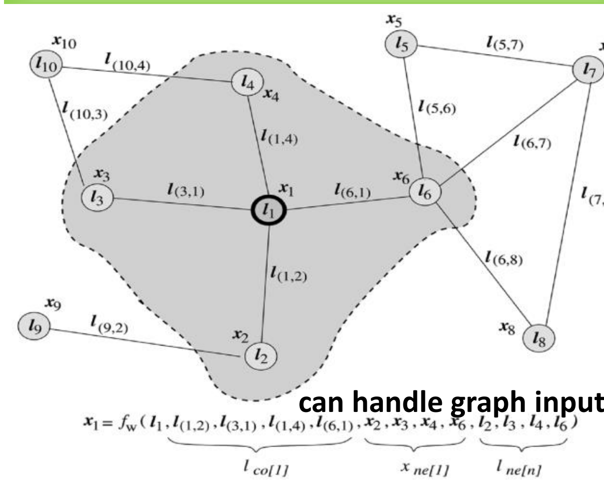
Self Organizing Maps



Deep Neural Networks



Graph Neural Networks



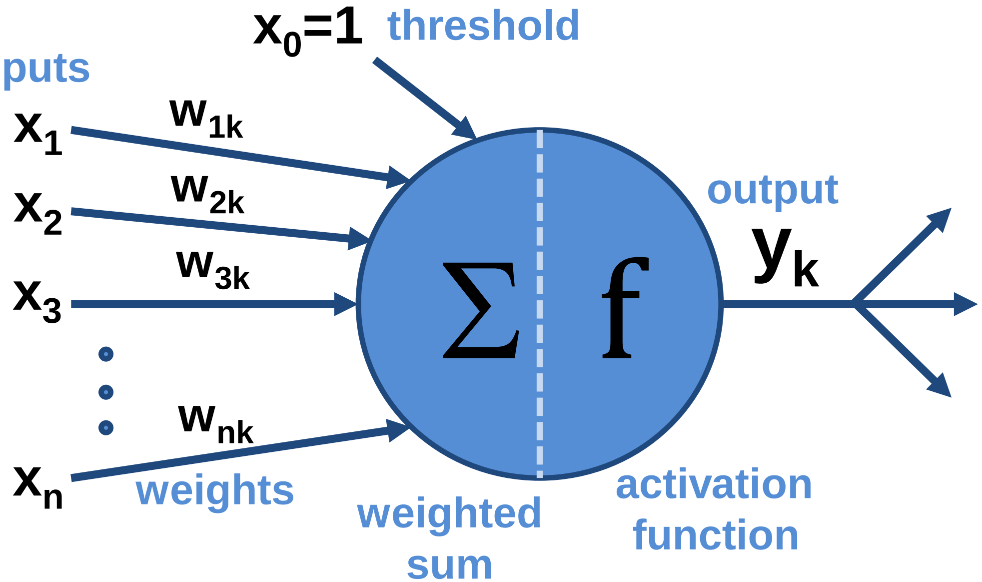
can handle graph inputs

We already need to create and train brain-like graph neural structures to represent knowledge!

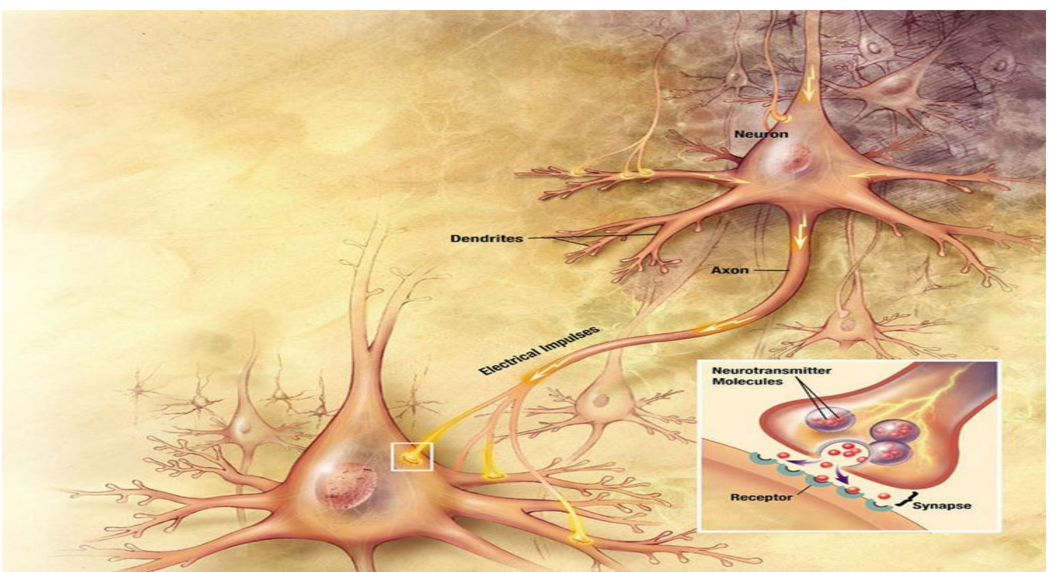
MAIN APPROACHES IN NEURON MODELING

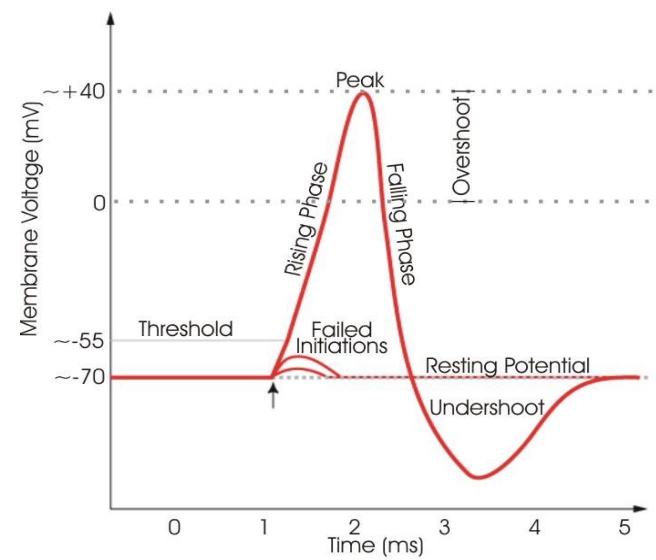
1. Artificial Neurons

$$y_k = f\left(\sum_{i=0}^{n} w_{ik} x_i\right)$$



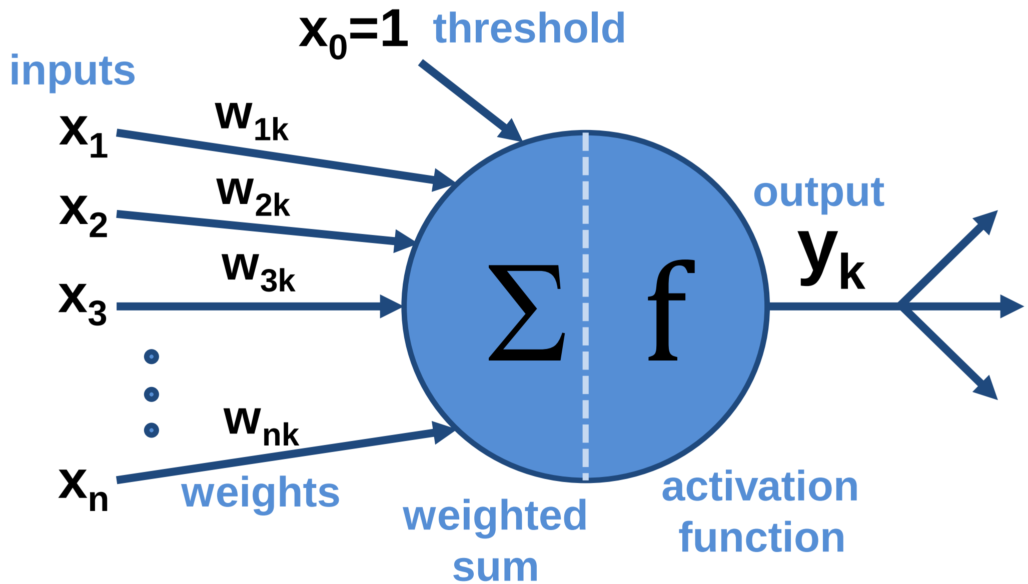
2. Spiking and Non-Spiking Neurons





ARTIFICIAL NEURON MODELS

$$y_k = f\left(\sum_{i=0}^{n} w_{ik} x_i\right)$$



All inputs usually simultaneously influence on a neuron.

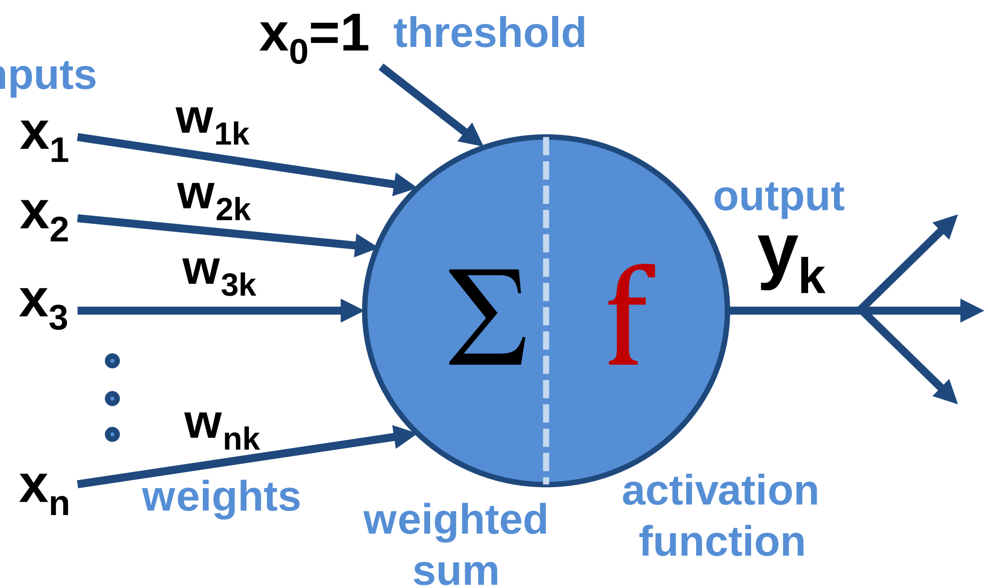
The previous states of a neuron do not impact on its current state.

No time dependencies between states are taken into consideration.

All stimulation and operation processes happen immediatelly without any interval.

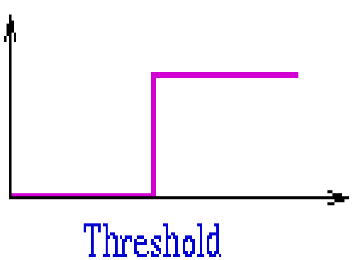
ARTIFICIAL NEURON MODELS

$$y_k = f\left(\sum_{i=0}^{n} w_{ik} x_i\right)$$

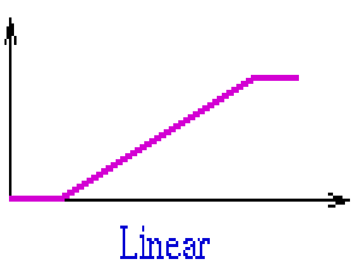


Variety of Activation Functions of Artificial Neurons

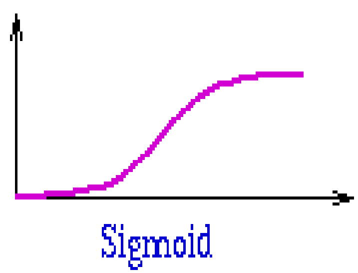
Threshold/Step Functions f with binary outputs



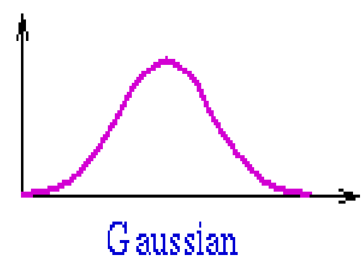
Linear Functions f with graded outputs



Sigmoid Functions f with graded outputs

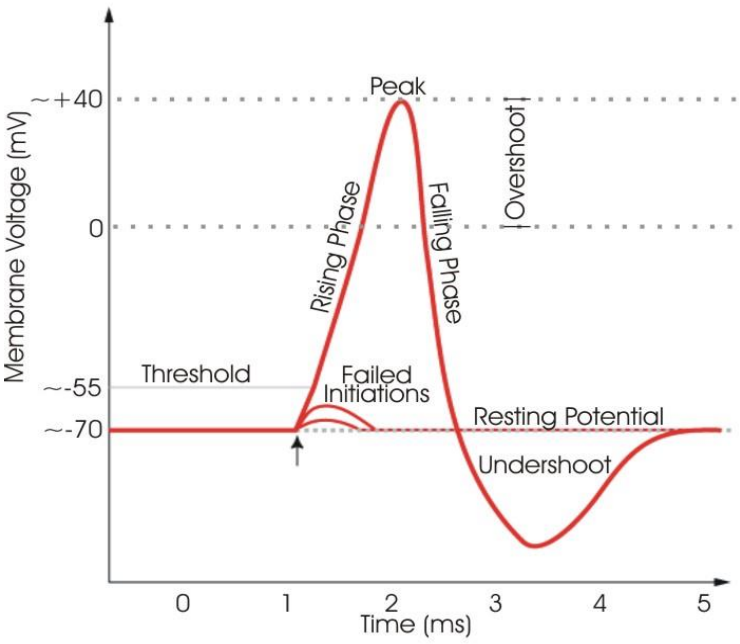


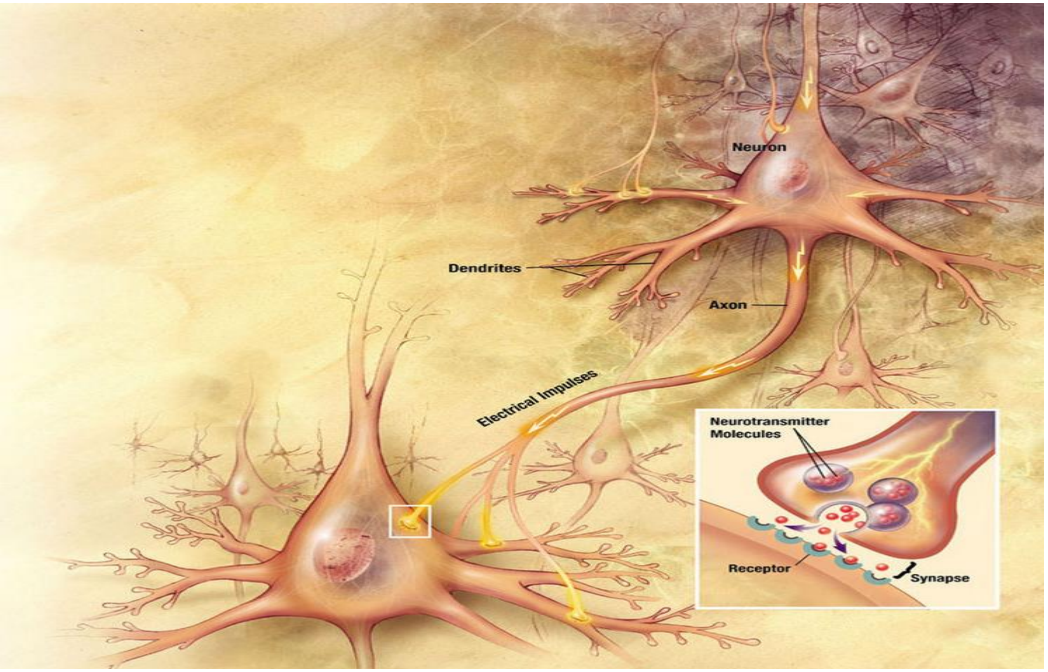
Gaussian Functions f with graded outputs



The functions with a graded outputs are usually used for approximation or clusterization of training data in classification tasks.

SPIKING AND NON-SPIKING NEURONS





- **Used to construct spiking neural networks (SNN)**
- **Incorporate the <u>concept of time</u> into their operating model.**
- **Fire when a membrane potential reaches a <u>threshold value</u>.**
- **Fundamental question of neuroscience is to determinate if neurons communicate by <u>a rate or temporal code</u>?**
- **They have proved useful in neuroscience, but not yet in engineering!**

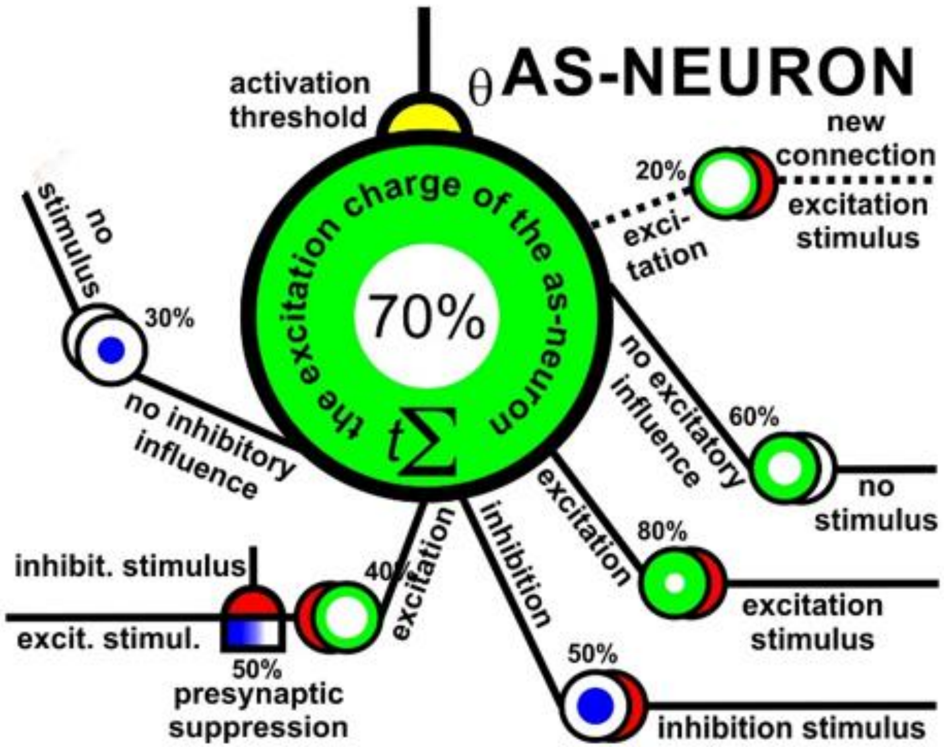
AS-NEURONS & ACTIVE ASSOCIATIONS

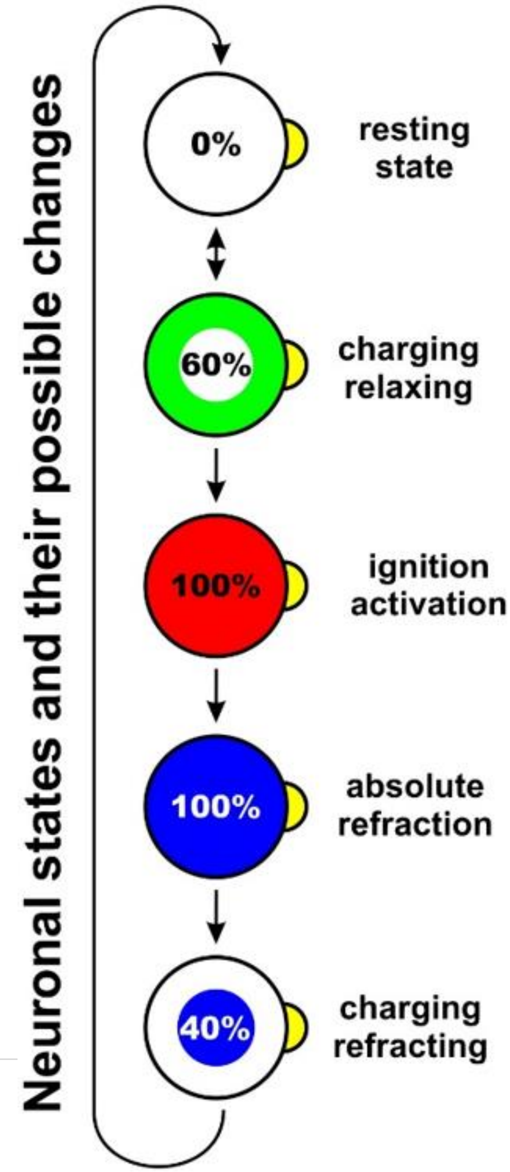
ARTIFICIAL NEURONS	associative AS-NEURONS	SPIKING NEURONS

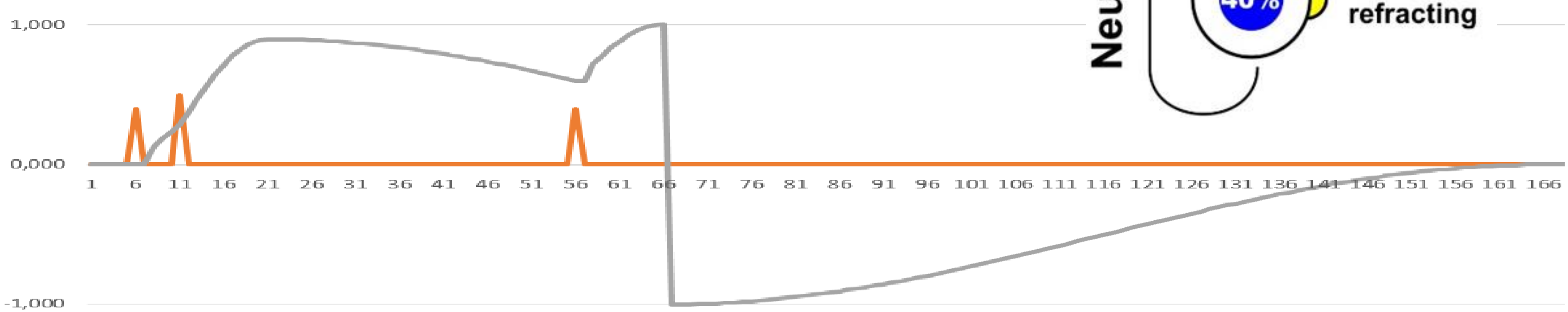
- ✓ **Use synaptic efficiency to compute weights for engineering tasks!**
- ✓ **Relax and refract in time (time dependent).**
- ✓ **Connect to other as-neurons automatically (plasticity) to reflect various relations between data (associate).**
- ✓ **Represent all time-spread combinations of input stimuli <u>that activate them</u>.**
- ✓ **Represent objects semantically in a context of other connected neurons or receptors (semassel – semantic associative element).**
- ✓ ***Each as-neuron represents a class of objects or their part when it activates as a result of a time-spread combination of input stimuli triggered by any object of this class.***

STATES OF AS-NEURONS

Charged as-neurons start stimulating other connected as-neurons.



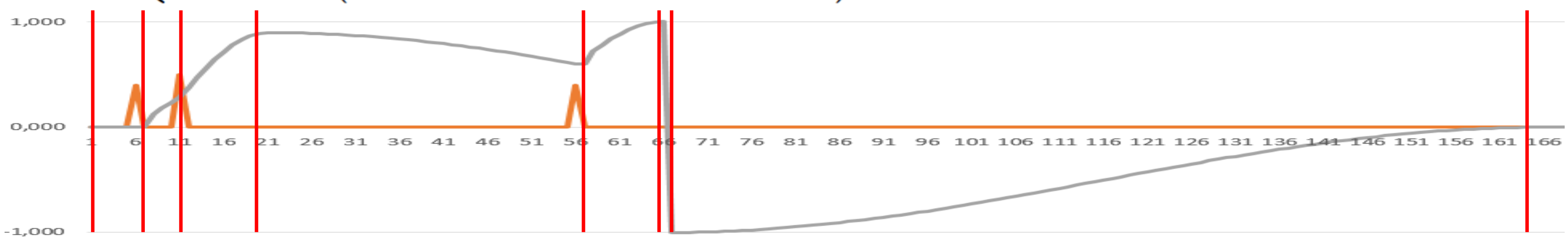




COMPUTATION OF STATES OF AS-NEURONS of ANAKG-3

AS-NEURONS work continuously in time but we can very efficiently update them in discrete moments of time using following formulas:

$$X^t_{\widehat{S}} = \begin{cases} X^{t_1}_{\widehat{S}} + \left(\sum_{S \rightsquigarrow \widehat{S}} w_{S,\widehat{S}} \cdot x^{t_1}_S\right) \cdot sin\left(\frac{\pi \cdot (t - t_1)}{2 \cdot \Delta t^{\mathrm{CHARGE}}}\right) & \text{if } t_1 < t < t_1 + \Delta t^{\mathrm{CHARGE}} \\ X^t_{\widehat{S}} \cdot \frac{1}{2} \cdot \left(1 + cos\left(\frac{\pi \cdot (t - t_1)}{X^t_{\widehat{S}} \cdot \Delta t^{\mathrm{RECOVER}}}\right)\right) & \text{if } t_1 < t < t_1 + \Delta t^{\mathrm{RECOVER}} \\ X^t_{\widehat{S}} \cdot \frac{1}{2} \cdot \left(1 + cos\left(\frac{\pi \cdot (t - t_1)}{|X^t_{\widehat{S}}| \cdot \Delta t^{\mathrm{REFRACT}}}\right)\right) & \text{if } t_1 < t < t_1 + \Delta t^{\mathrm{REFRACT}} \end{cases}$$



$$X^{t_2}_{\widehat{S}} = \begin{cases} X^{t_1}_{\widehat{S}} + \sum_{S \rightsquigarrow \widehat{S}} w_{S,\widehat{S}} \cdot x^{t_1}_S & \text{if } X^{t_1}_{\widehat{S}} + \Delta X^{t_1}_{\widehat{S}} < \theta \bigwedge t_2 = t_1 + \Delta t^{\mathrm{CHARGE}} \\ \theta & \text{if } X^{t_1}_{\widehat{S}} + \Delta X^{t_1}_{\widehat{S}} \geq \theta \bigwedge t_2 = t_1 + \frac{2 \cdot \Delta t^{\mathrm{CHARGE}}}{\pi} \cdot asin\left(\frac{\theta - X^{t_1}_{\widehat{S}}}{\Delta X^{t_1}_{\widehat{S}}}\right) \\ -\theta & \text{if } t_2 = t_1 + \Delta t^{\mathrm{ABSREFR}} \\ 0 & \text{if } t_2 = t_1 + \Delta t^{\mathrm{RELREFR}} \\ 0 & \text{if } t_2 = t_1 + \Delta t^{\mathrm{RECOVER}} \end{cases}$$

Achilles' heel of contemporary computer science is in the necessity for using many nested loops to find interesting data and process them.

This is because data are stored in redundant form without important relations in database tables!

We can change it using neurons and connections between data in the similar way our brains do.

Transformation of a data table into an associative structure

ASSORT is an associative algorithm that can sort records of data simultaneously for all parameters and simplify next computations.

TABLE

	A1	A2
R1	2	3
R2	8	1
R3	3	9
R4	1	3
R5	4	8
R6	4	5
R7	1	3
R8	9	1
R9	6	8

(A)

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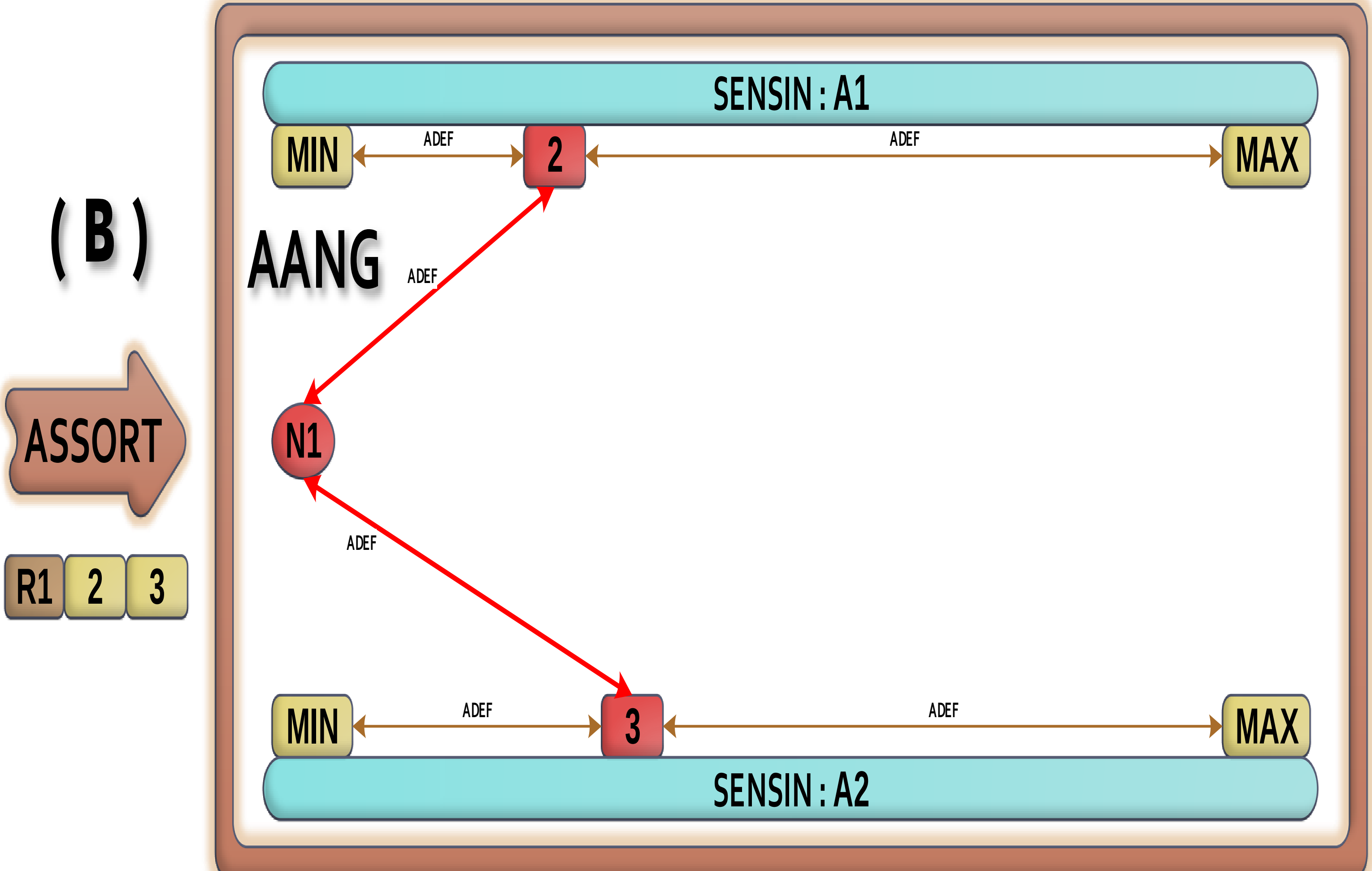
Transformation of a data table into an associative structure

ASSORT creates a basis associative graph structure that consolidates representation of similar and subsequent groups of data.

TABLE

	A1	A2
R1	2	3
R2	8	1
R3	3	9
R4	1	3
R5	4	8
R6	4	5
R7	1	3
R8	9	1
R9	6	8

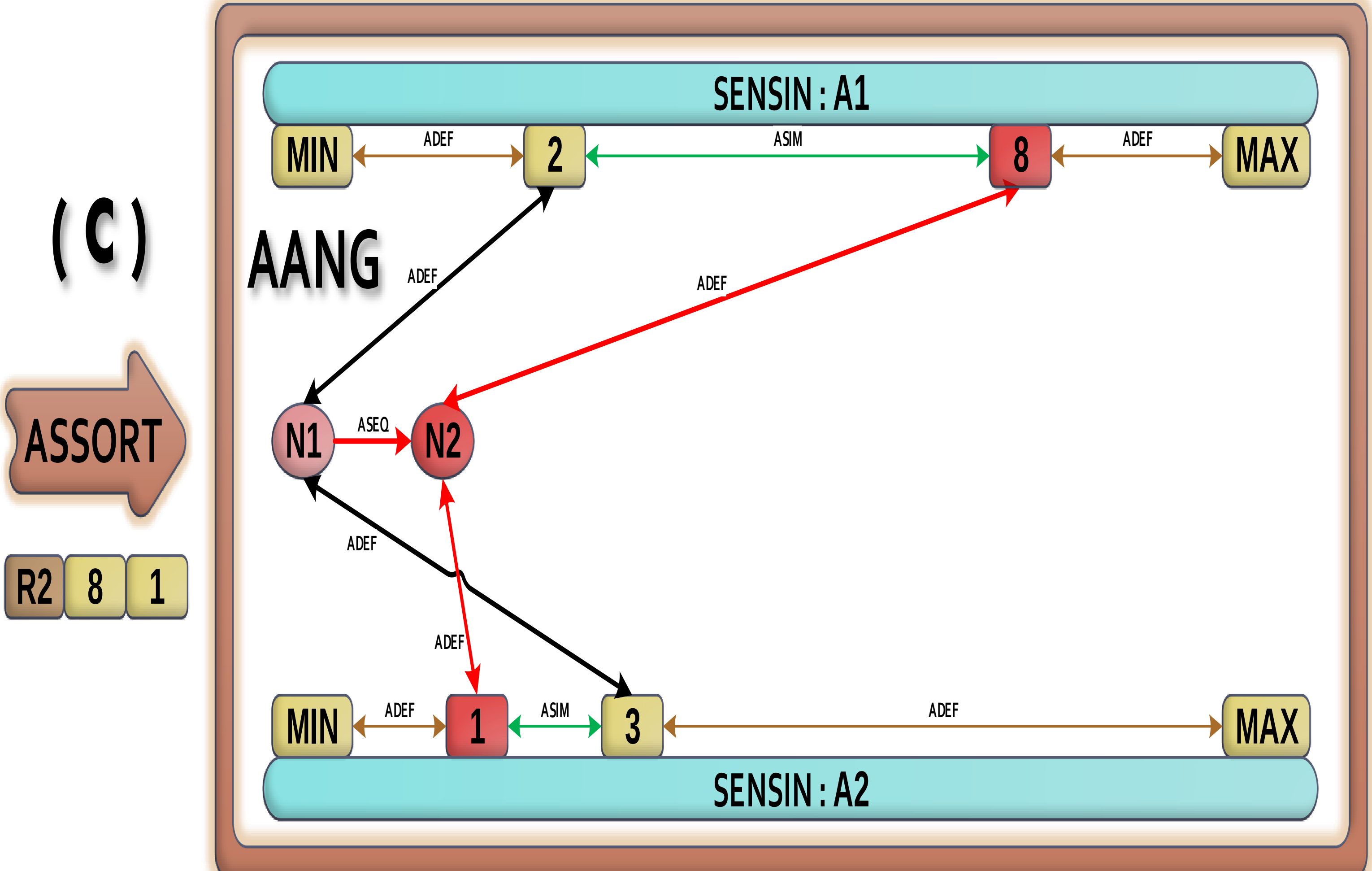


Transformation of a data table into an associative structure

ASSORT represents each not redundant data record by a single neuron that is connected to data values defining this record.

TABLE

	A1	A2
R1	2	3
R2	8	1
R3	3	9
R4	1	3
R5	4	8
R6	4	5
R7	1	3
R8	9	1
R9	6	8

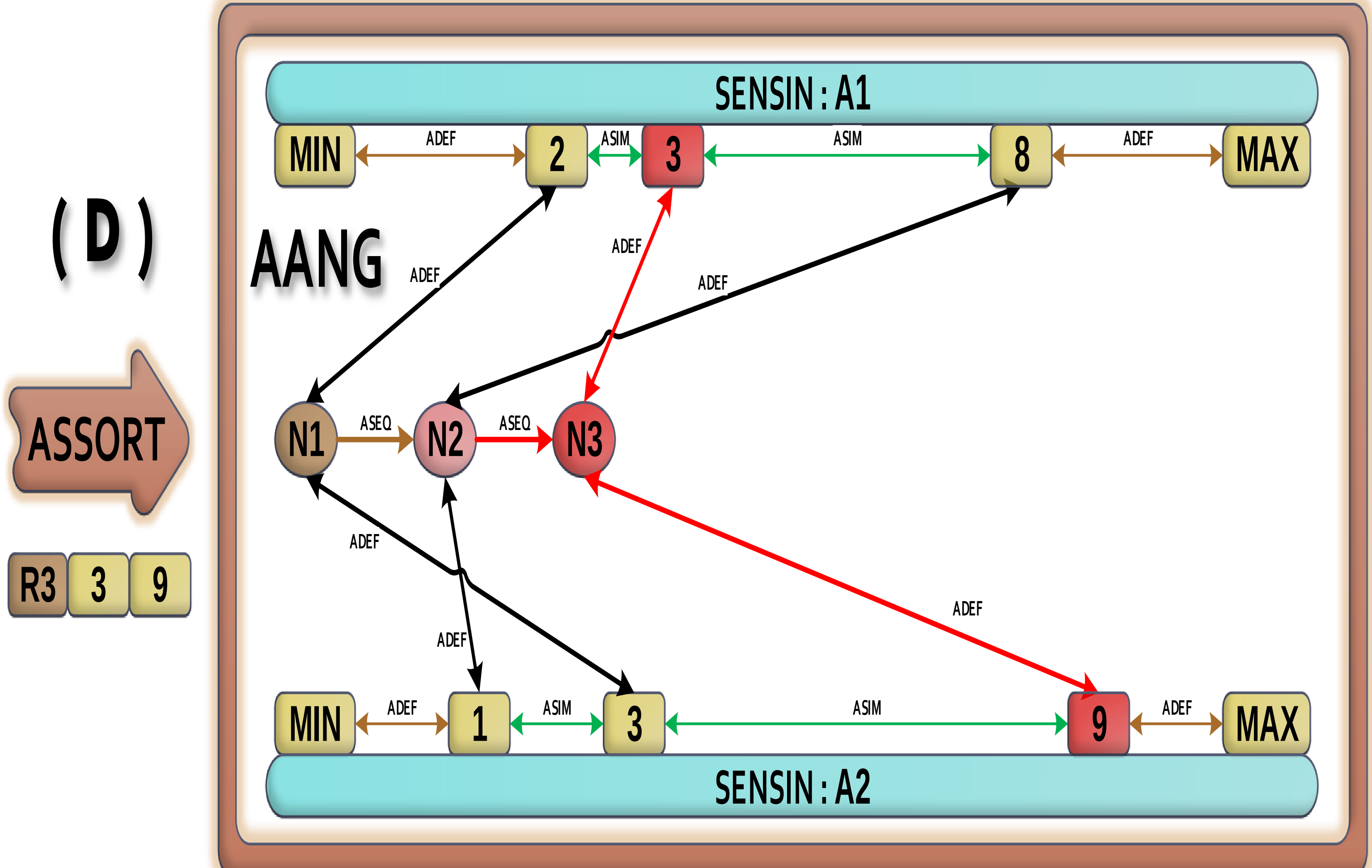


Transformation of a data table into an associative structure

ASSORT can also represent the sequence of records by special connections between neurons.

TABLE

	A1	A2
R1	2	3
R2	8	1
R3	3	9
R4	1	3
R5	4	8
R6	4	5
R7	1	3
R8	9	1
R9	6	8

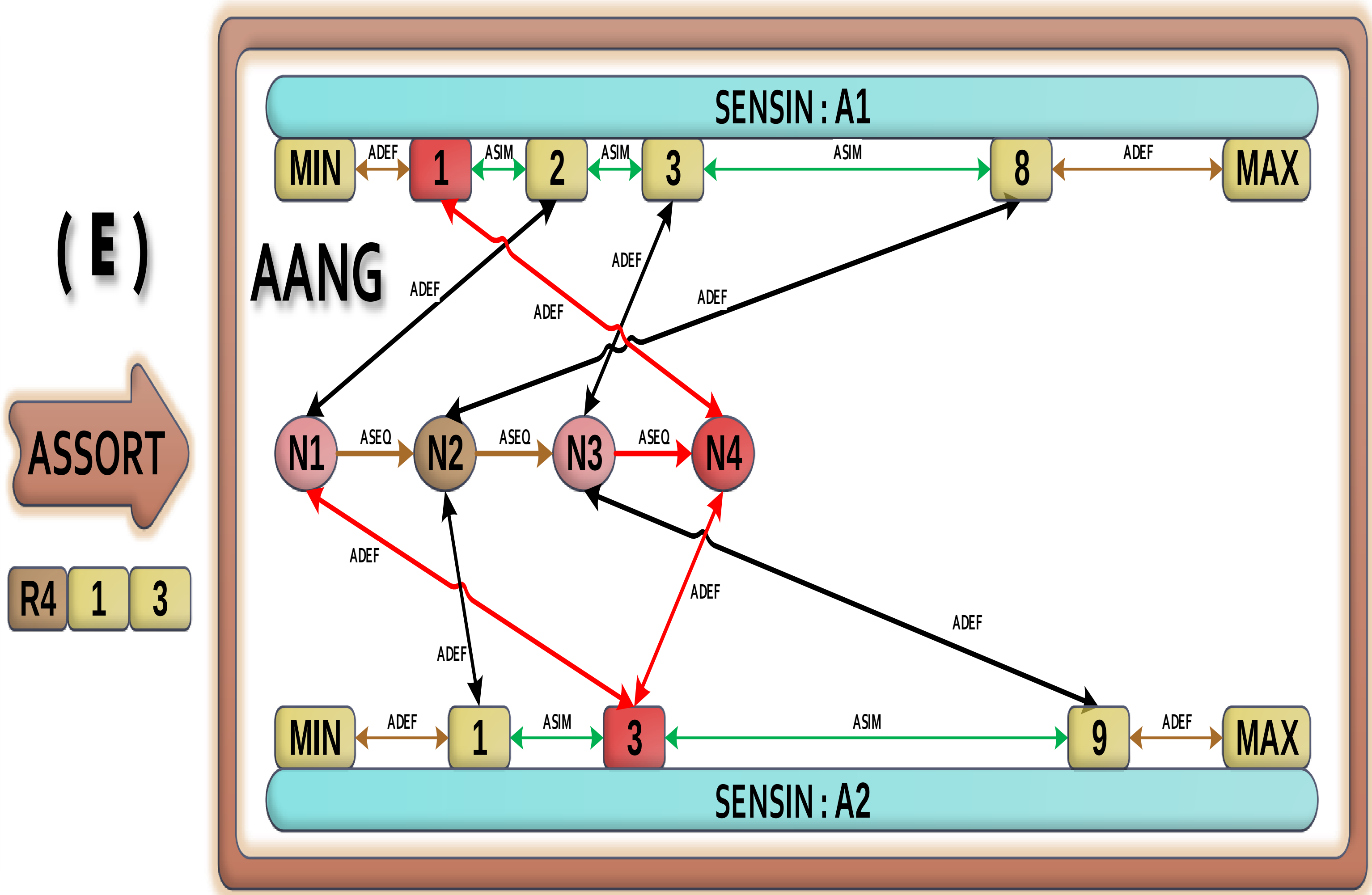


Transformation of a data table into an associative structure

Repeated values of represented features (e.g. 3 for P2) are not duplicated but represent only once.

TABLE

	A1	A2
R1	2	3
R2	8	1
R3	3	9
R4	1	3
R5	4	8
R6	4	5
R7	1	3
R8	9	1
R9	6	8



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Transformation of a data table into an associative structure

All values for all parameters are separatelly added in a sorted order.
Neural representation of values enables to add them in constant time.

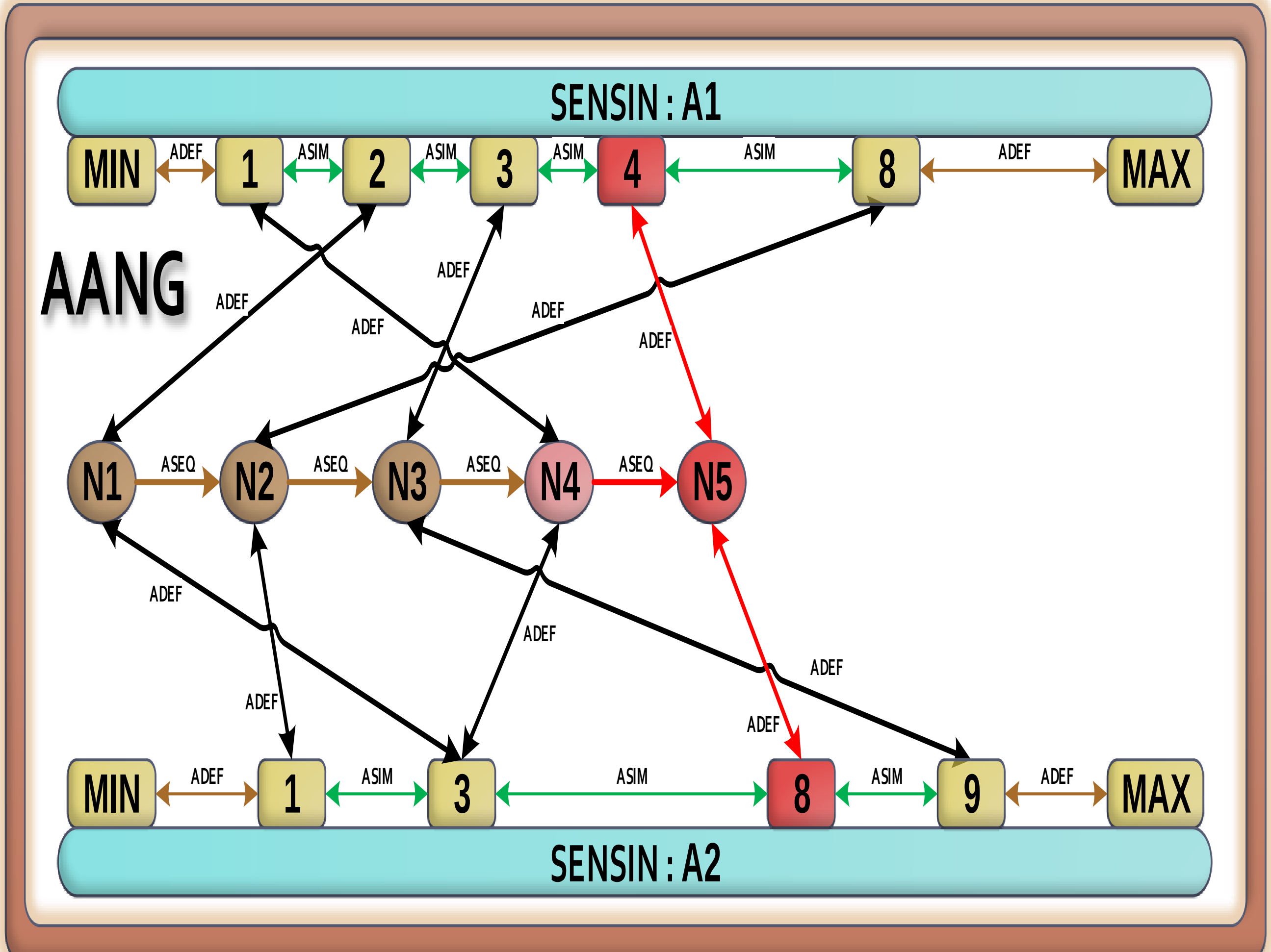
TABLE

	A1	A2
R1	2	3
R2	8	1
R3	3	9
R4	1	3
R5	4	8
R6	4	5
R7	1	3
R8	9	1
R9	6	8

(F)

ASSORT

R5	4	8



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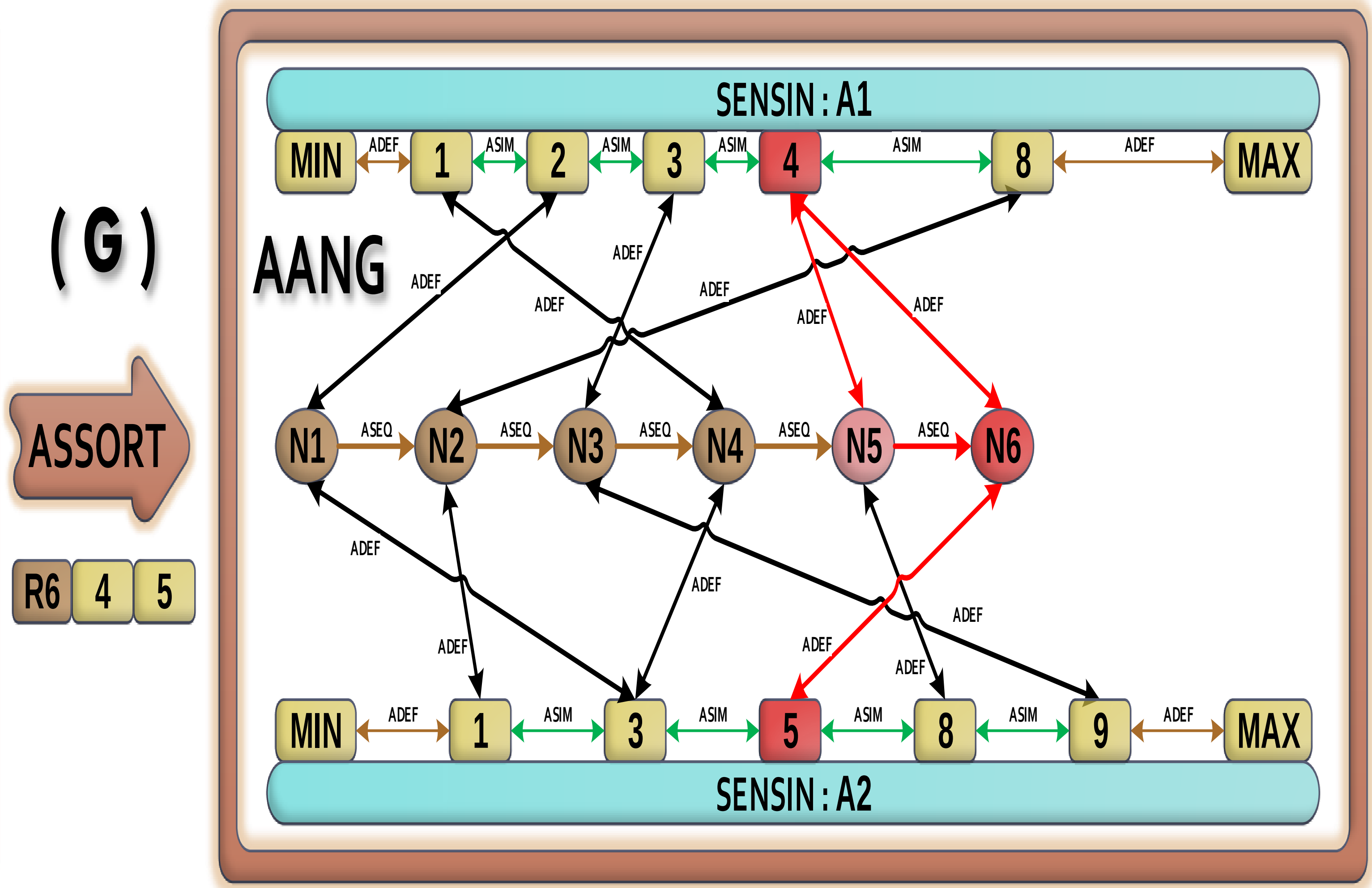
Transformation of a data table into an associative structure

Aggregated representation of repeated values (e.g. 4 for P1) enables to quickly find similarities between data records.

TABLE

	A1	A2
R1	2	3
R2	8	1
R3	3	9
R4	1	3
R5	4	8
R6	4	5
R7	1	3
R8	9	1
R9	6	8



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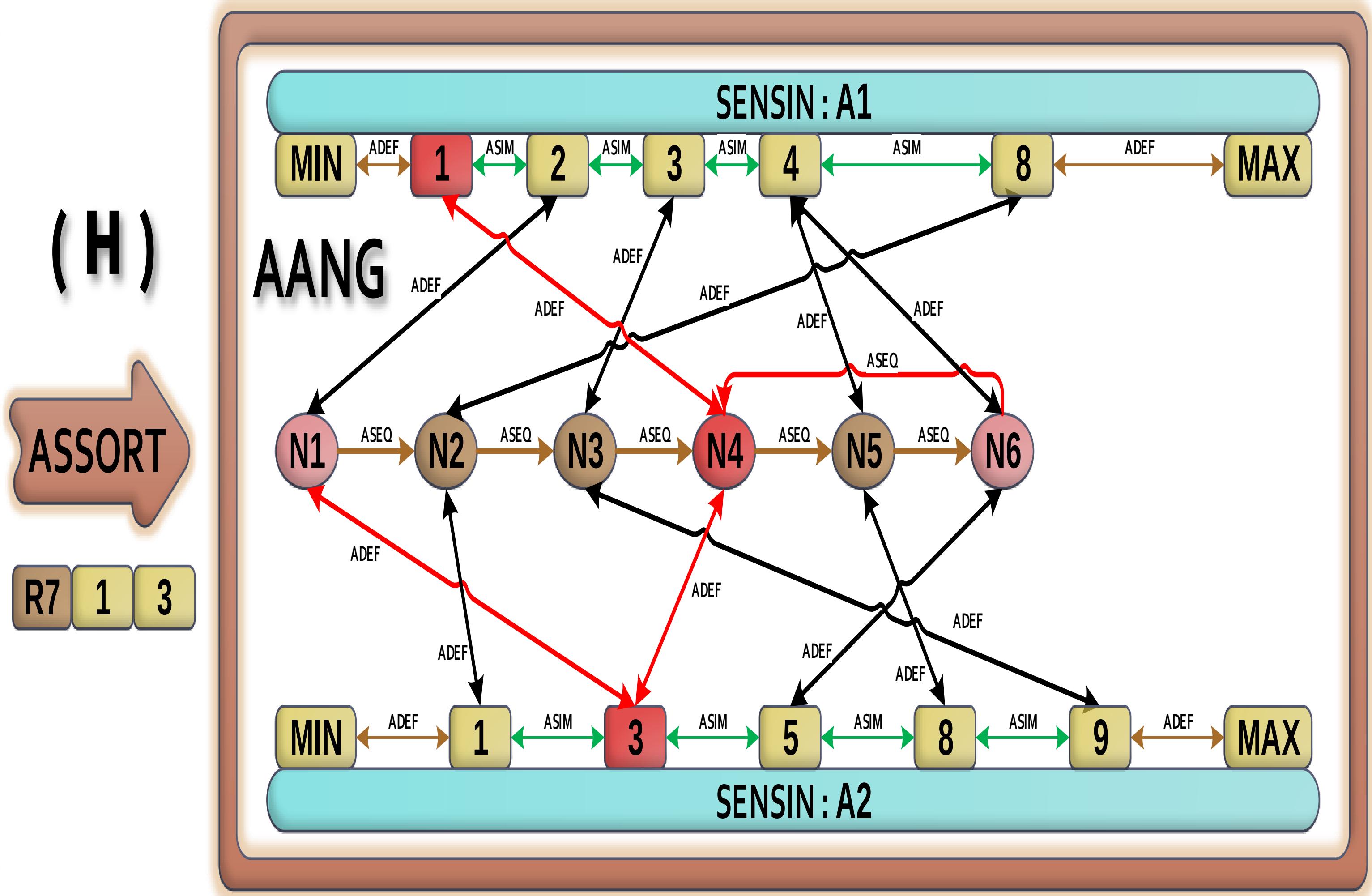
Transformation of a data table into an associative structure

The same records (e.g. R4 and R7) are represented by the same neurons.
Extra connections enable to represent their sequence unambiguously.

TABLE

	A1	A2
R1	2	3
R2	8	1
R3	3	9
R4	1	3
R5	4	8
R6	4	5
R7	1	3
R8	9	1
R9	6	8



Adrian Horzyk, horzyk@agh.edu.pl, AGH University of Science and Technology

Transformation of a data table into an associative structure

Aggregation of the same (and possibly also similar) values values enable to quickly draw conclusions about related records.

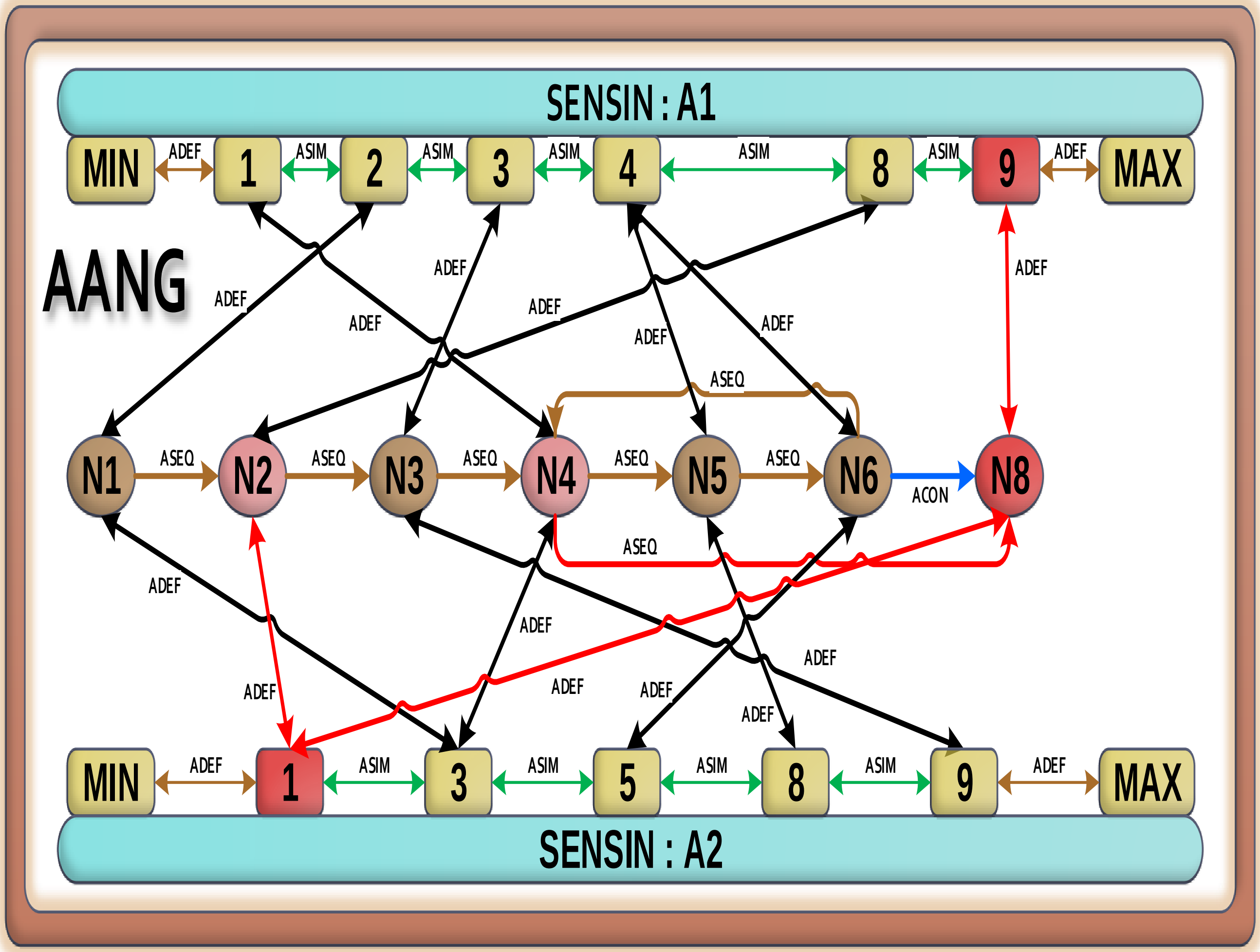
TABLE

	A1	A2
R1	2	3
R2	8	1
R3	3	9
R4	1	3
R5	4	8
R6	4	5
R7	1	3
R8	9	1
R9	6	8

(I)

ASSORT

R8	9	1



Transformation of a data table into an associative structure

All records have been represented in this neural structure but the data will be looked through once again to add contextual connections.

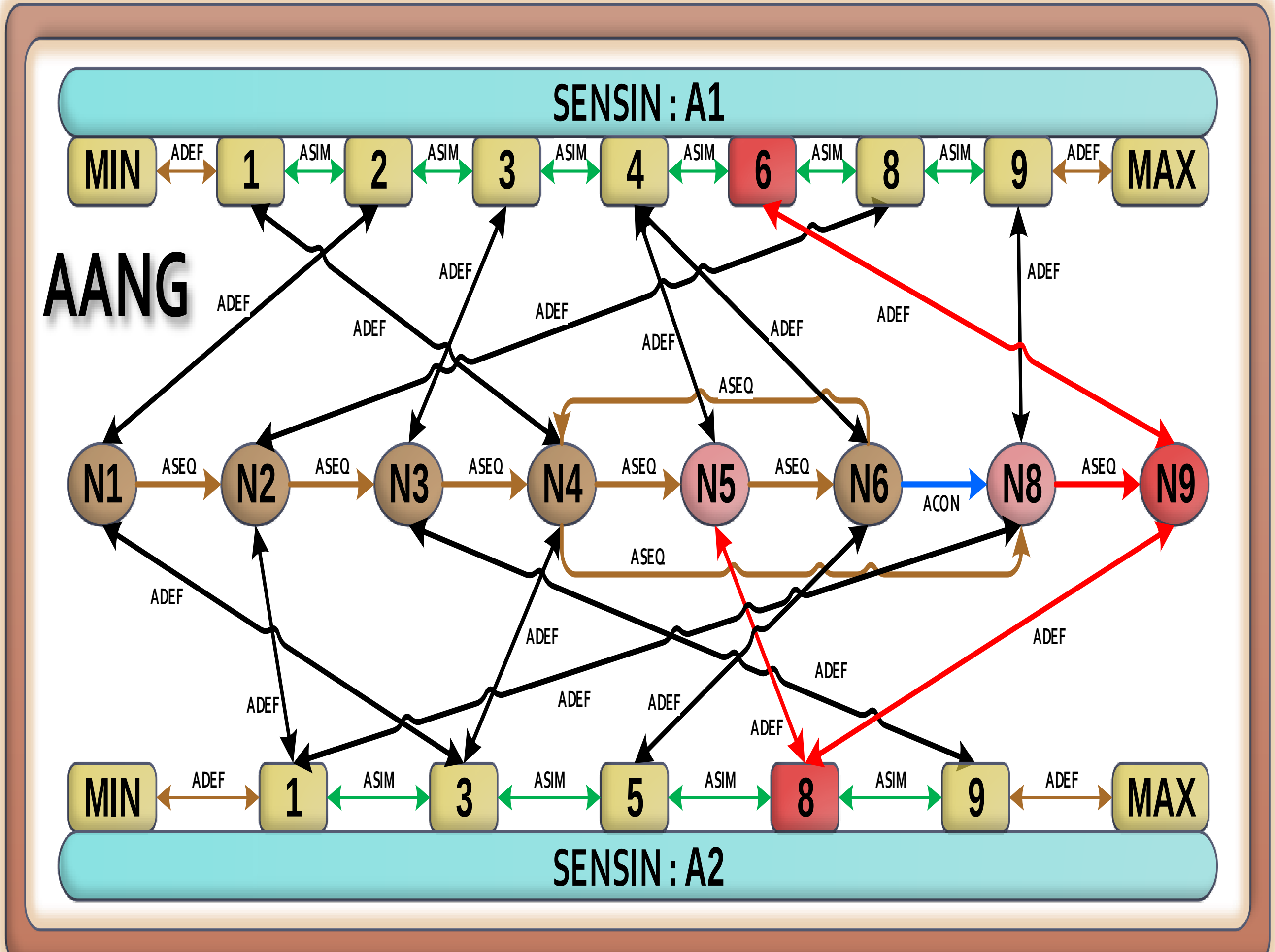
TABLE

	A1	A2
R1	2	3
R2	8	1
R3	3	9
R4	1	3
R5	4	8
R6	4	5
R7	1	3
R8	9	1
R9	6	8

(J)

ASSORT

R9	6	8



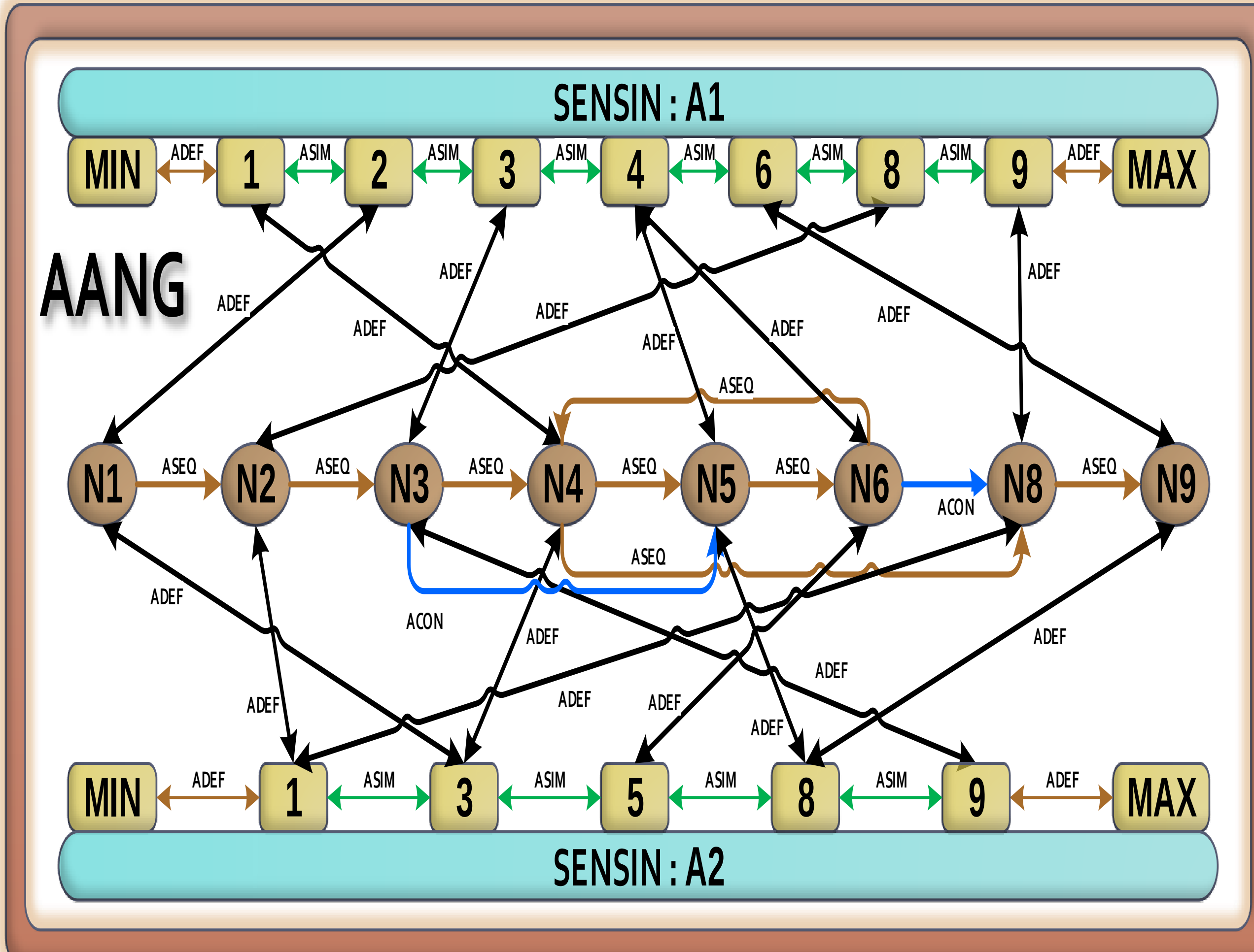
Adrian Horzyk, horzyk@agh.edu.pl, AGH University of Science and Technology

Transformation of a data table into an associative structure

Adding contextual connections allows to represent the sequence of records unambiguously when using adequate weight values.

TABLE

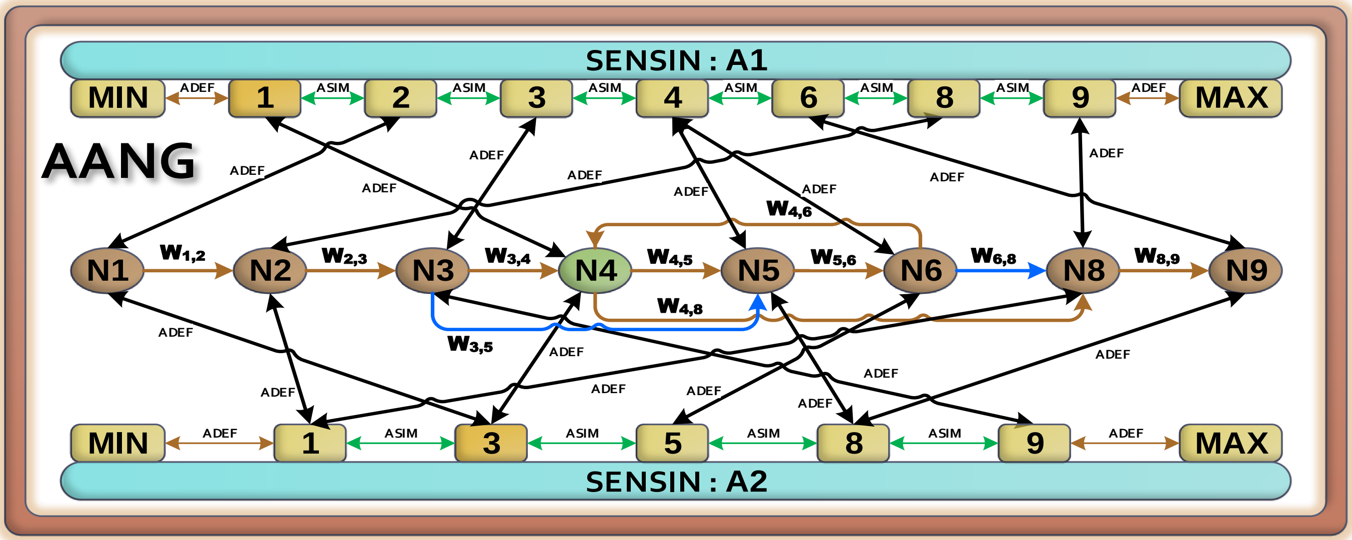
	A1	A2
R1	2	3
R2	8	1
R3	3	9
R4	1	3
R5	4	8
R6	4	5
R7	1	3
R8	9	1
R9	6	8

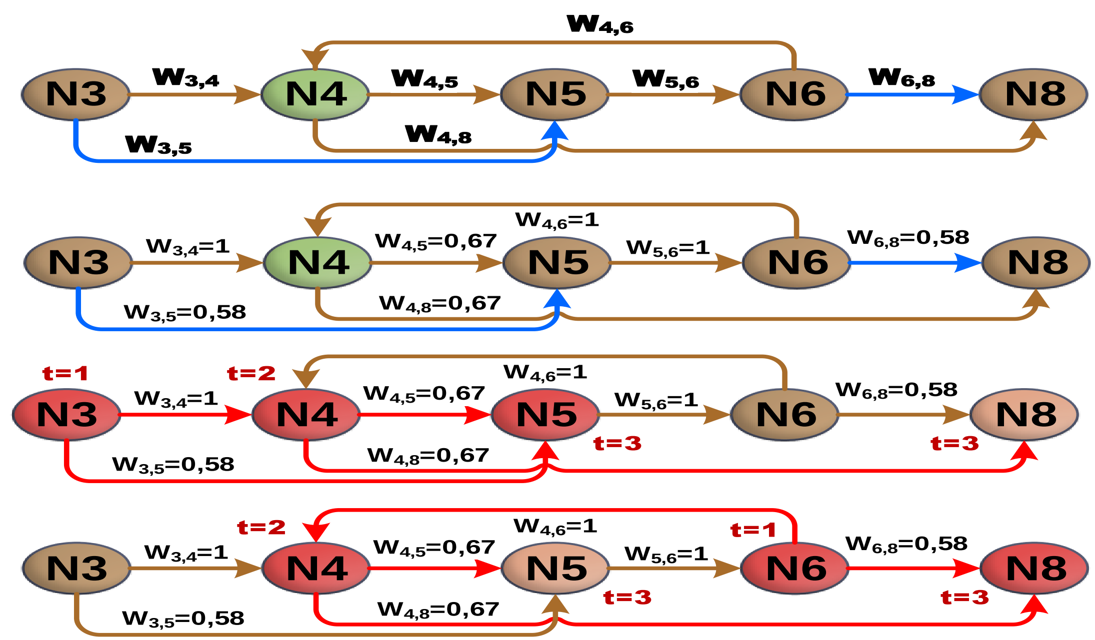


Transformation of a data table into an associative structure

TABLE

	A1	A2
R1	2	3
R2	8	1
R3	3	9
R4	1	3
R5	4	8
R6	4	5
R7	1	3
R8	9	1
R9	6	8





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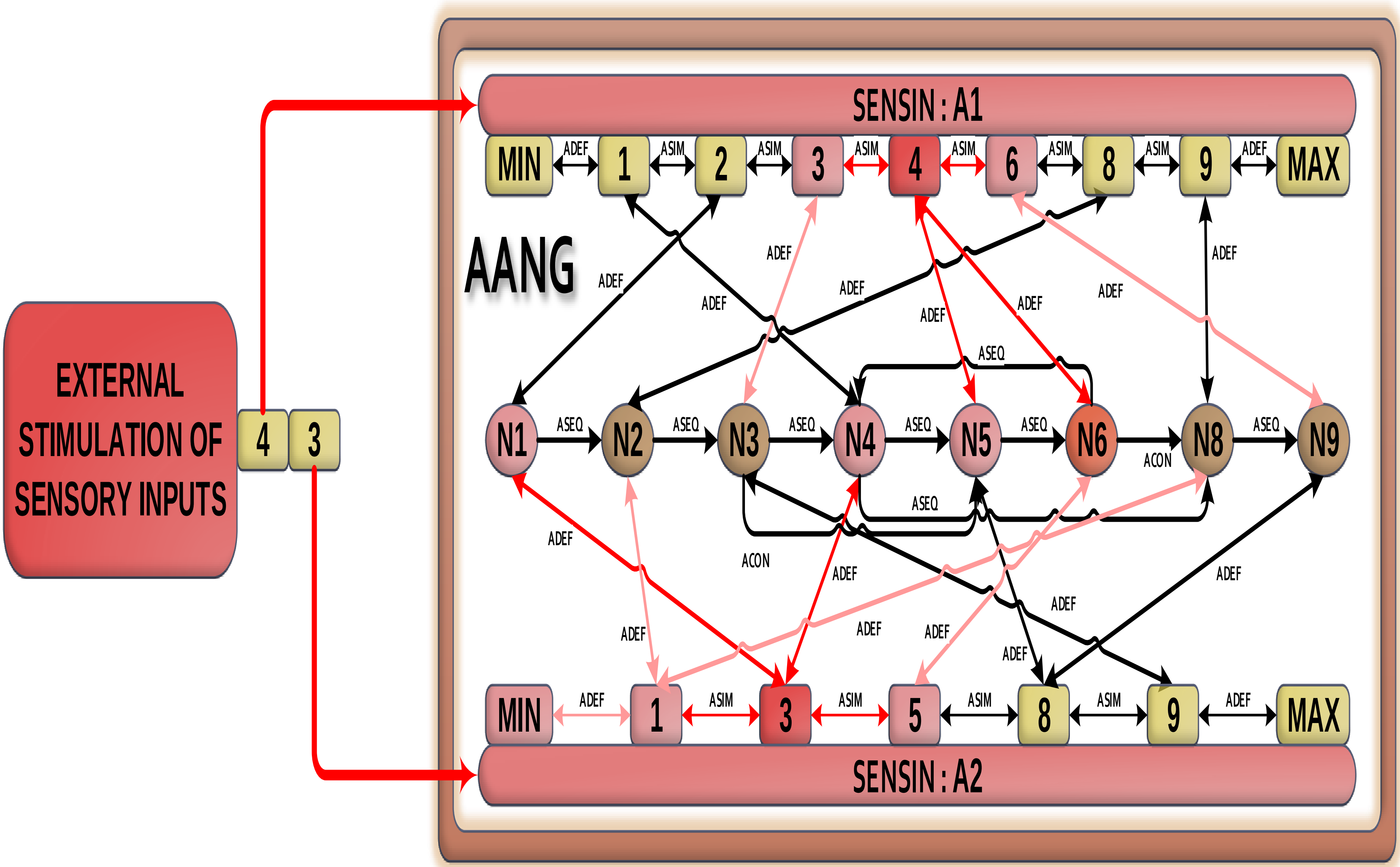
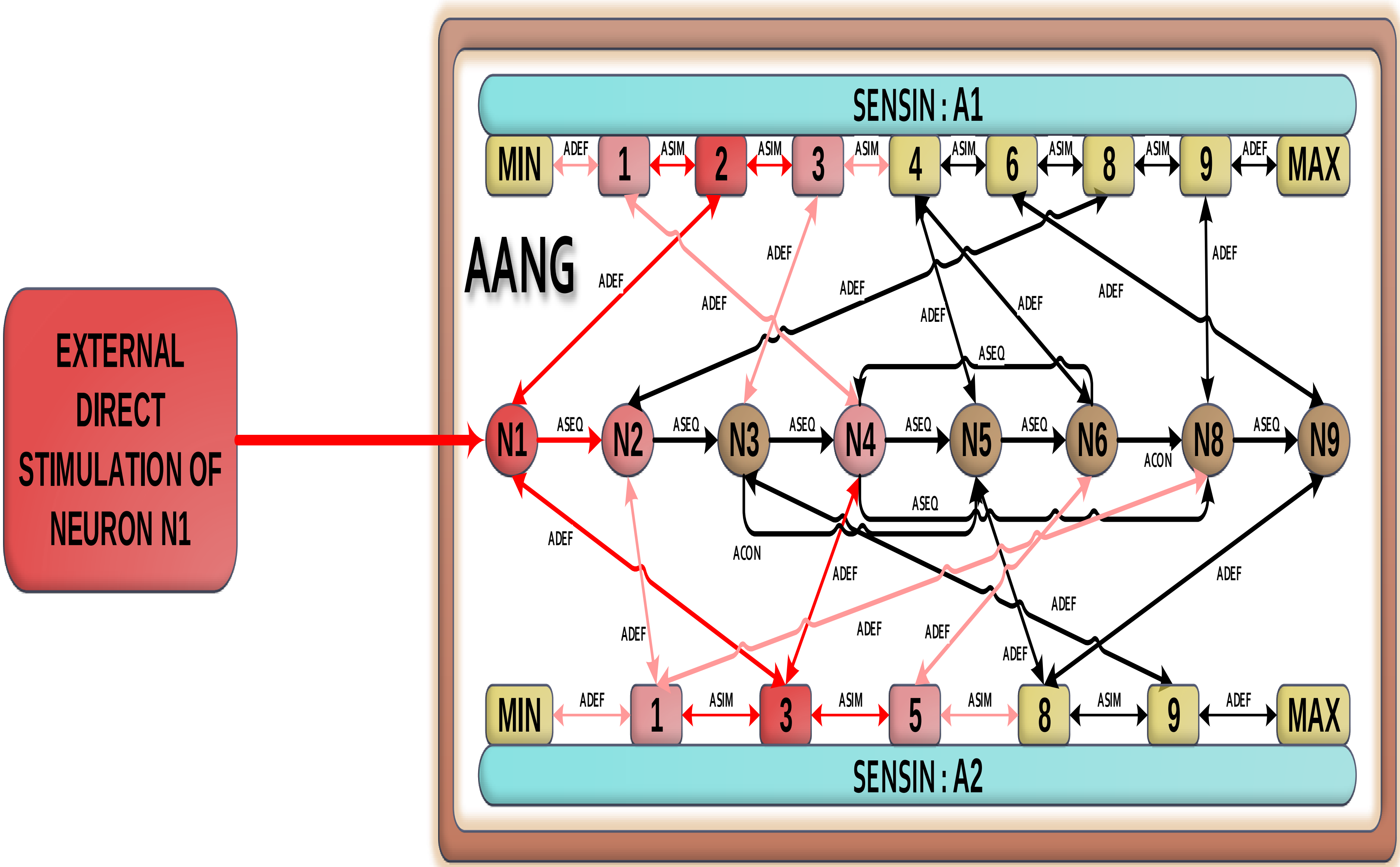
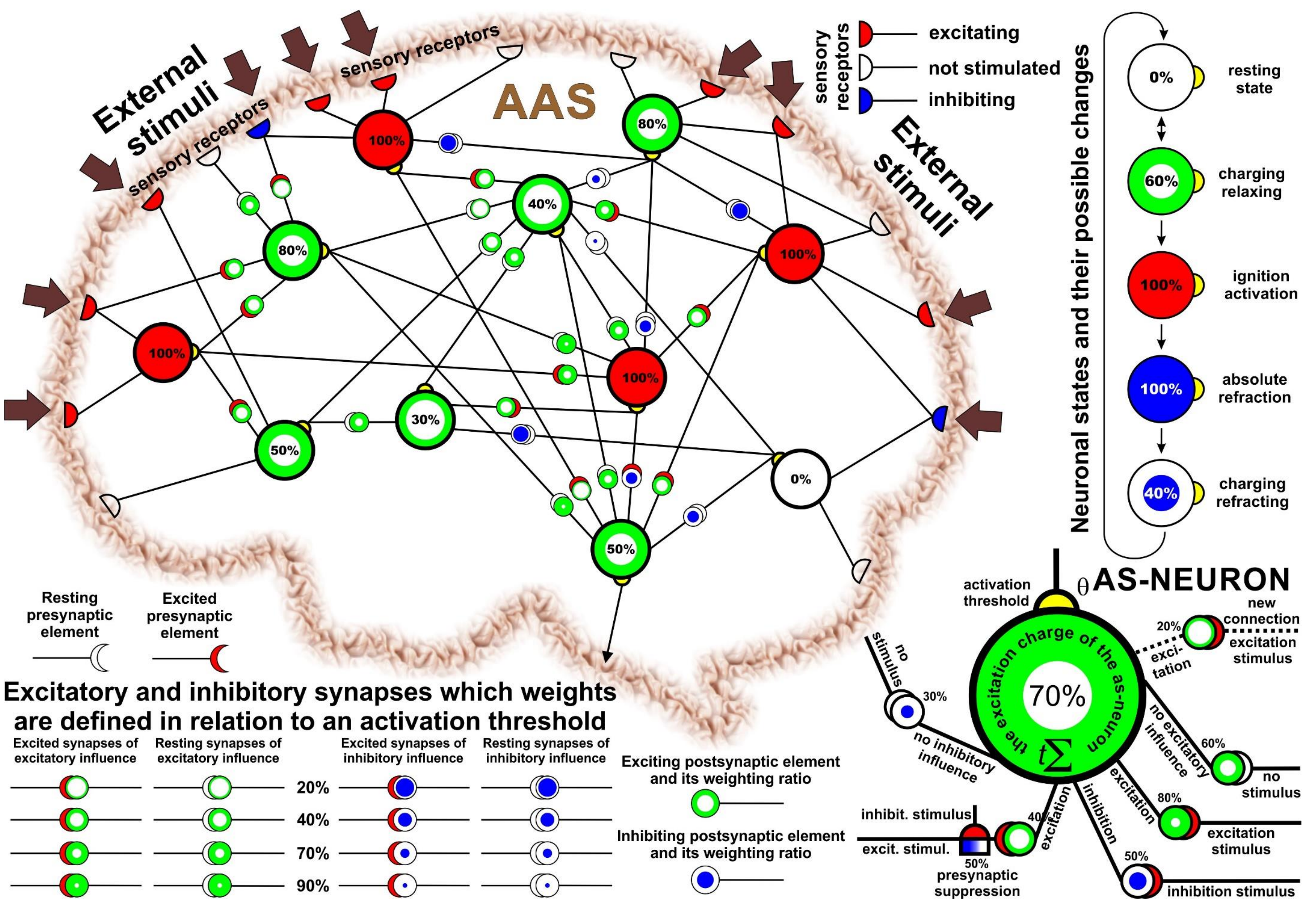
Drawing conclusions from this associative structure



Drawing conclusions from this associative structure



AS-NEURONS – What should they model?

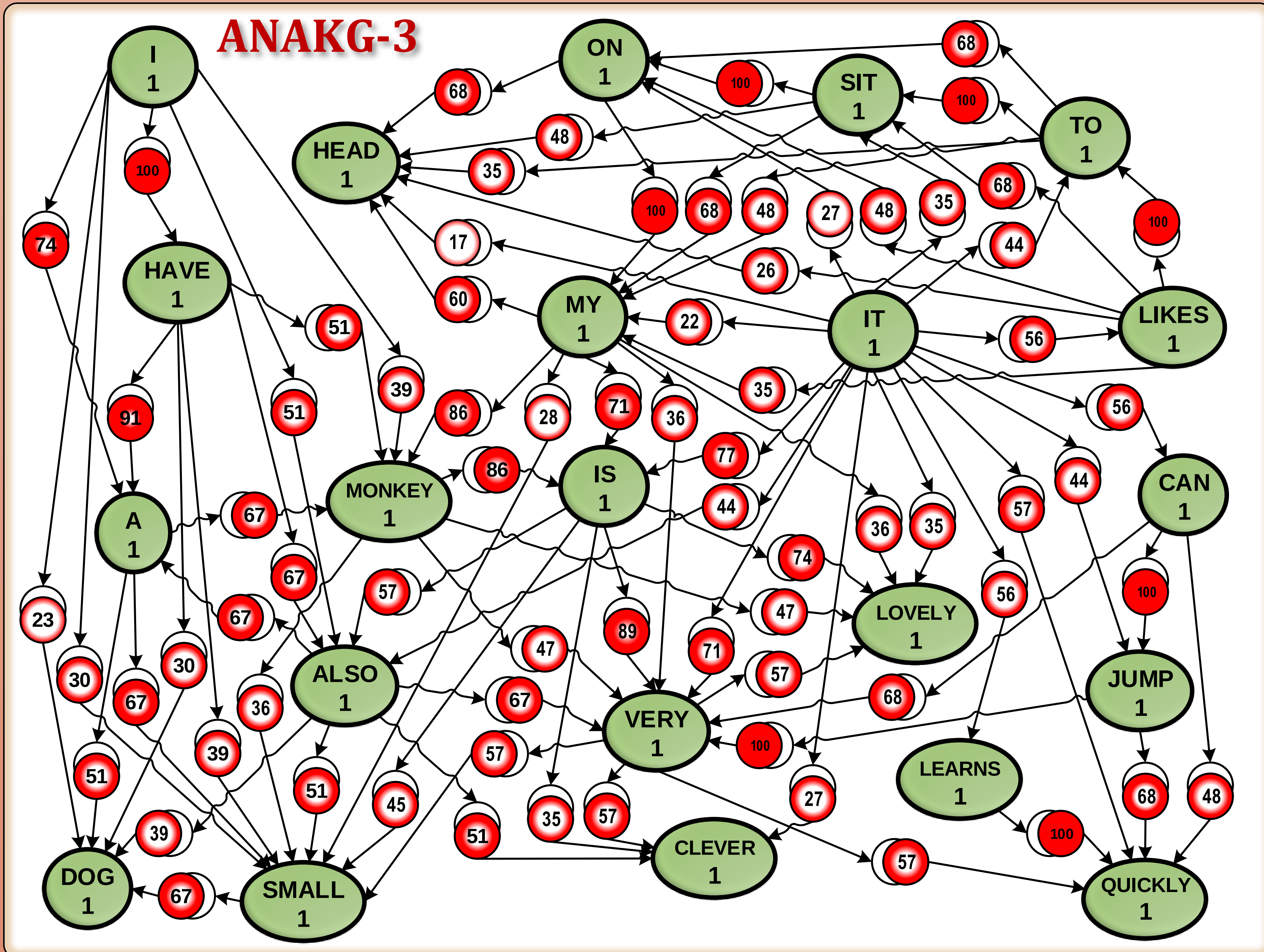


MONKEY

TRAINING SEQUENCE 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 have also a small dog."

QUESTION: What is this monkey like?



ANAKG-3
I 1
ON 1
SIT 1
TO 1
HEAD 1
HAVE 1
MY 1
IT 1
LIKES 1
MONKEY 1
IS 1
A 1
CAN 1
LOVELY 1
ALSO 1
VERY 1
JUMP 1
LEARNS 1
CLEVER 1
DOG 1
SMALL 1
QUICKLY 1

CONSTRUCTION OF ASSOCIATIVE NEURAL GRAPH ANAKG-3

TRAINING SEQUENCES

1x	S1	I	HAVE	A	MONKEY				
1x	S2	MY	MONKEY	IS	VERY	SMALL			
1x	S3	IT	IS	VERY	LOVELY				
1x	S4	IT	LIKES	TO	SIT	ON	MY	HEAD	
1x	S5	IT	CAN	JUMP	VERY	QUICKLY			
1x	S6	IT	IS	ALSO	VERY	CLEVER			
1x	S7	IT	LEARNS	QUICKLY					
1x	S8	MY	MONKEY	IS	LOVELY				
1x	S9	I	HAVE	ALSO	A	SMALL	DOG		

I
1

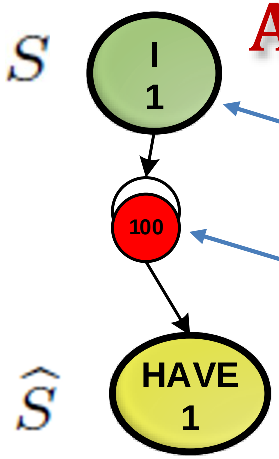
ANAKG-3

S1

S1 | I | HAVE | A | MONKEY

ANAKG-3

S1



SYNAPTIC WEIGHT (CONDUCTANCE)

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

$$\theta_{\widehat{S}} = 1$$

ACTIVATION THRESHOLD

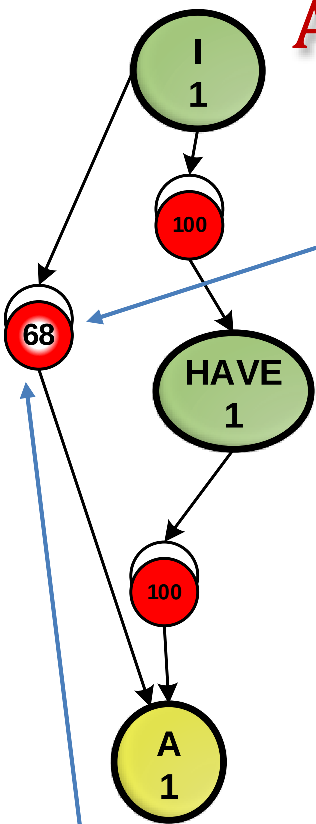
SYNAPTIC EFFICIENCY

$$\delta_{S,\widehat{S}} = \sum_{\{S \rightsquigarrow \widehat{S}\ :\ (\cdots \rightsquigarrow S \rightsquigarrow \cdots \rightsquigarrow \widehat{S} \rightsquigarrow \dots) \in \mathbb{S}\}} \left(\frac{1}{1 + \frac{\Delta t^{ACT} - \Delta t^{CHARGE}}{\theta_{\widehat{S}} \cdot \Delta t^{RECOVER}}} \right)^{\gamma}$$

S1 | I | HAVE | A | MONKEY

ANAKG-3

S1



SYNAPTIC WEIGHT

$$w_{S,\widehat{S}} = \frac{\eta_S \cdot \delta_{S,\widehat{S}} \cdot \theta_{\widehat{S}}}{\eta_S + (\eta_S - 1) \cdot \delta_{S,\widehat{S}}} = \frac{1 \cdot 0.683 \cdot 1}{1 + (1-1) \cdot 0.683} = 0.683$$

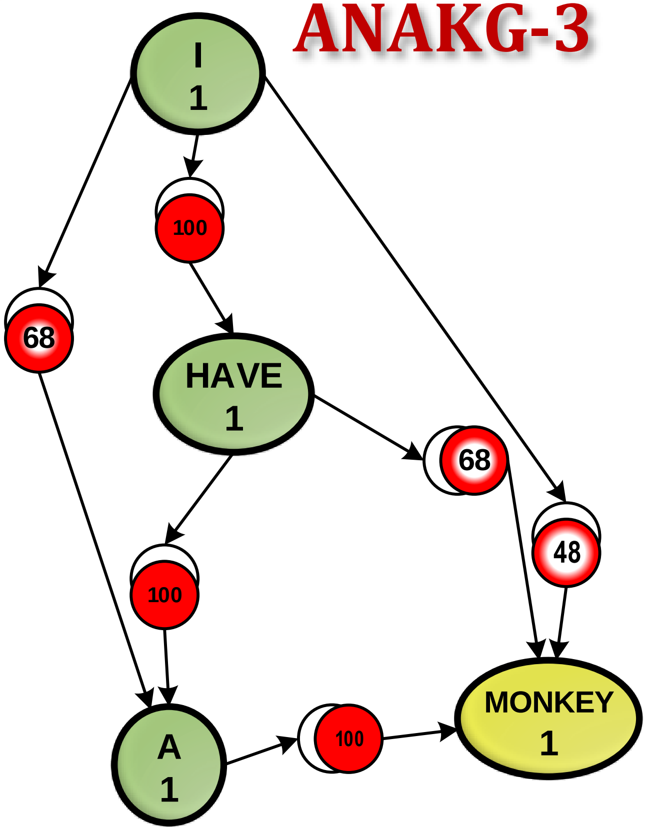
SYNAPTIC EFFICIENCY

$$\delta_{S,\widehat{S}} = \left(\frac{1}{1 + \frac{\Delta t^{ACT} - \Delta t^{CHARGE}}{\theta_{\widehat{S}} \cdot \Delta t^{RECOVER}}} \right)^{\gamma} = \left(\frac{1}{1 + \frac{5-2}{1 \cdot 30}} \right)^{4} = 0.683$$

S1 | I | HAVE | A | MONKEY

ANAKG-3

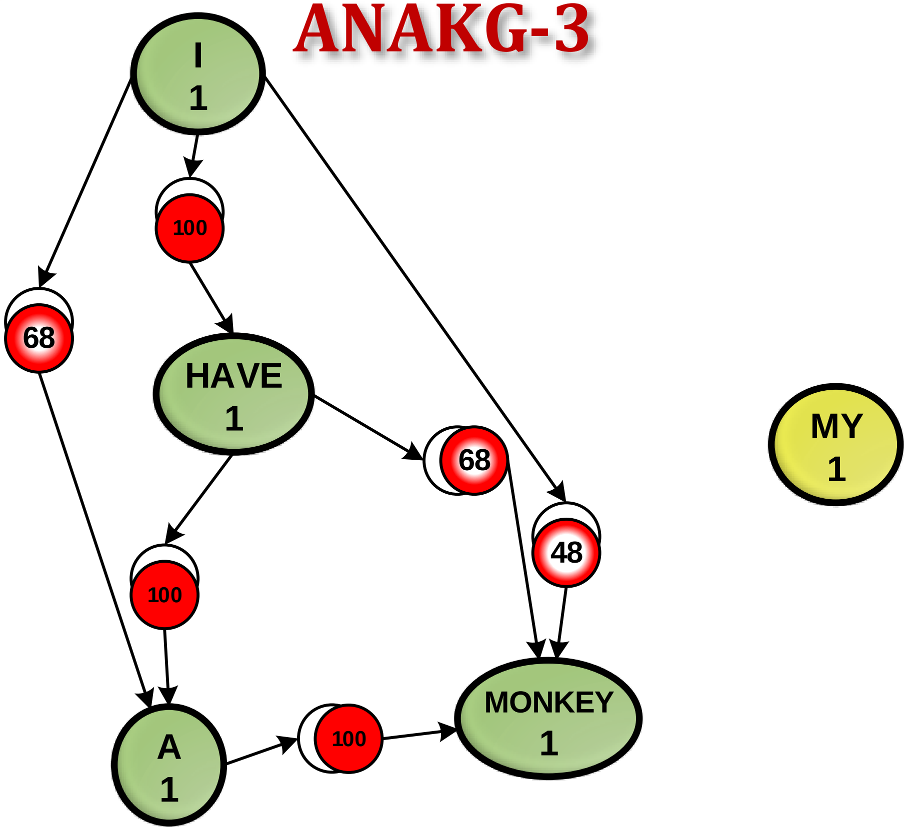
S1



S1 | I | HAVE | A | MONKEY

ANAKG-3

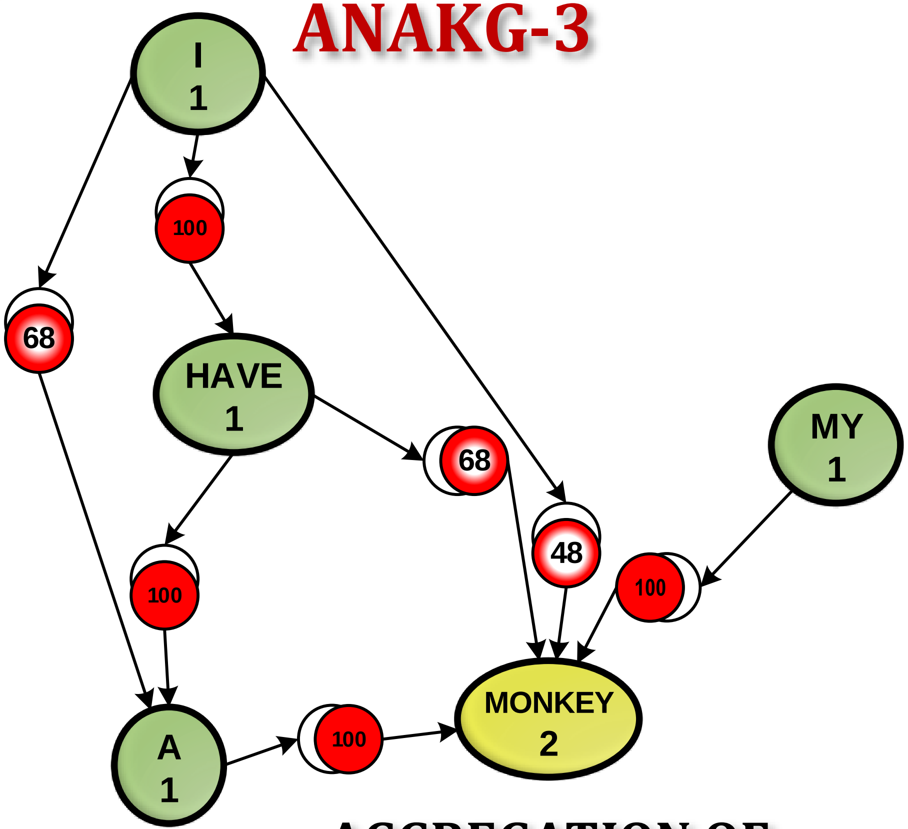
S2



S2 MY MONKEY IS VERY SMALL

ANAKG-3

S2

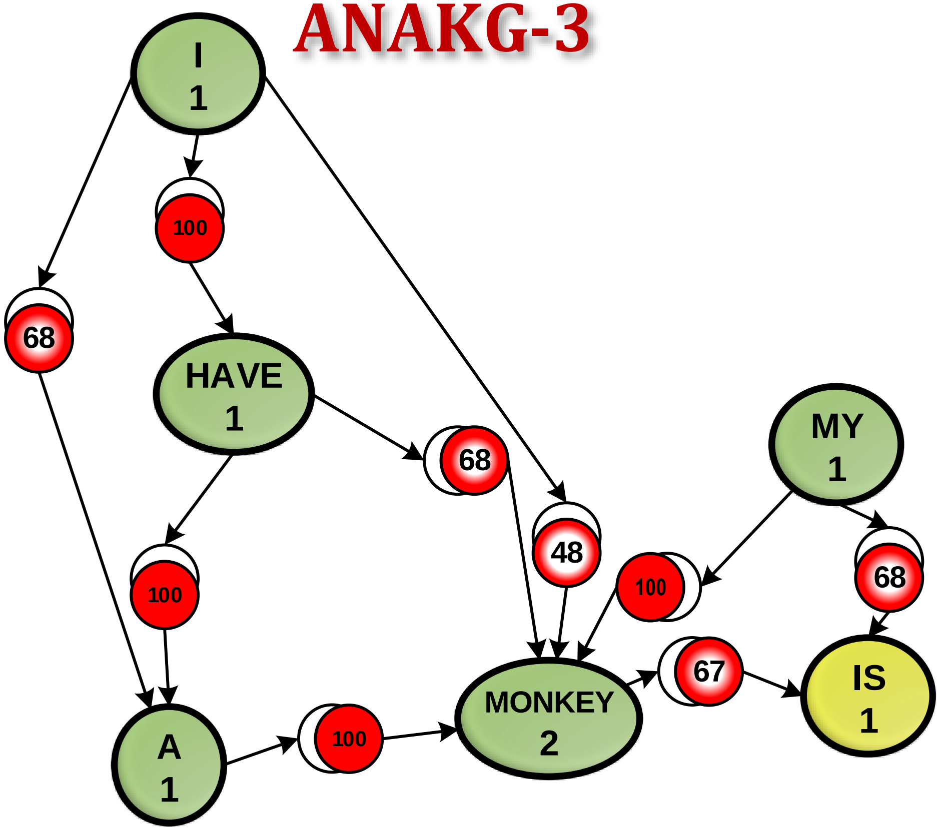


AGGREGATION OF REPRESENTATION

S2 MY MONKEY IS VERY SMALL

ANAKG-3

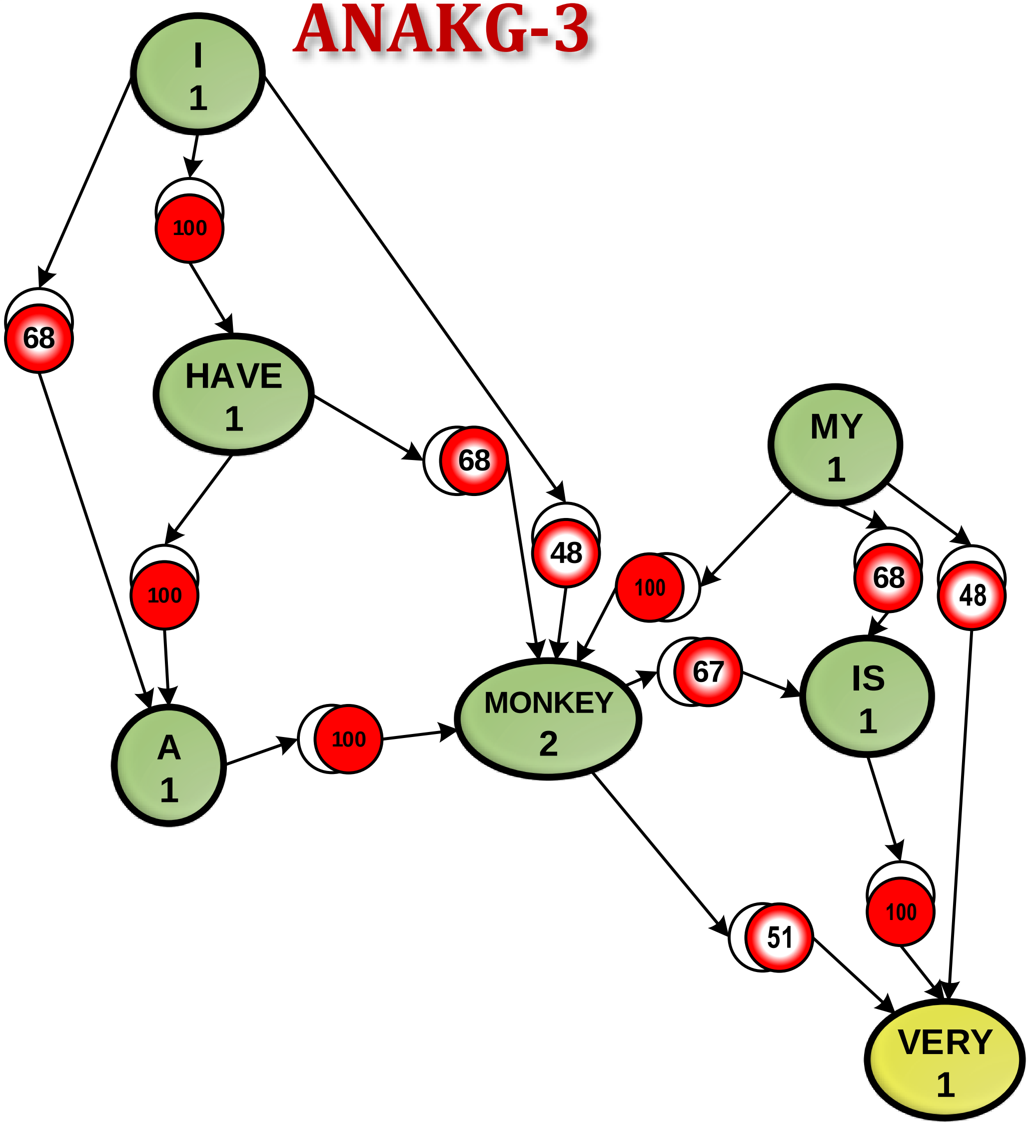
S2



S2 | MY | MONKEY | IS | VERY | SMALL

ANAKG-3

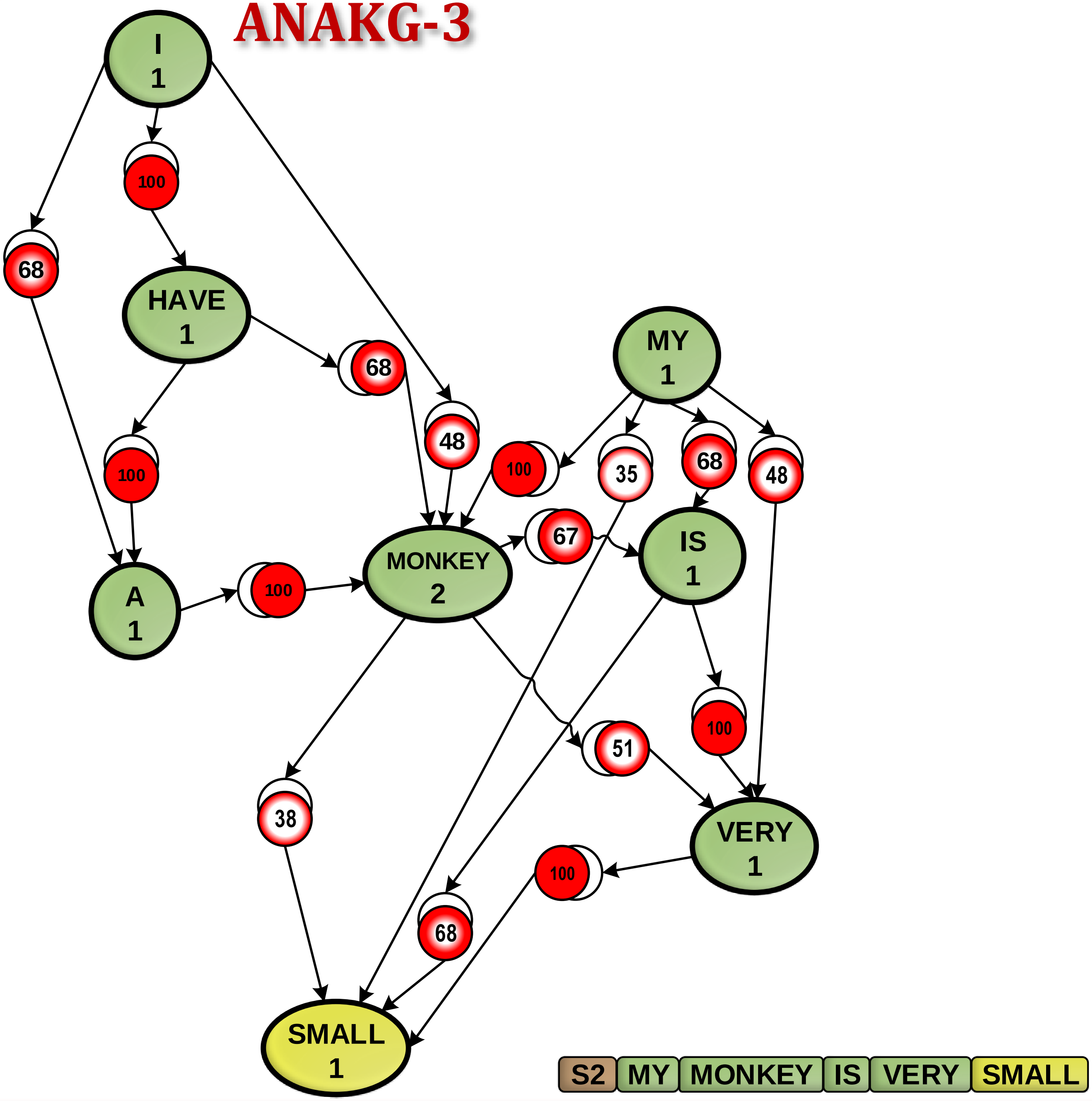
S2



S2 | MY | MONKEY | IS | VERY | SMALL

ANAKG-3

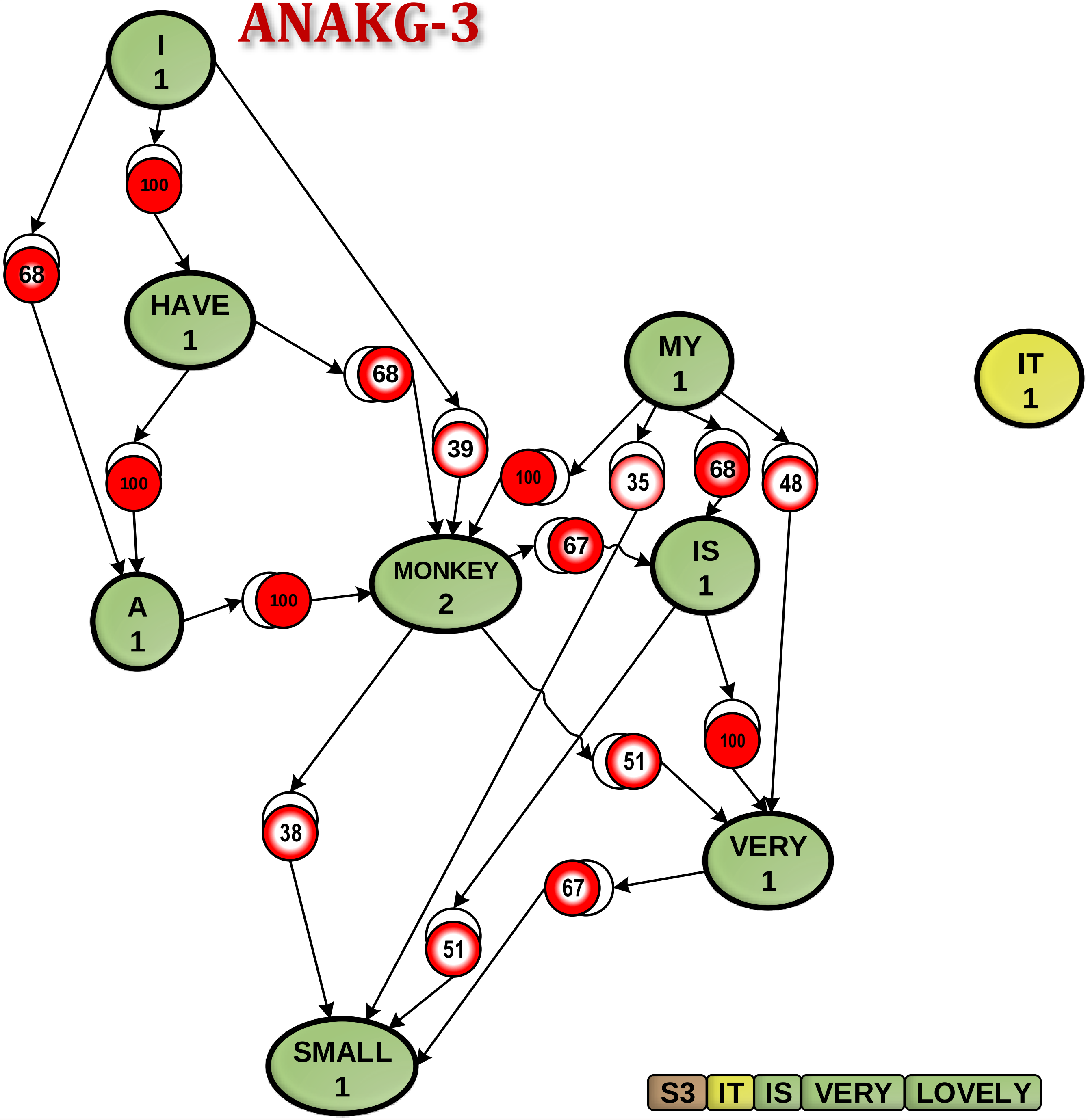
S2



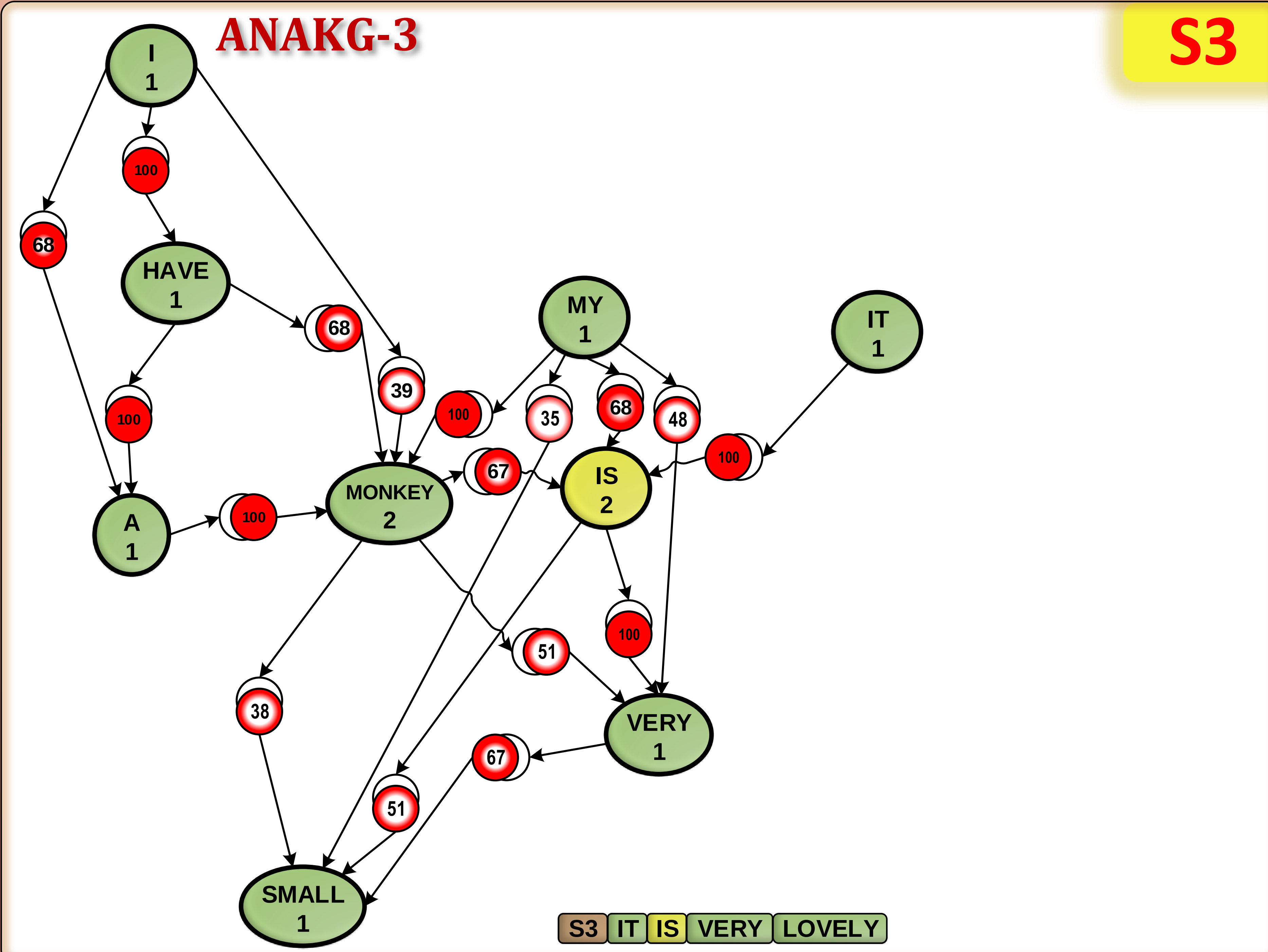
I 1
100
68
HAVE 1
68
48
100
A 1
100
MONKEY 2
MY 1
100
35
68
48
67
IS 1
51
100
38
VERY 1
100
68
SMALL 1
S2 MY MONKEY IS VERY SMALL

ANAKG-3

S3

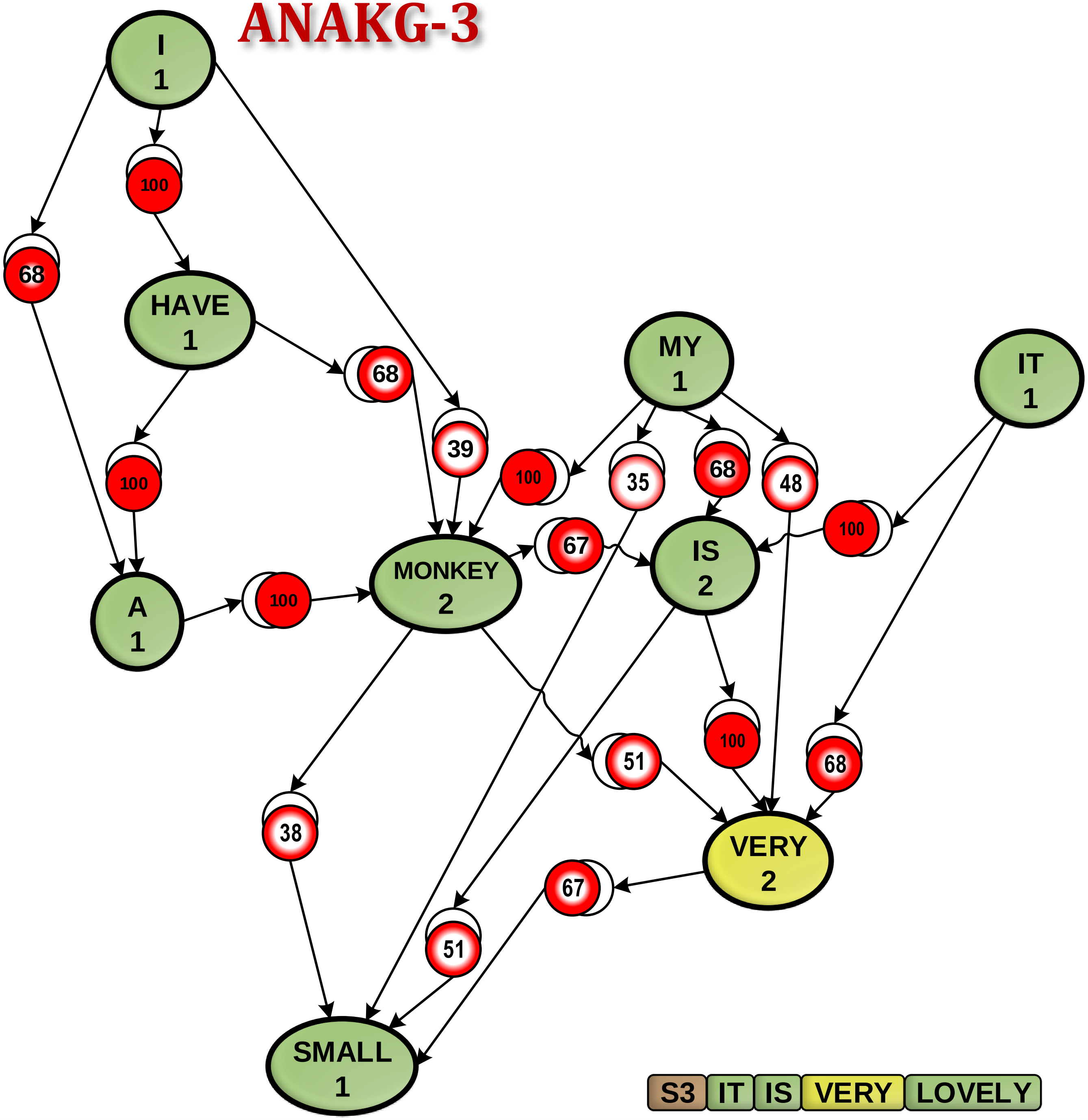


S3 IT IS VERY LOVELY


ANAKG-3
S3
I 1
68
100
HAVE 1
68
39
100
A 1
100
MONKEY 2
MY 1
IT 1
100
35
68
48
67
IS 2
100
51
100
38
VERY 1
67
51
SMALL 1
S3 IT IS VERY LOVELY

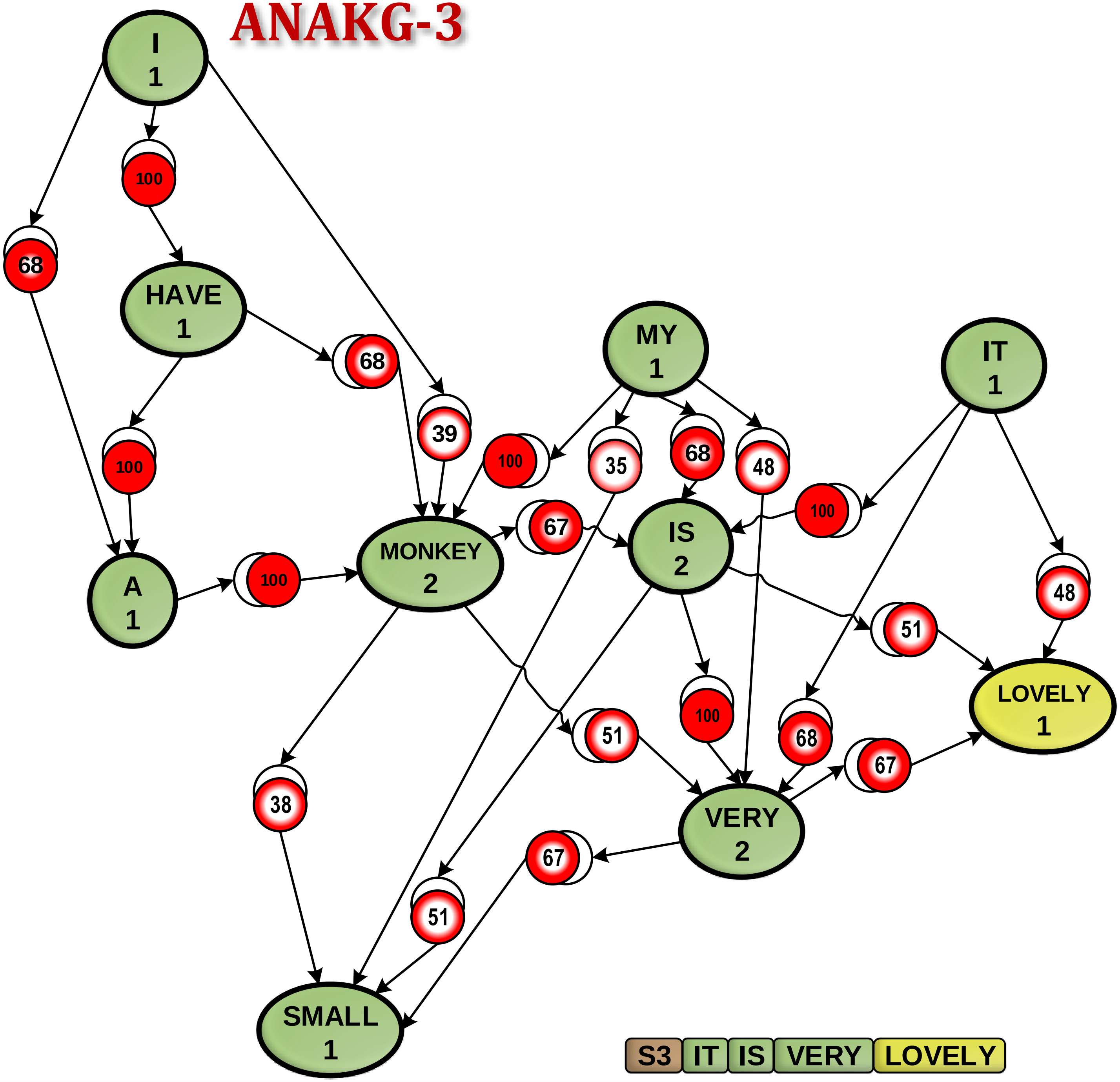
ANAKG-3

S3

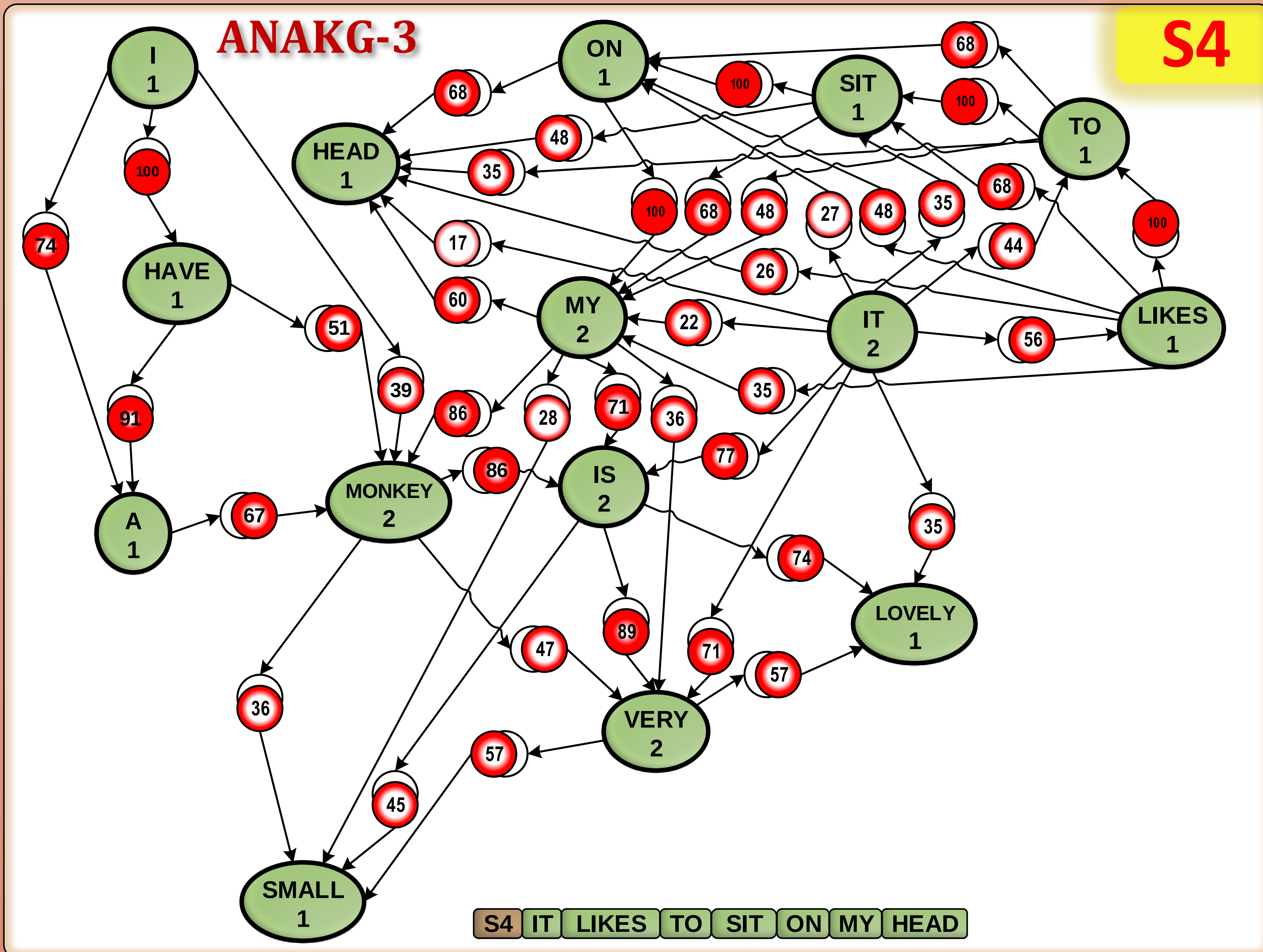

I 1
HAVE 1
A 1
MONKEY 2
MY 1
IT 1
IS 2
VERY 2
SMALL 1
100
68
100
68
39
100
100
35
68
48
100
67
51
100
68
38
67
51
S3 IT IS VERY LOVELY

ANAKG-3

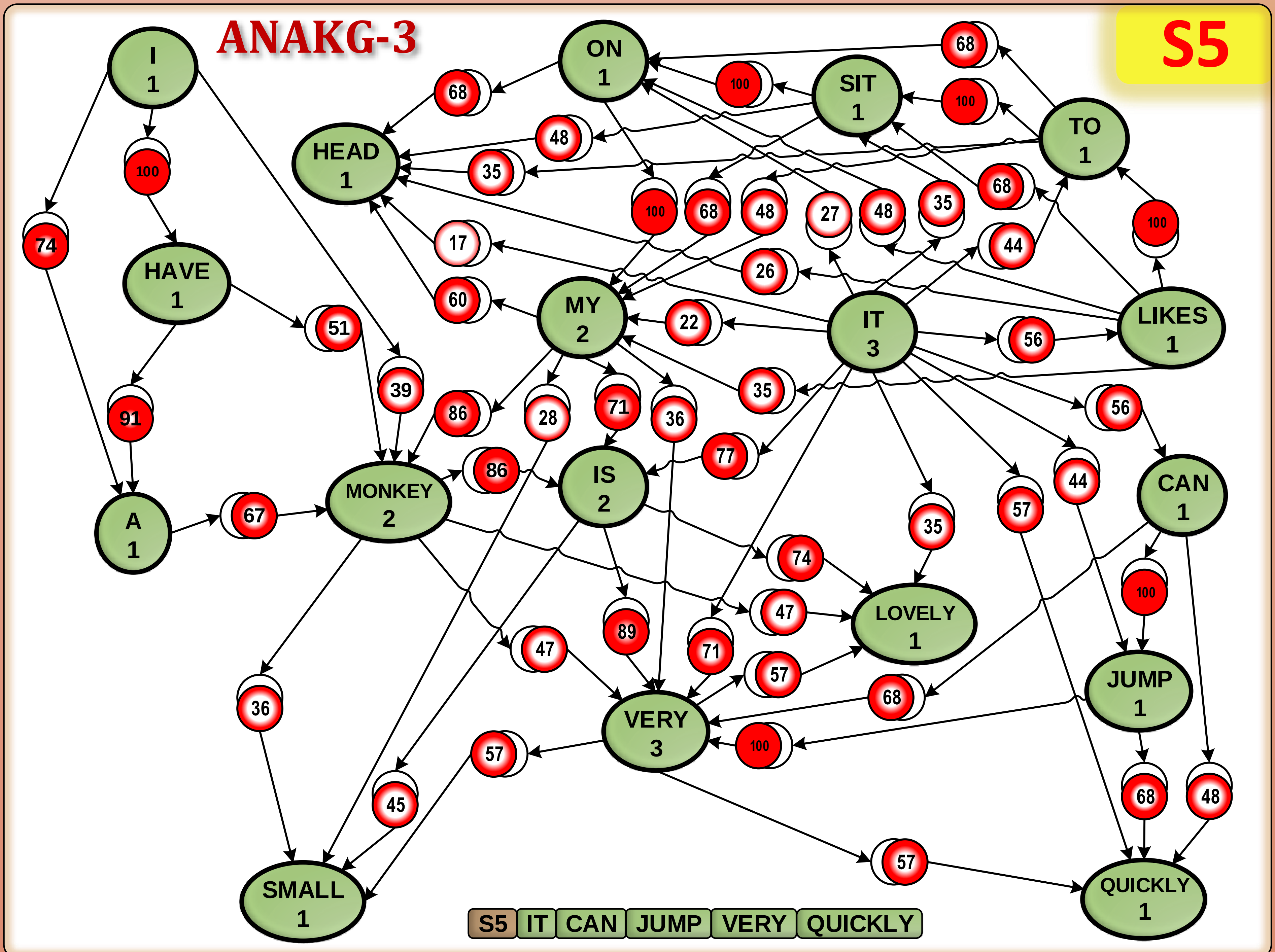
S3



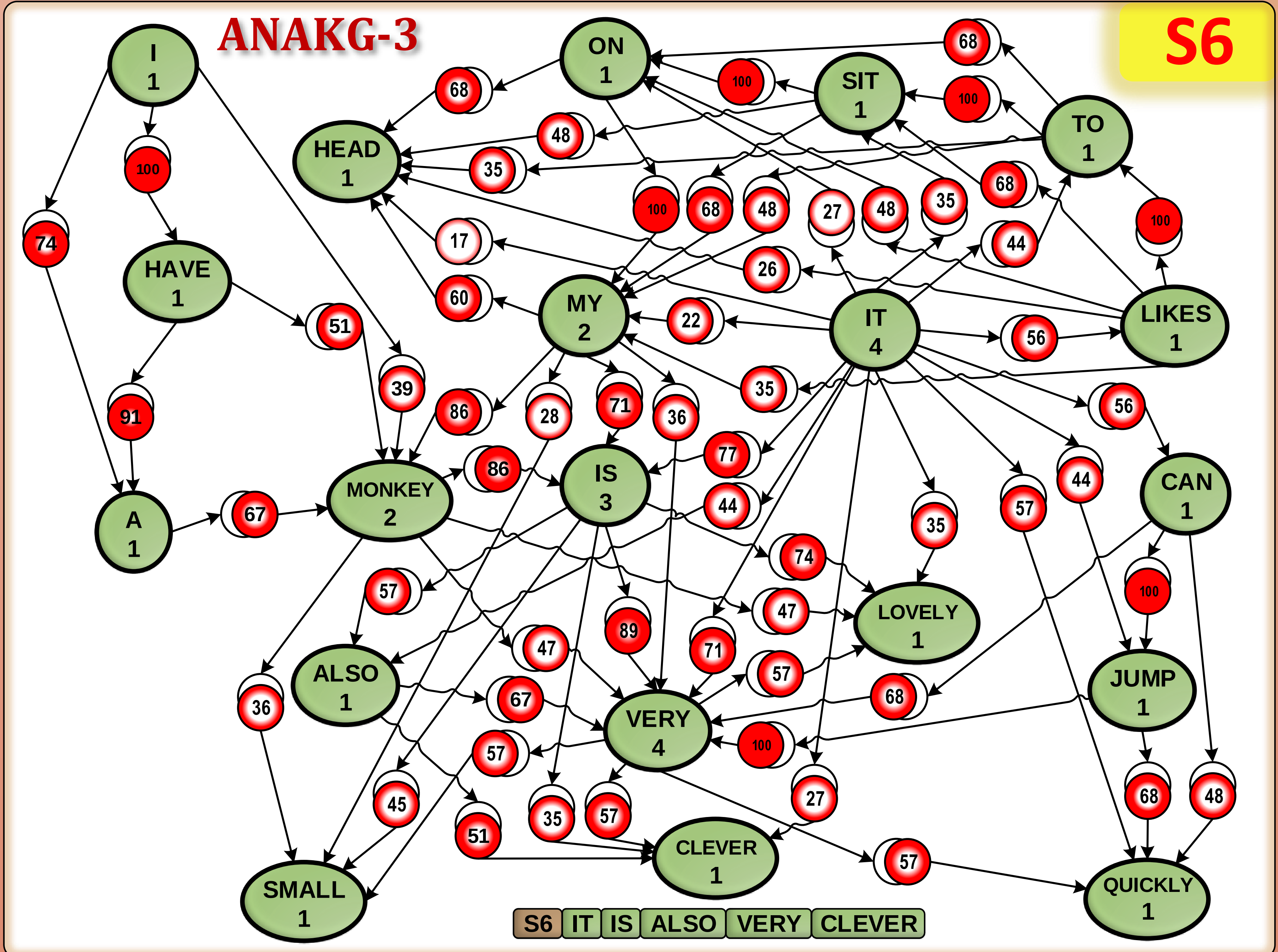
S3 | IT | IS | VERY | LOVELY



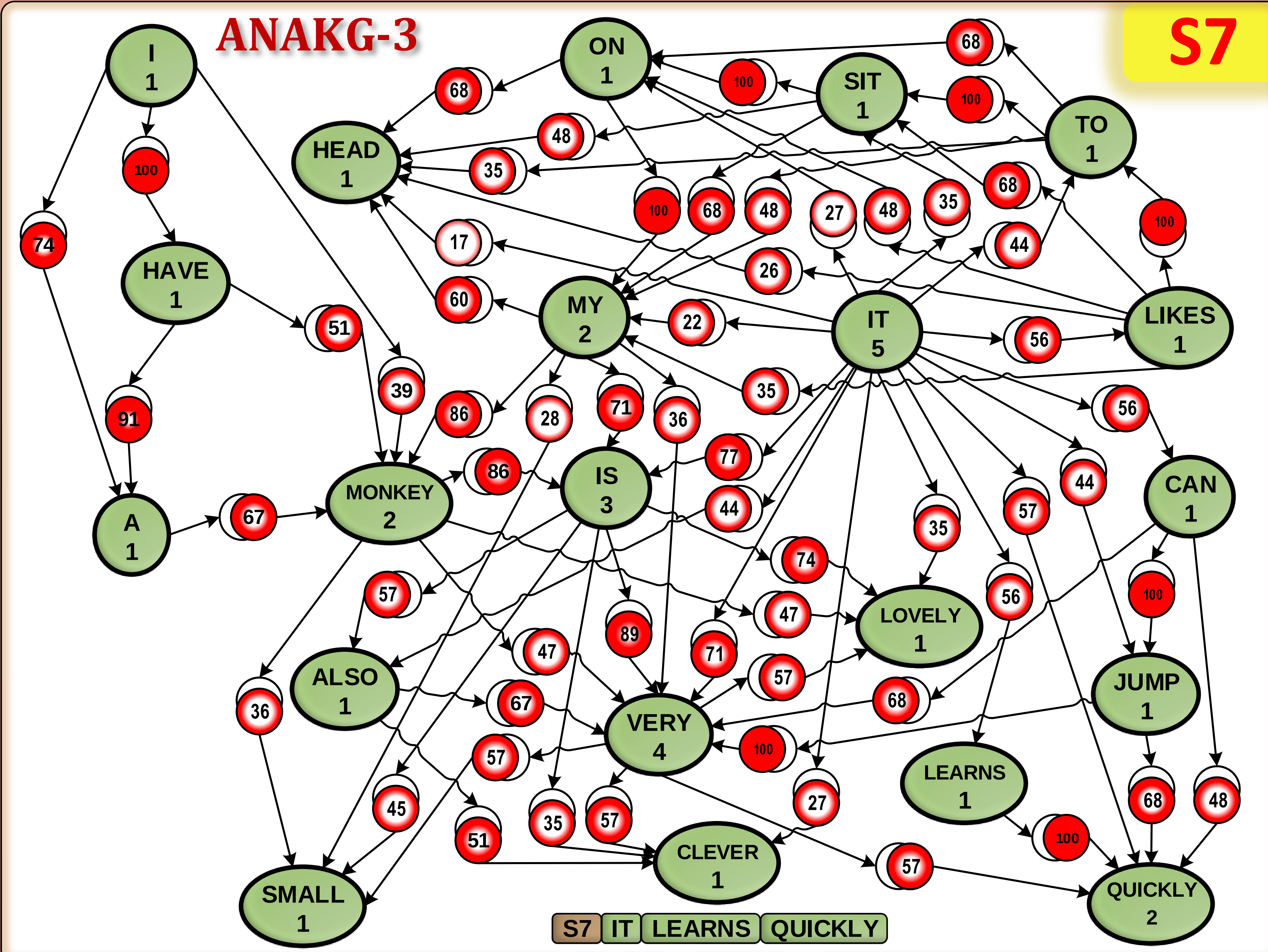
ANAKG-3
S4
I
1
ON
1
SIT
1
TO
1
HEAD
1
HAVE
1
MY
2
IT
2
LIKES
1
A
1
MONKEY
2
IS
2
LOVELY
1
VERY
2
SMALL
1
68
68
100
100
48
100
35
100
68
48
27
48
35
68
74
17
44
100
26
60
51
22
56
39
35
91
86
28
71
36
77
86
67
35
74
89
47
71
57
36
57
45
S4
IT
LIKES
TO
SIT
ON
MY
HEAD



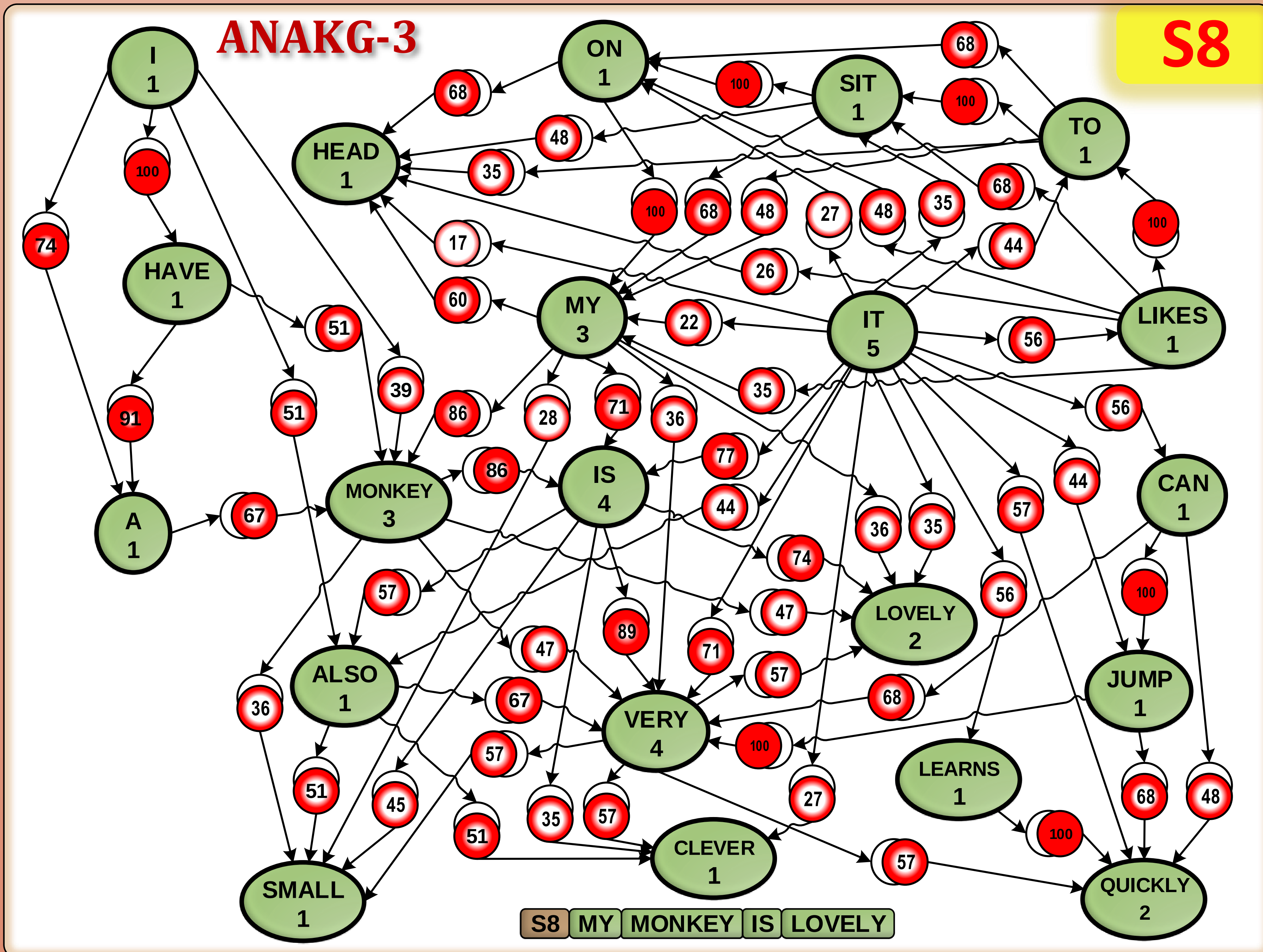
ANAKG-3
S5
I 1
ON 1
SIT 1
TO 1
HEAD 1
HAVE 1
MY 2
IT 3
LIKES 1
A 1
MONKEY 2
IS 2
CAN 1
LOVELY 1
JUMP 1
VERY 3
SMALL 1
QUICKLY 1
S5 IT CAN JUMP VERY QUICKLY



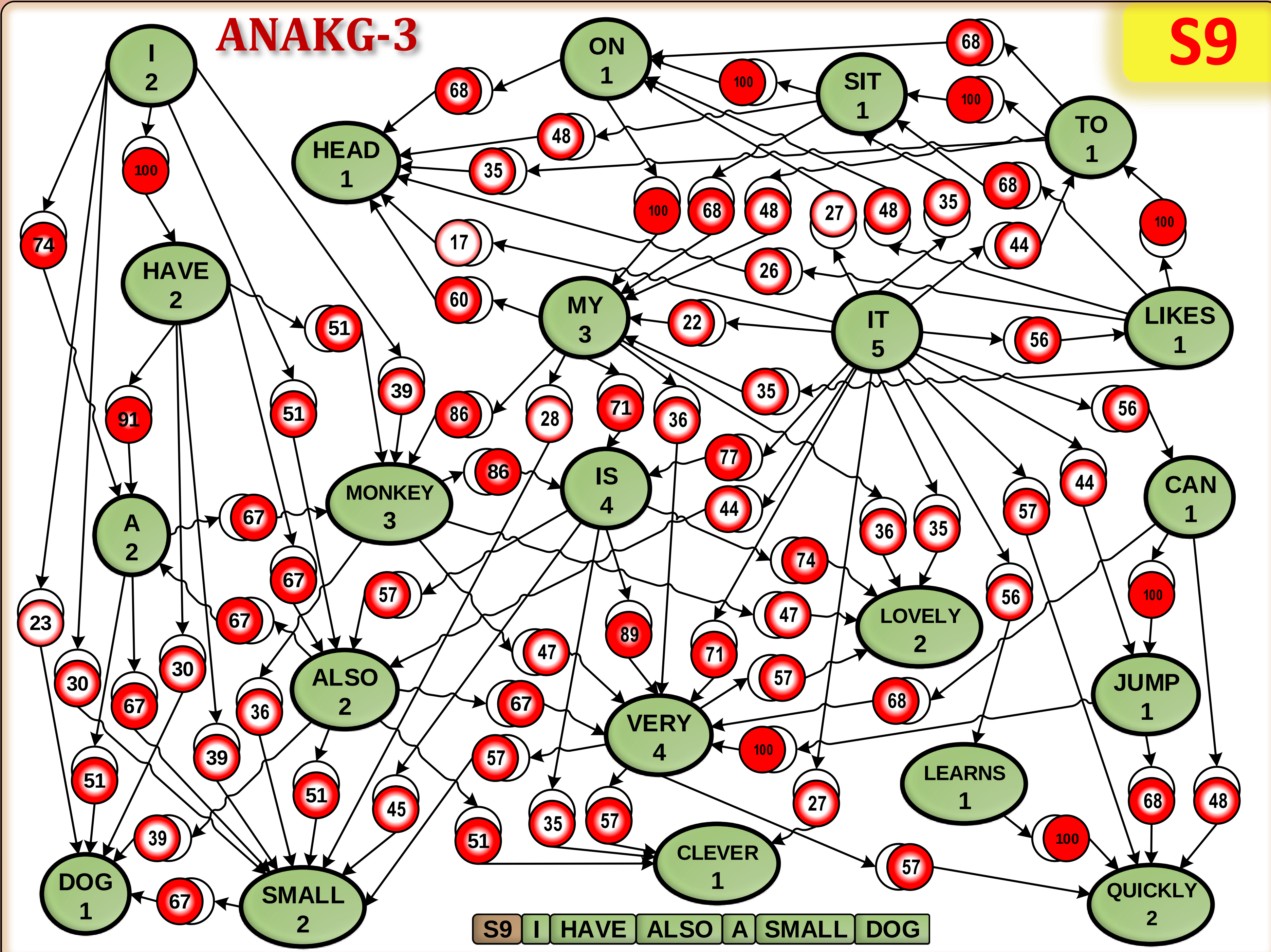
ANAKG-3
S6
I 1
ON 1
SIT 1
TO 1
HEAD 1
HAVE 1
MY 2
IT 4
LIKES 1
A 1
MONKEY 2
IS 3
CAN 1
LOVELY 1
ALSO 1
VERY 4
JUMP 1
SMALL 1
CLEVER 1
QUICKLY 1
S6 IT IS ALSO VERY CLEVER



ANAKG-3
S7
I 1
ON 1
SIT 1
TO 1
HEAD 1
HAVE 1
MY 2
IT 5
LIKES 1
A 1
MONKEY 2
IS 3
CAN 1
LOVELY 1
JUMP 1
ALSO 1
VERY 4
LEARNS 1
CLEVER 1
SMALL 1
QUICKLY 2
S7 IT LEARNS QUICKLY



ANAKG-3
S8
I 1
ON 1
SIT 1
TO 1
HEAD 1
HAVE 1
MY 3
IT 5
LIKES 1
A 1
MONKEY 3
IS 4
CAN 1
LOVELY 2
ALSO 1
VERY 4
JUMP 1
LEARNS 1
CLEVER 1
SMALL 1
QUICKLY 2
S8 MY MONKEY IS LOVELY


ANAKG-3
S9
I 2
ON 1
SIT 1
TO 1
HEAD 1
HAVE 2
MY 3
IT 5
LIKES 1
A 2
MONKEY 3
IS 4
CAN 1
LOVELY 2
JUMP 1
ALSO 2
VERY 4
LEARNS 1
CLEVER 1
DOG 1
SMALL 2
QUICKLY 2
S9 I HAVE ALSO A SMALL DOG

COMPUTATION OF SYNAPTIC EFFICIENCES

$$\delta_{S,\widehat{S}} = \sum_{\{S \rightsquigarrow \widehat{S} \;:\; (\cdots \rightsquigarrow S \rightsquigarrow \cdots \rightsquigarrow \widehat{S} \rightsquigarrow \dots) \in \mathbb{S}\}} \left(\frac{1}{1 + \frac{\Delta t^{ACT} - \Delta t^{CHARGE}}{\theta_{\widehat{S}} \cdot \Delta t^{RECOVER}}} \right)^{\gamma}$$

PRESYNAPTIC AS-NEURON (rows) / POSTSYNAPTIC AS-NEURON (columns)

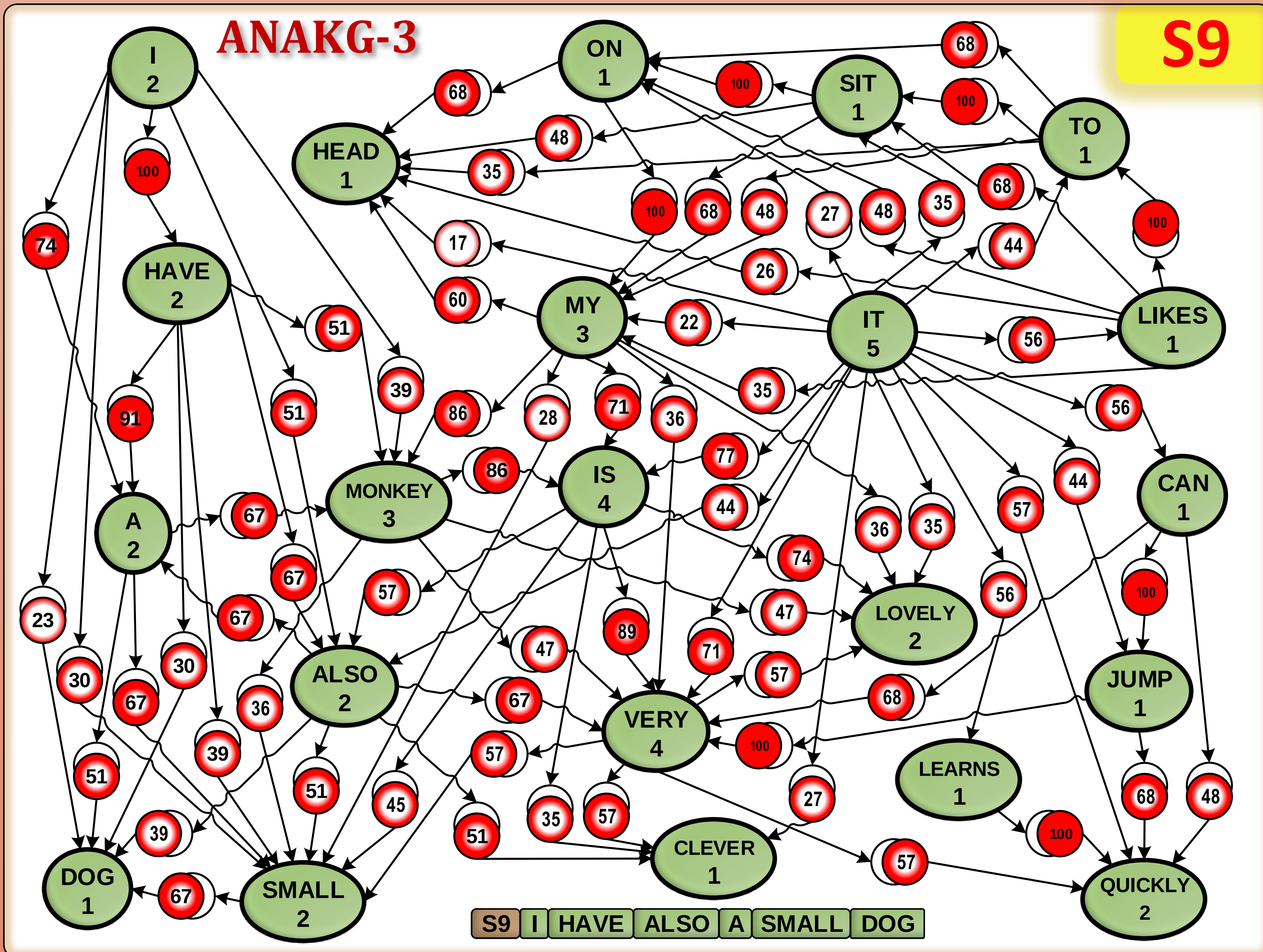
η	Σδ	A	ALSO	CAN	CLEVER	DOG	HAVE	HEAD	I	IS	IT	JUMP	LEARNS	LIKES	LOVELY	MONKEY	MY	ON	QUICKLY	SIT	SMALL	TO	VERY
2	A					0,683										1,000					1,000		
2	ALSO	1,000			0,683	0,482															0,683		1,000
1	CAN											1,000							0,482				0,683
1	CLEVER																						
1	DOG																						
2	HAVE	1,683	1,000			0,350										0,683					0,482		
1	HEAD																						
2	I	1,165	0,683			0,260	2,000									0,482					0,350		
4	IS		1,000		0,482										1,683						0,683		2,683
5	IT		0,683	1,000	0,350			0,198		2,000		0,683	1,000	1,000	0,482		0,260	0,350	1,033	0,482		0,683	1,647
1	JUMP																		0,683				1,000
1	LEARNS																		1,000				
1	LIKES							0,260									0,350	0,482		0,683		1,000	
2	LOVELY																						
3	MONKEY									2,000					0,683						0,482		0,683
3	MY							1,000		1,366					0,482	2,000					0,350		0,482
1	ON							0,683									1,000						
2	QUICKLY																						
1	SIT							0,482									0,683	1,000					
2	SMALL					1,000																	
1	TO							0,350									0,482	0,683		1,000			
4	VERY				1,000										1,000				1,000		1,000		

COMPUTATION OF WEIGHTS FOR CREATED SYNAPSES

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

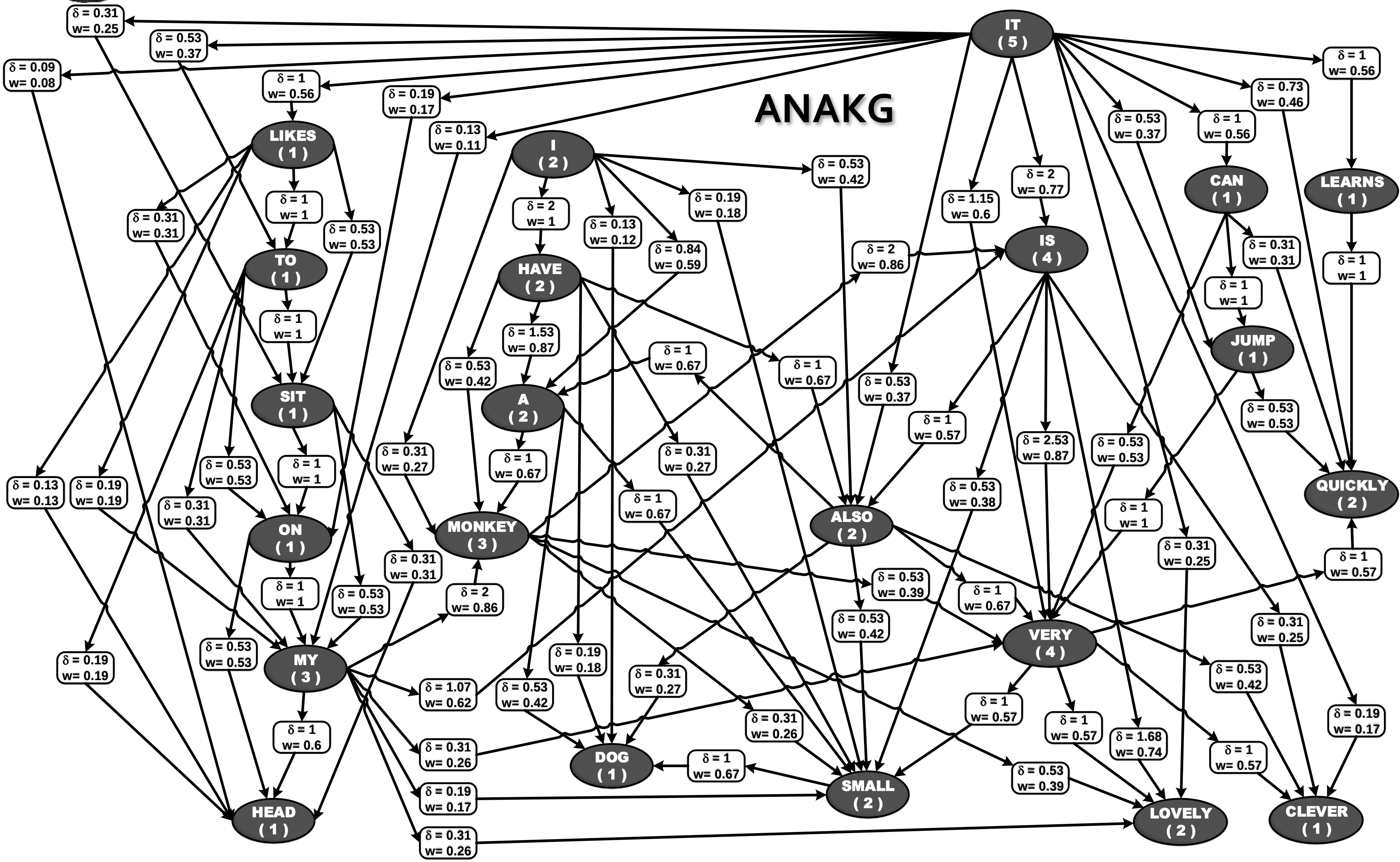
ANAKG-3

	POSTSYNAPTIC AS-NEURON																					
PRESYNAPTIC AS-NEURON: w	A	ALSO	CAN	CLEVER	DOG	HAVE	HEAD	I	IS	IT	JUMP	LEARNS	LIKES	LOVELY	MONKEY	MY	ON	QUICKLY	SIT	SMALL	TO	VERY
A					0,509										0,667					0,667		
ALSO	0,667			0,509	0,388															0,509		0,667
CAN											1,000							0,482				0,683
CLEVER																						
DOG																						
HAVE	0,914	0,667			0,298										0,509					0,388		
HEAD																						
I	0,736	0,509			0,230	1,000									0,388					0,298		
IS		0,571		0,354										0,744						0,452		0,891
IT		0,442	0,556	0,273			0,171		0,769		0,442	0,556	0,556	0,348		0,215	0,273	0,566	0,348		0,442	0,711
JUMP																		0,683				1,000
LEARNS																		1,000				
LIKES							0,260									0,350	0,482		0,683		1,000	
LOVELY																						
MONKEY									0,857					0,469						0,365		0,469
MY							0,600		0,715					0,365	0,857					0,284		0,365
ON							0,683									1,000						
QUICKLY																						
SIT							0,482									0,683	1,000					
SMALL					0,667																	
TO							0,350									0,482	0,683		1,000			
VERY				0,571										0,571				0,571		0,571		

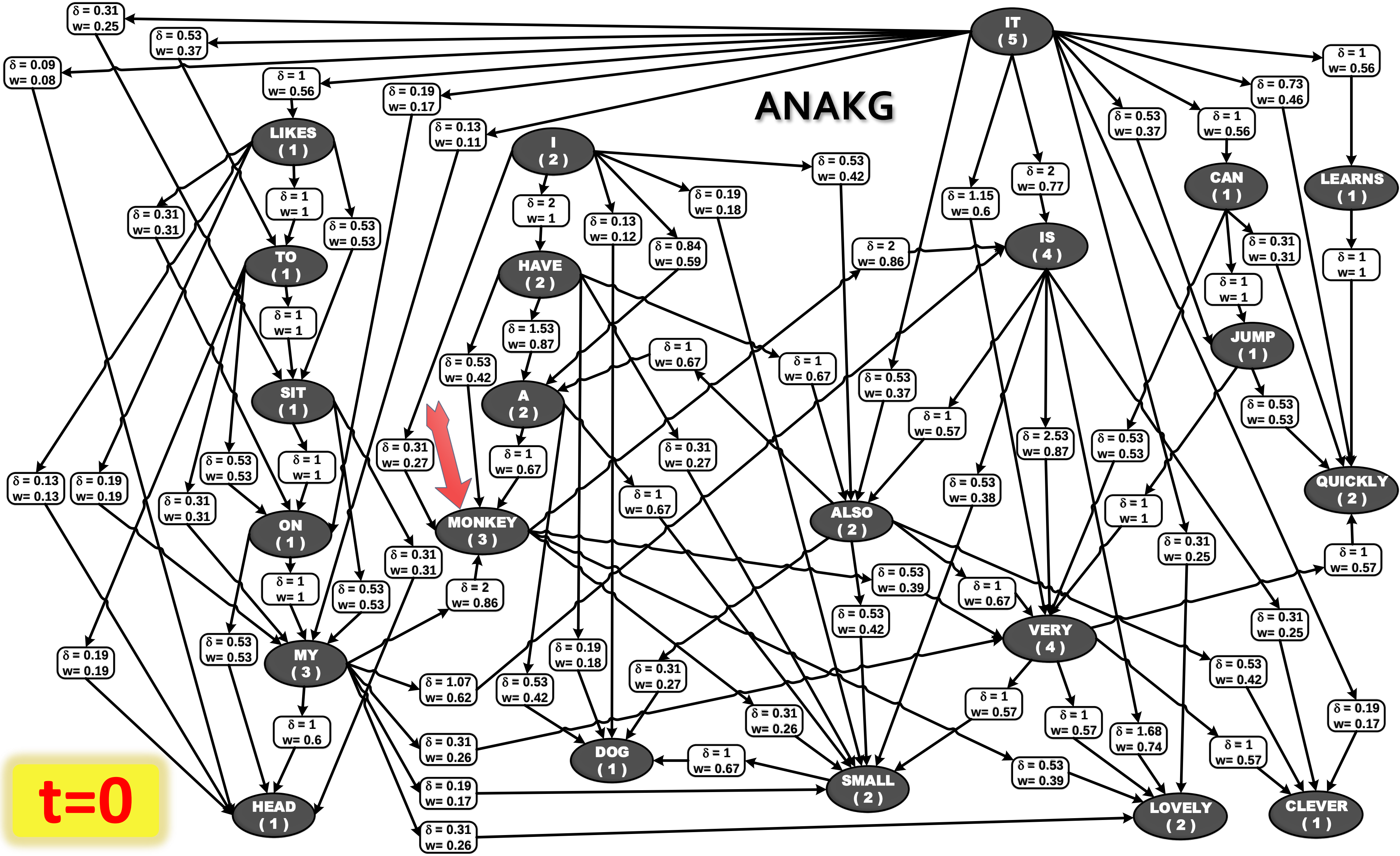


ANAKG-3
S9
I 2
HAVE 2
A 2
DOG 1
SMALL 2
ALSO 2
MONKEY 3
HEAD 1
ON 1
SIT 1
TO 1
MY 3
IT 5
LIKES 1
IS 4
LOVELY 2
CAN 1
JUMP 1
VERY 4
CLEVER 1
LEARNS 1
QUICKLY 2
S9 I HAVE ALSO A SMALL DOG

ASSOCIATIVE NEURAL GRAPH ANAKG-2
is ready for external stimulations

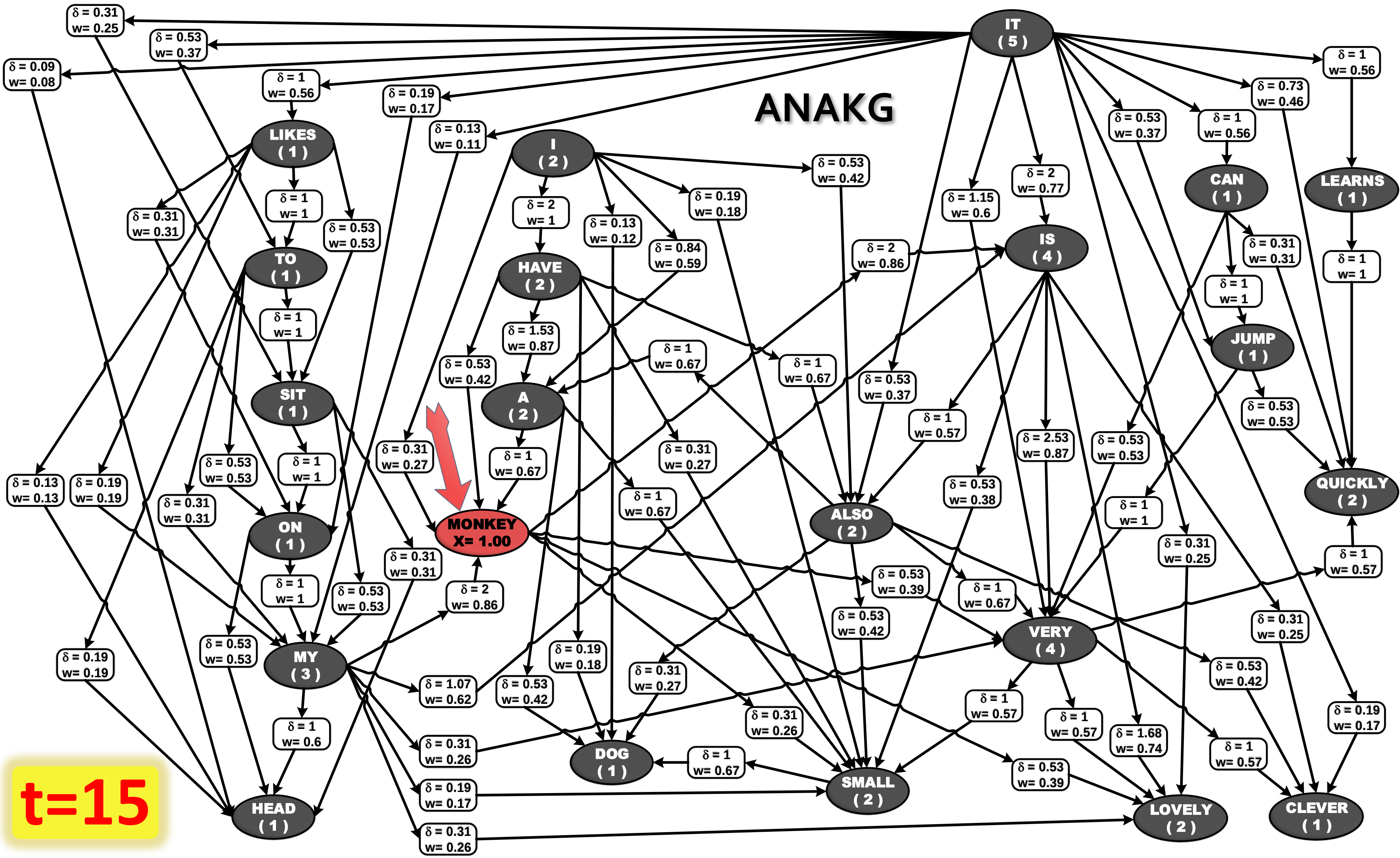


ASSOCIATIVE NEURAL GRAPH ANAKG-2
Neuron MONKEY is being stimulated.

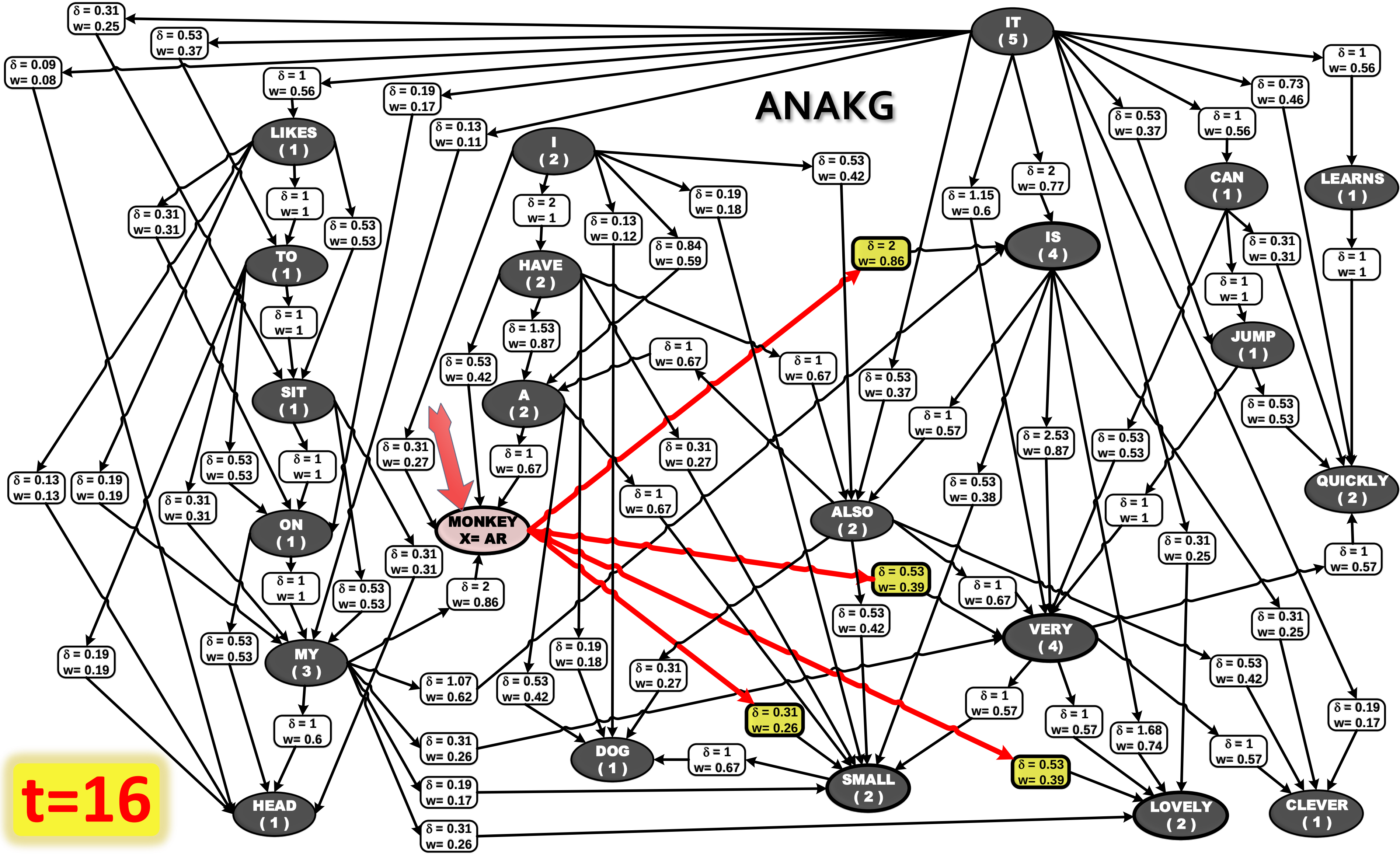


ASSOCIATIVE NEURAL GRAPH ANAKG-2

Neuron MONKEY is activated.

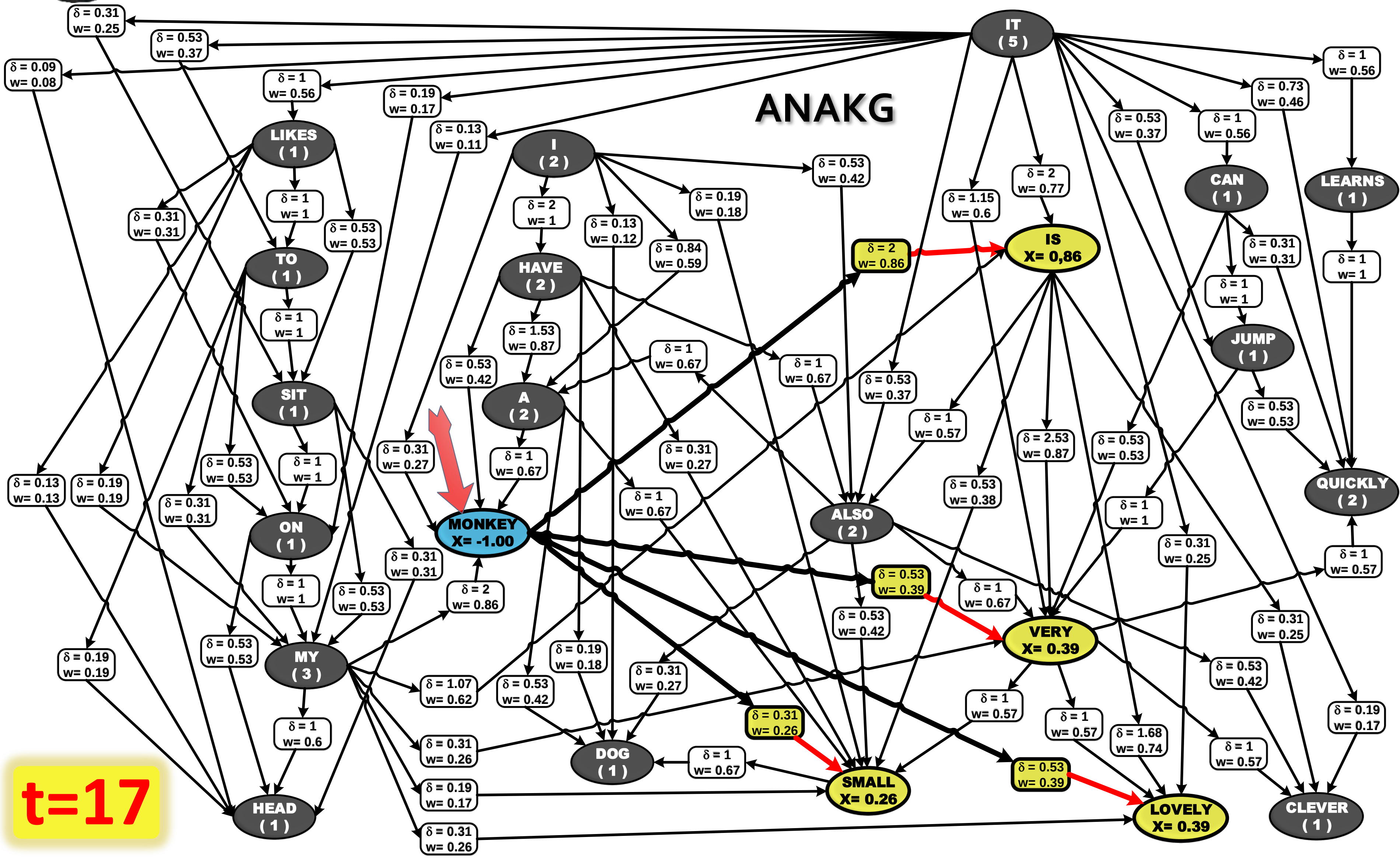


ASSOCIATIVE NEURAL GRAPH ANAKG-2
Neuron MONKEY stimulates synapses.



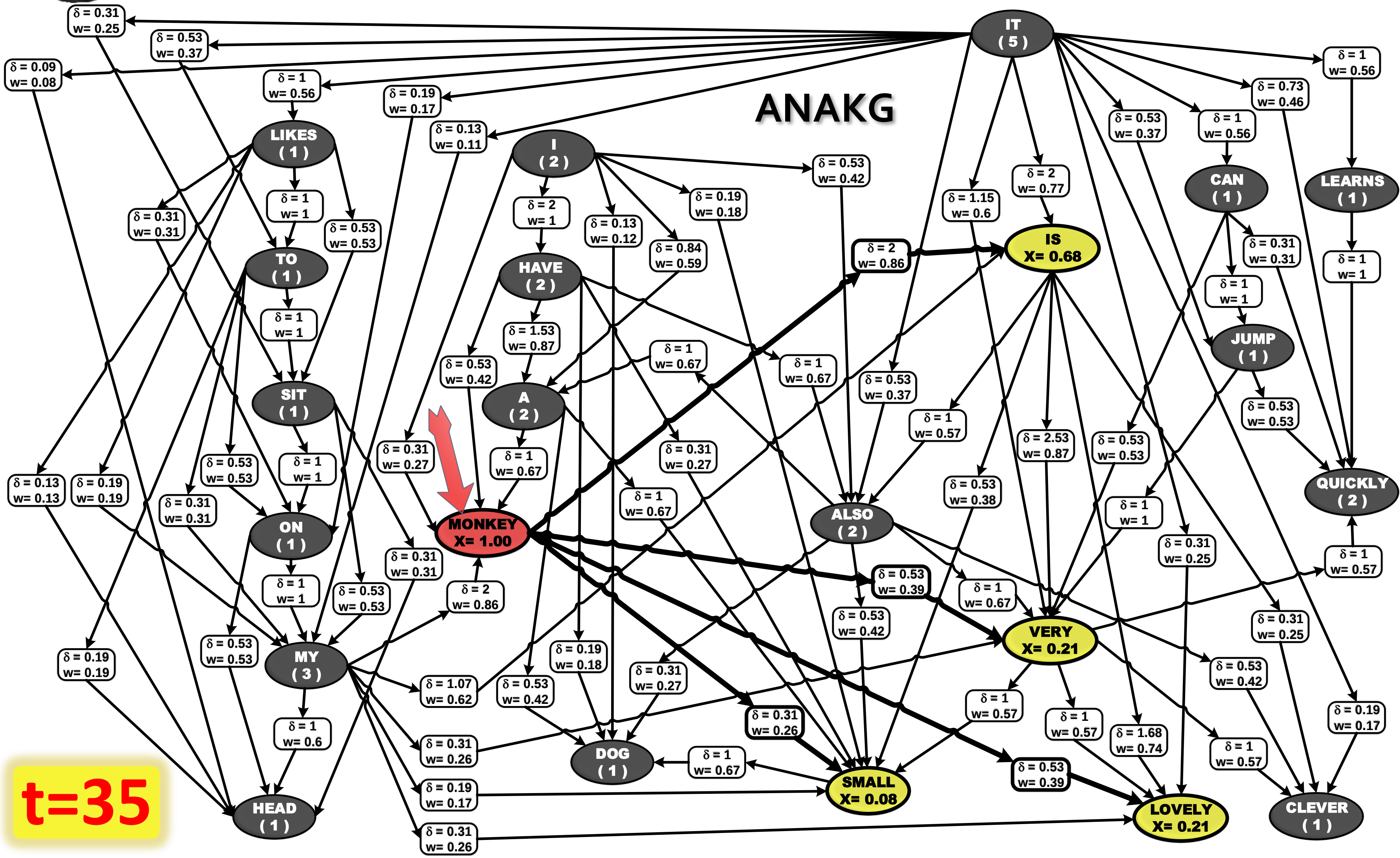
ASSOCIATIVE NEURAL GRAPH ANAKG

Neuron MONKEY stimulates connected neurons.

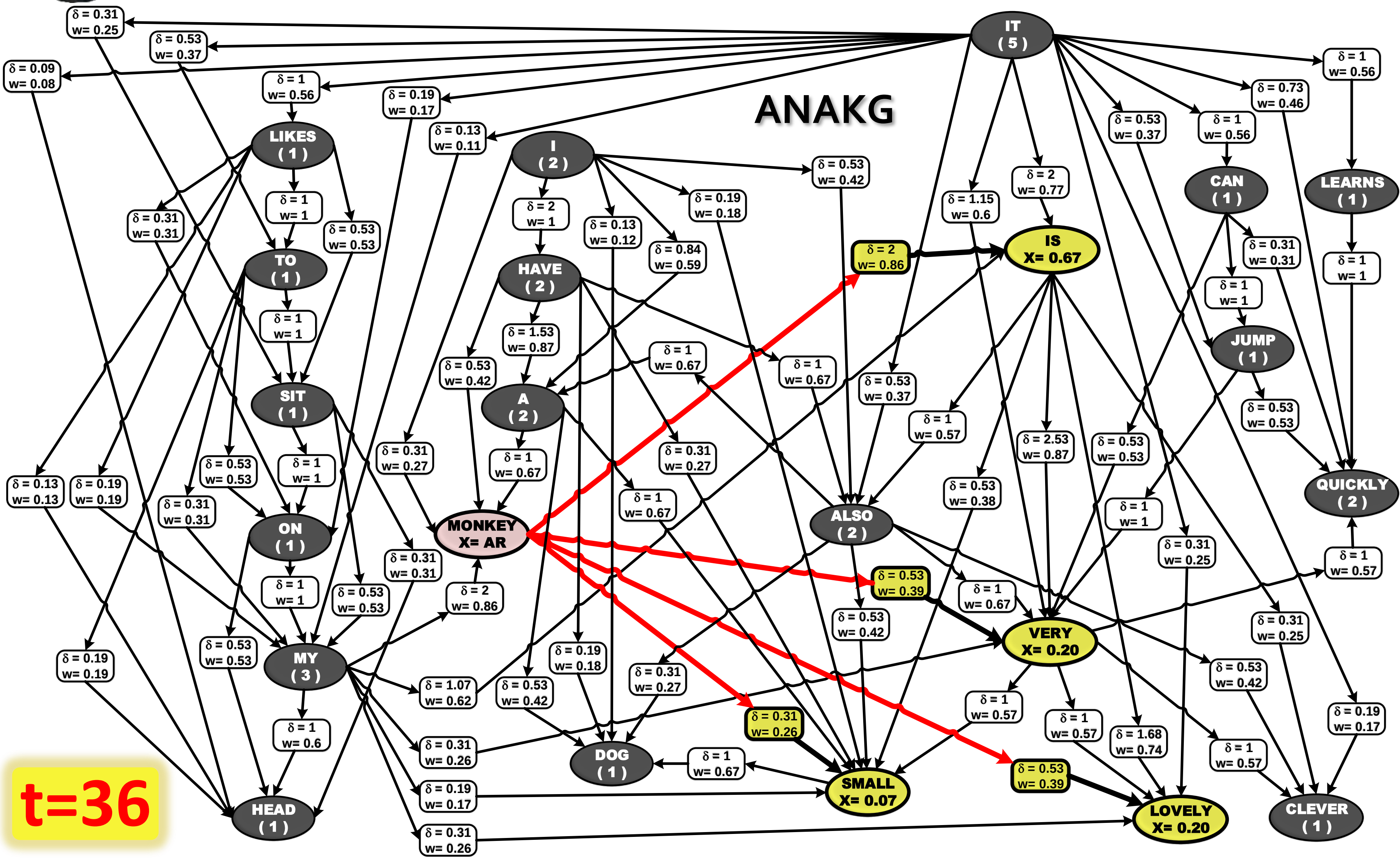


ASSOCIATIVE NEURAL GRAPH ANAKG-2

Neuron MONKEY is stimulated the 2nd time.

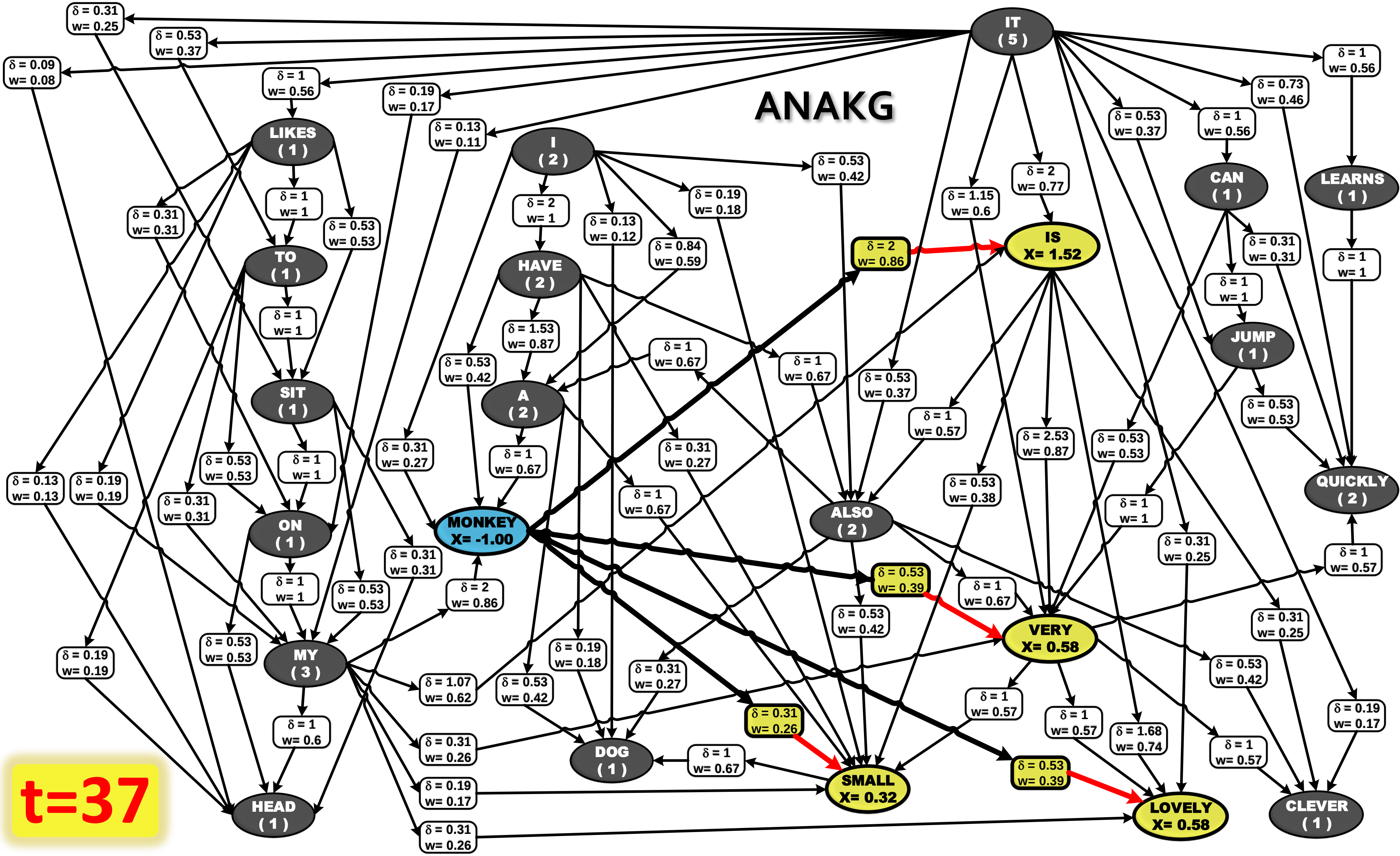


ASSOCIATIVE NEURAL GRAPH ANAKG-2
Neuron MONKEY stimulates synapses.



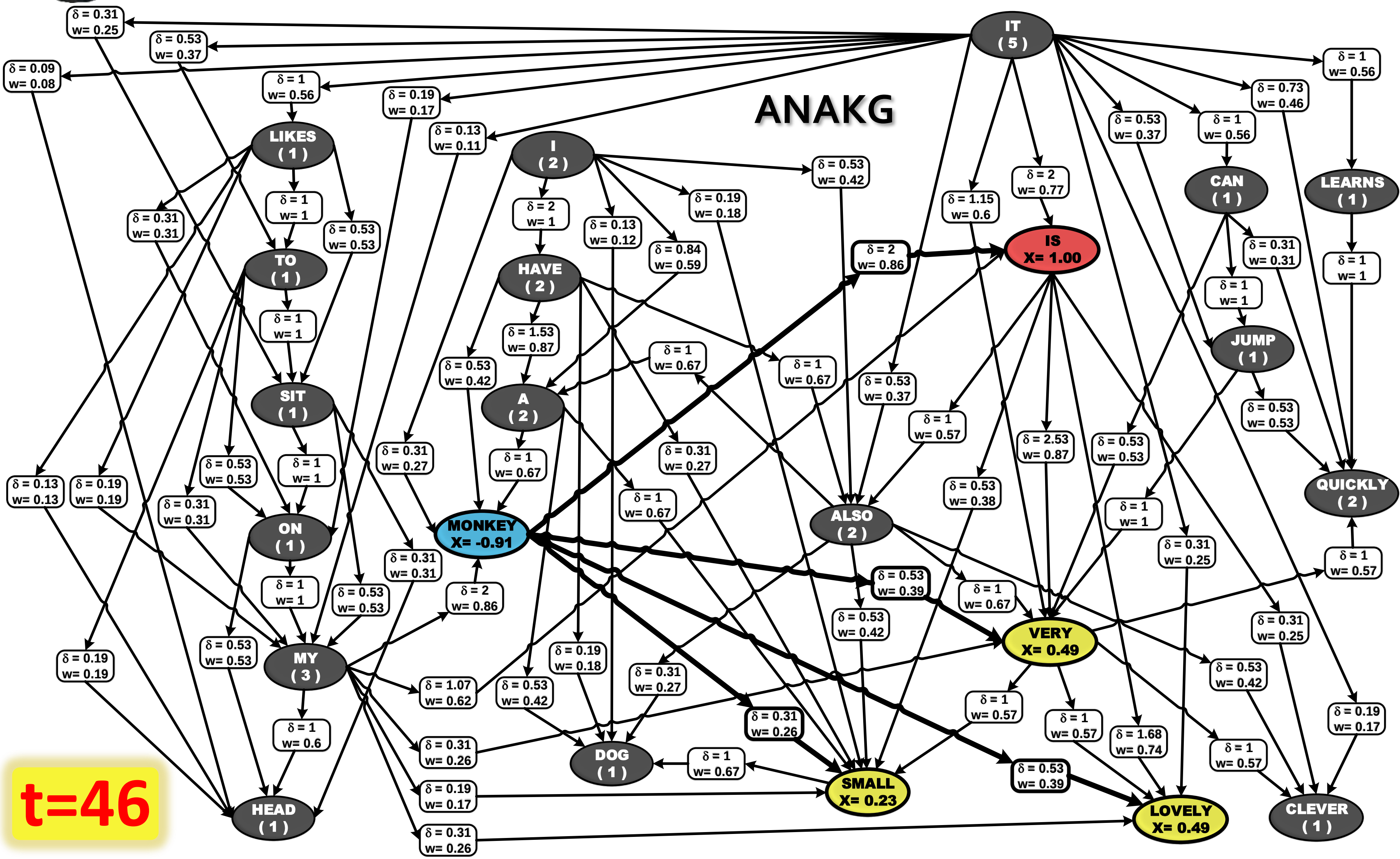
ASSOCIATIVE NEURAL GRAPH ANAKG-2

Neuron MONKEY stimulates connected neurons.



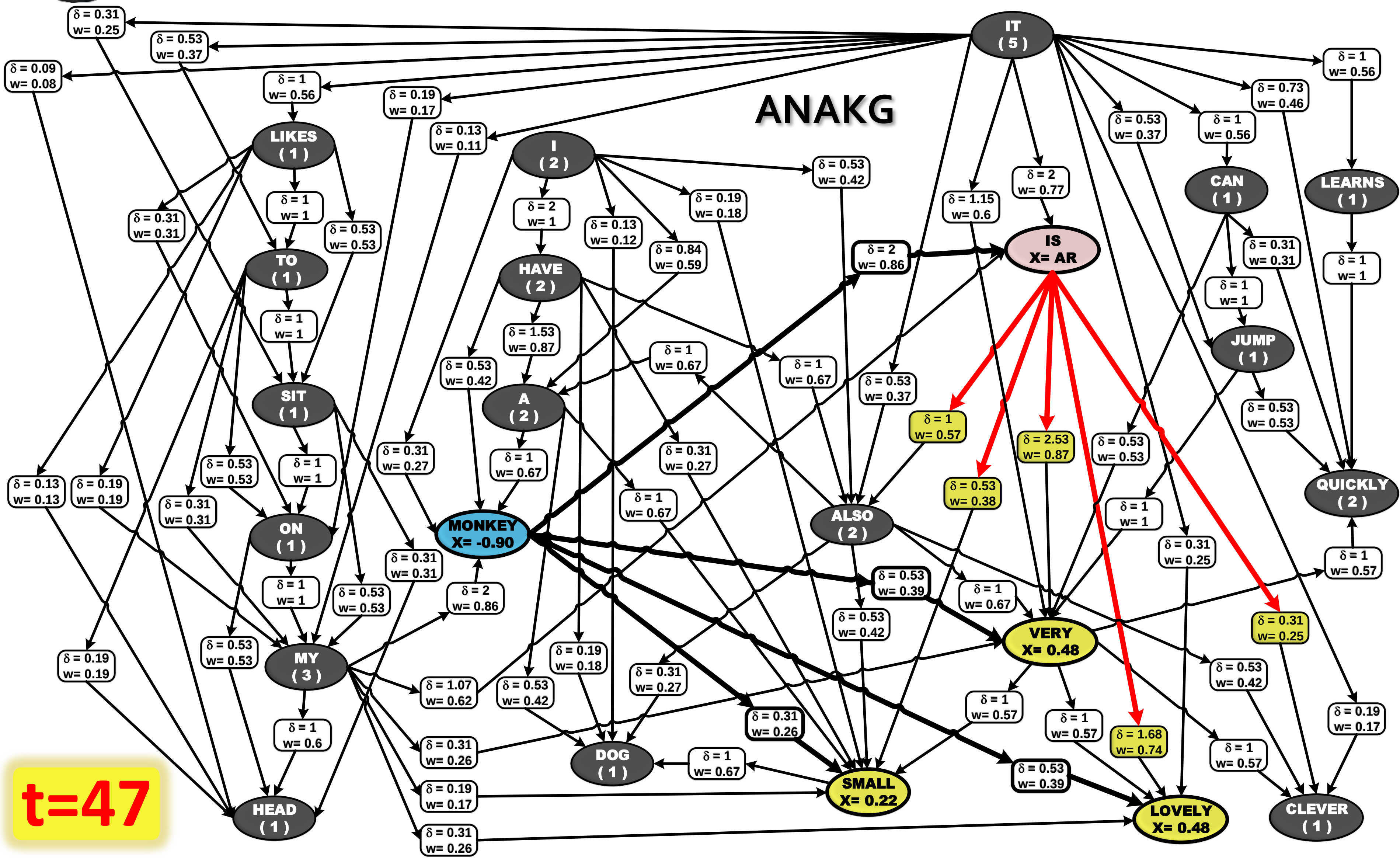
ASSOCIATIVE NEURAL GRAPH ANAKG-2

Neuron IS is activated as a result of the stimulations.



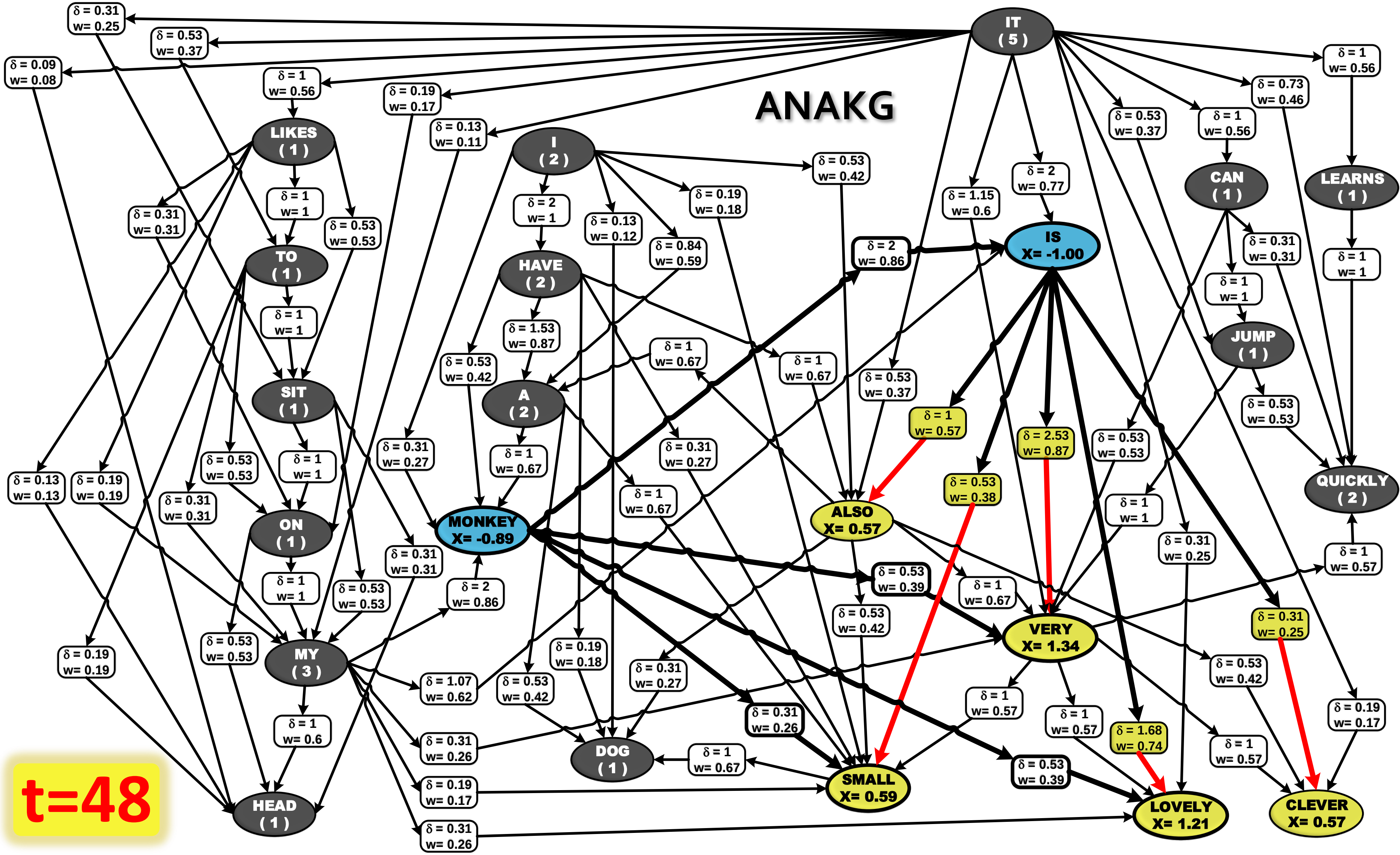
t=46

ASSOCIATIVE NEURAL GRAPH ANAKG-2
Neuron IS stimulates synapses.



ASSOCIATIVE NEURAL GRAPH ANAKG-2

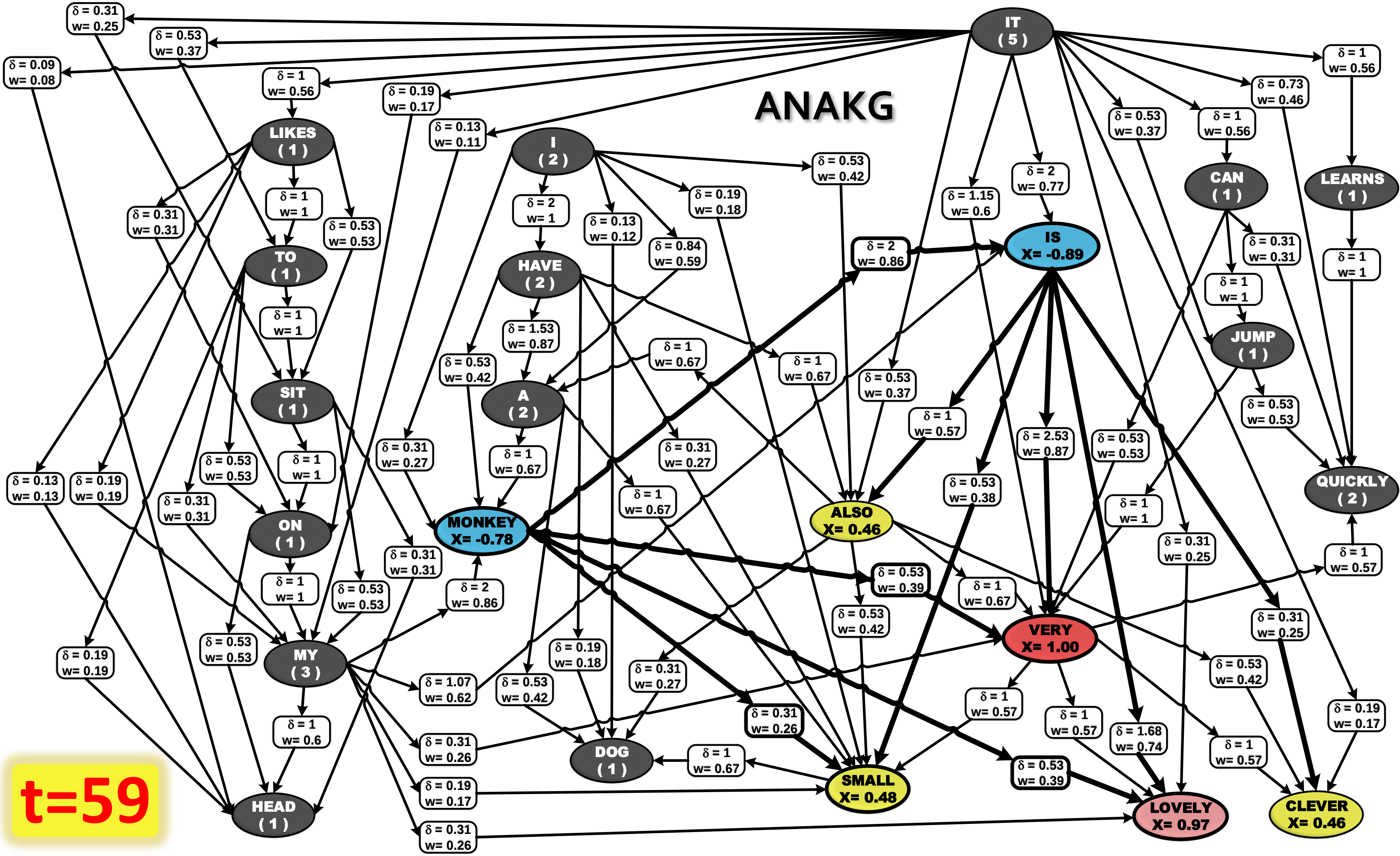
Neuron IS stimulates connected neurons.



t=48

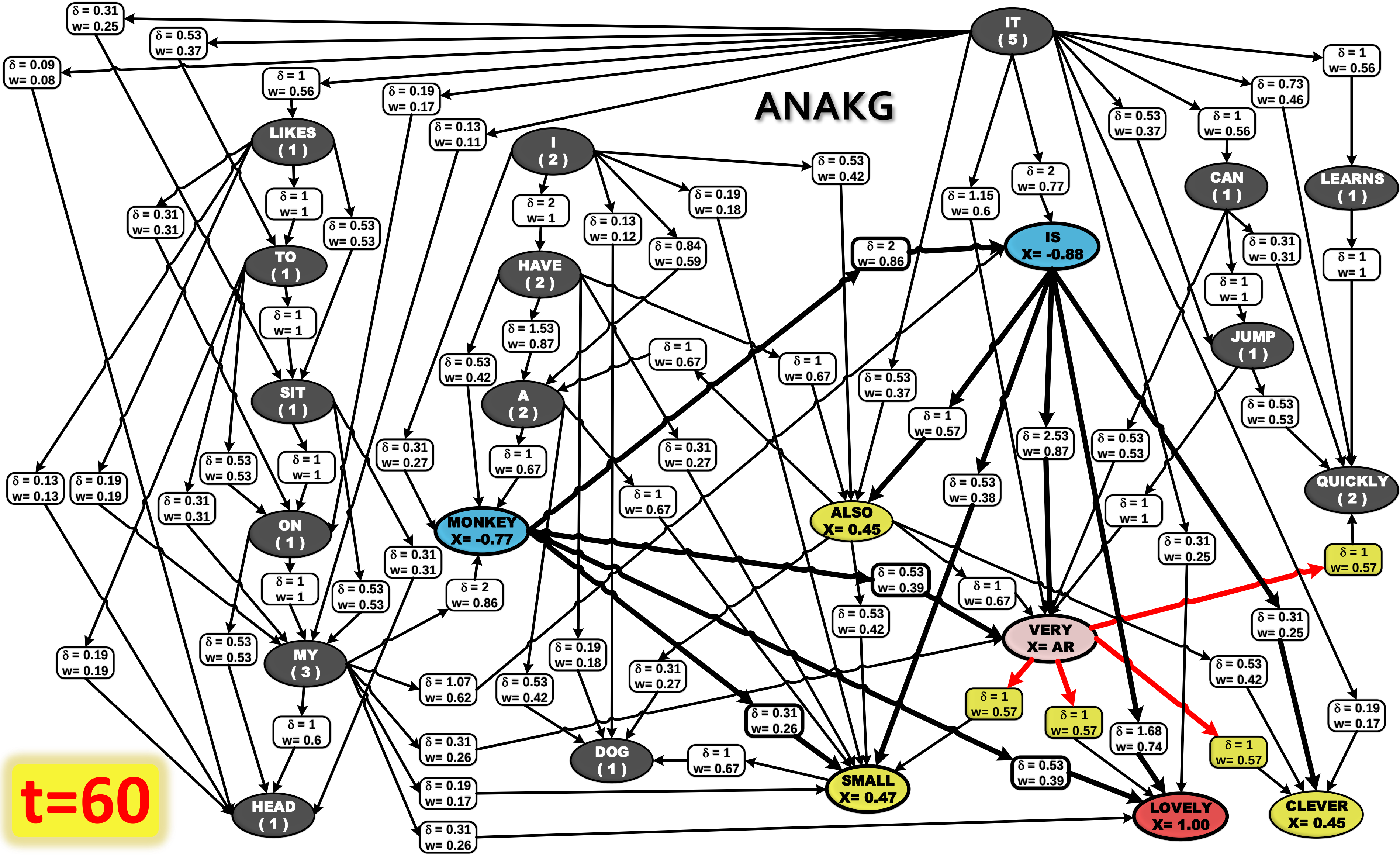
ASSOCIATIVE NEURAL GRAPH ANAKG-2

Neuron VERY is activated as a result of the stimulations



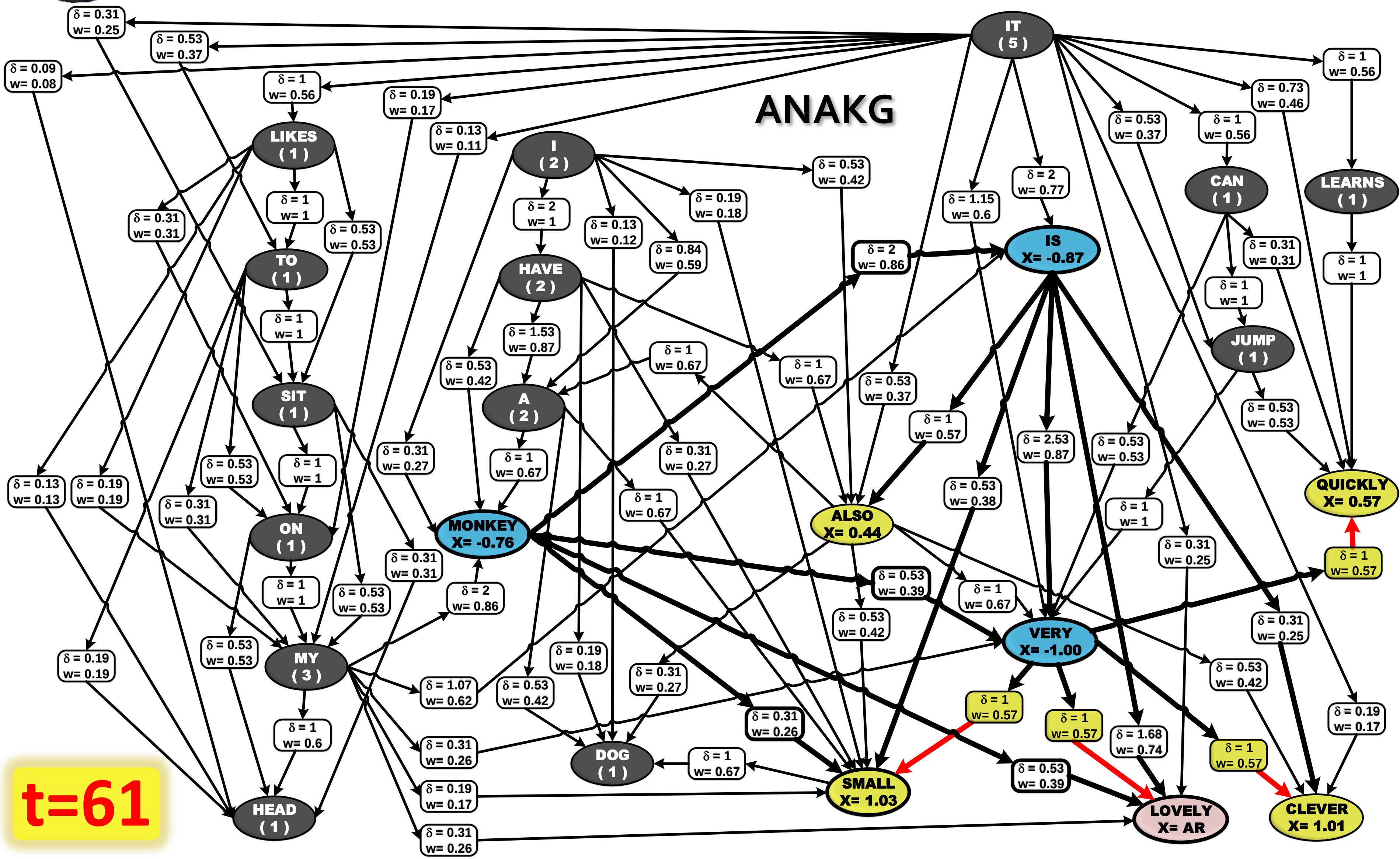
ASSOCIATIVE NEURAL GRAPH ANAKG-2

Neuron IS is activated as a result of the stimulations

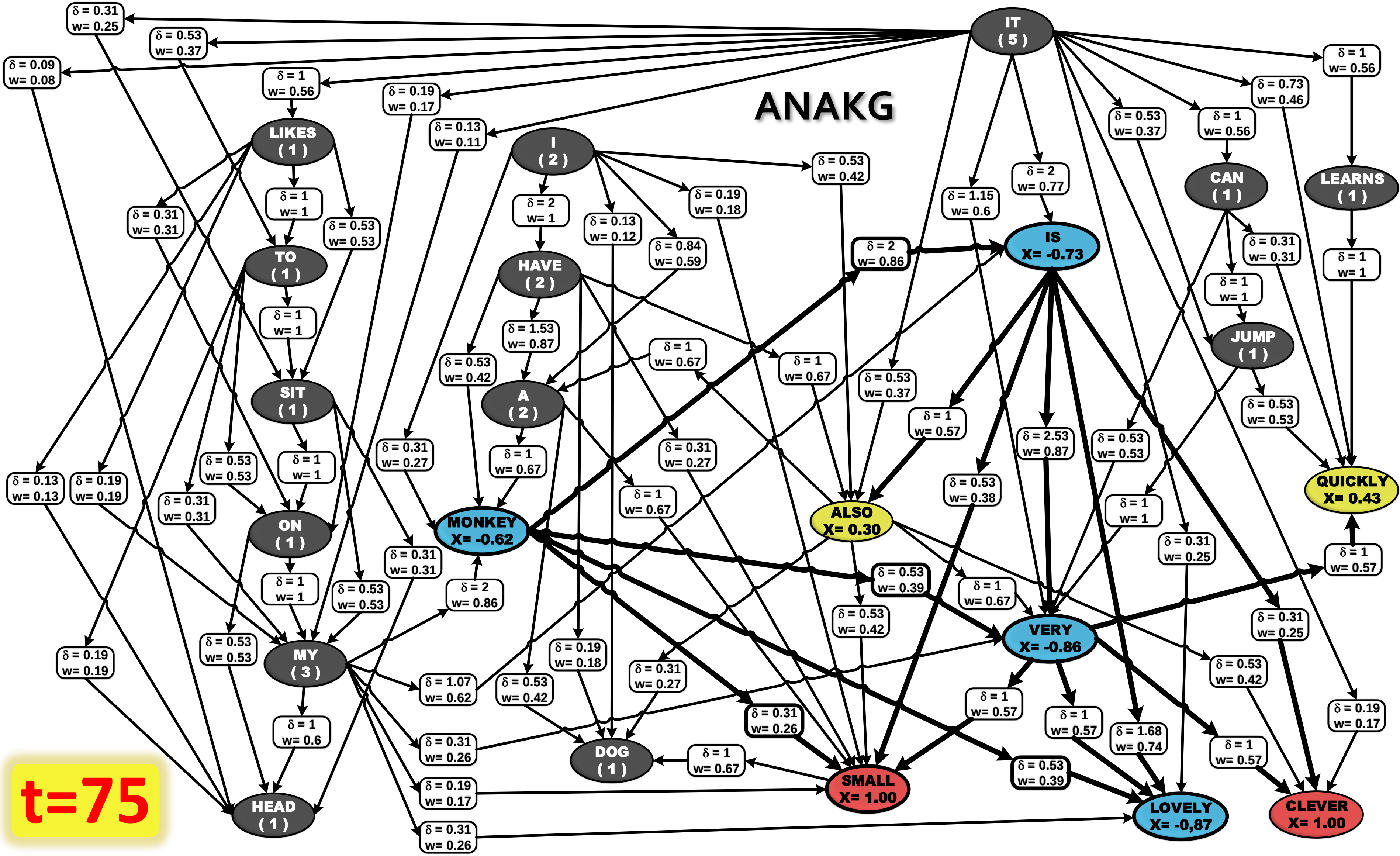


ASSOCIATIVE NEURAL GRAPH ANAKG-2

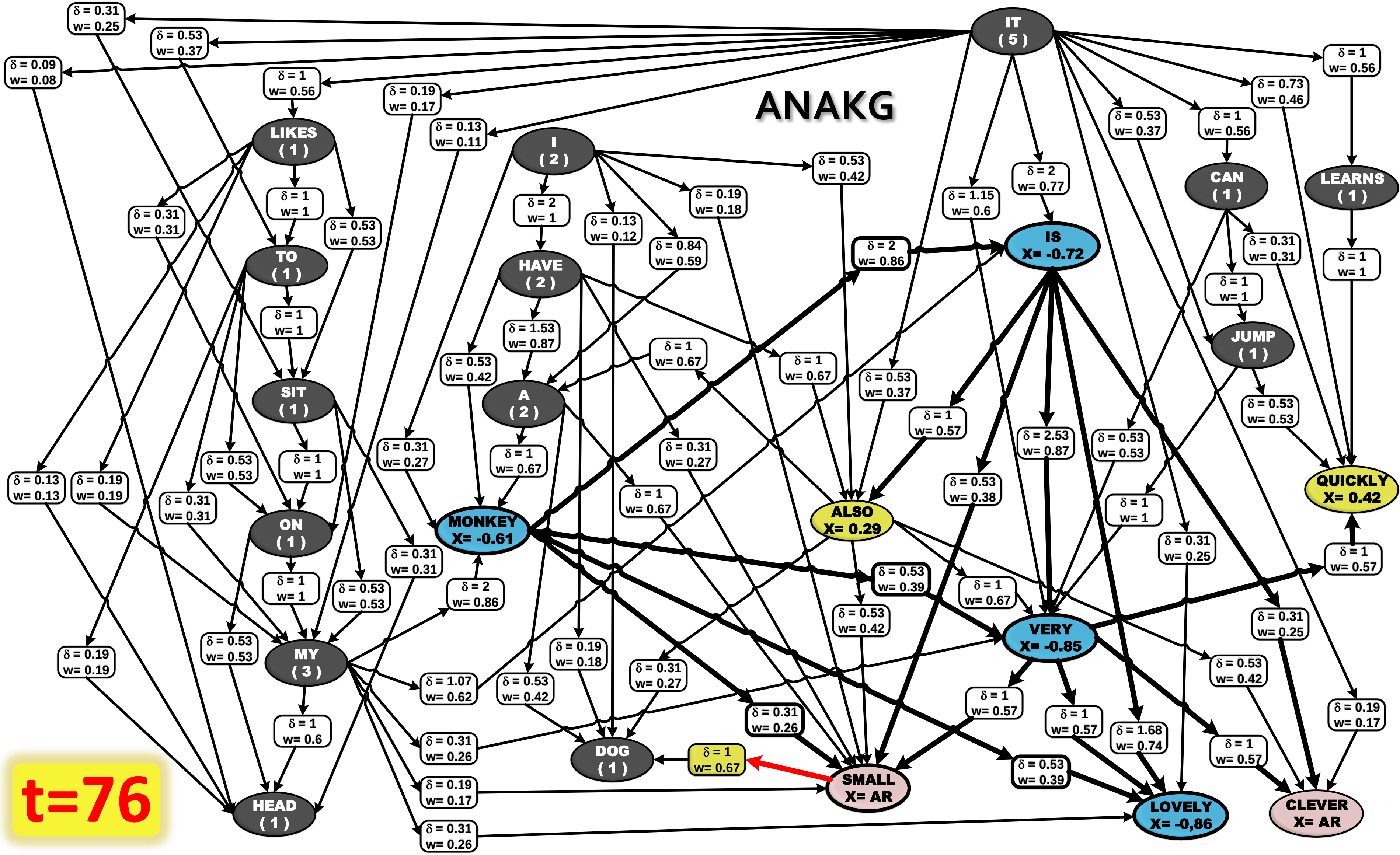
Neuron VERY stimulates connected neurons



ASSOCIATIVE NEURAL GRAPH ANAKG-2
Neurons SMALL and VERY are activated.

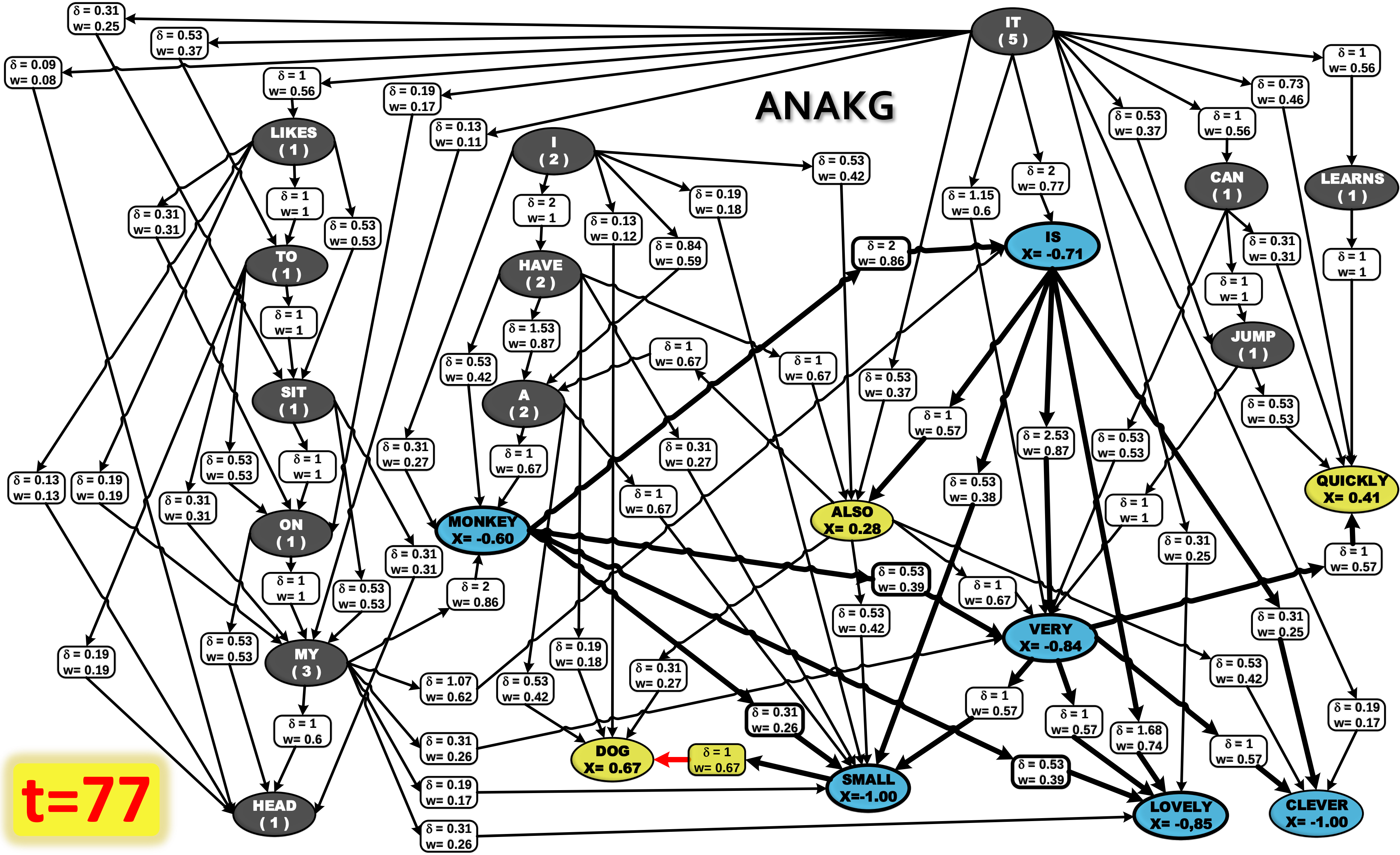


ASSOCIATIVE NEURAL GRAPH ANAKG-2
Neuron SMALL stimulates a synapsis.

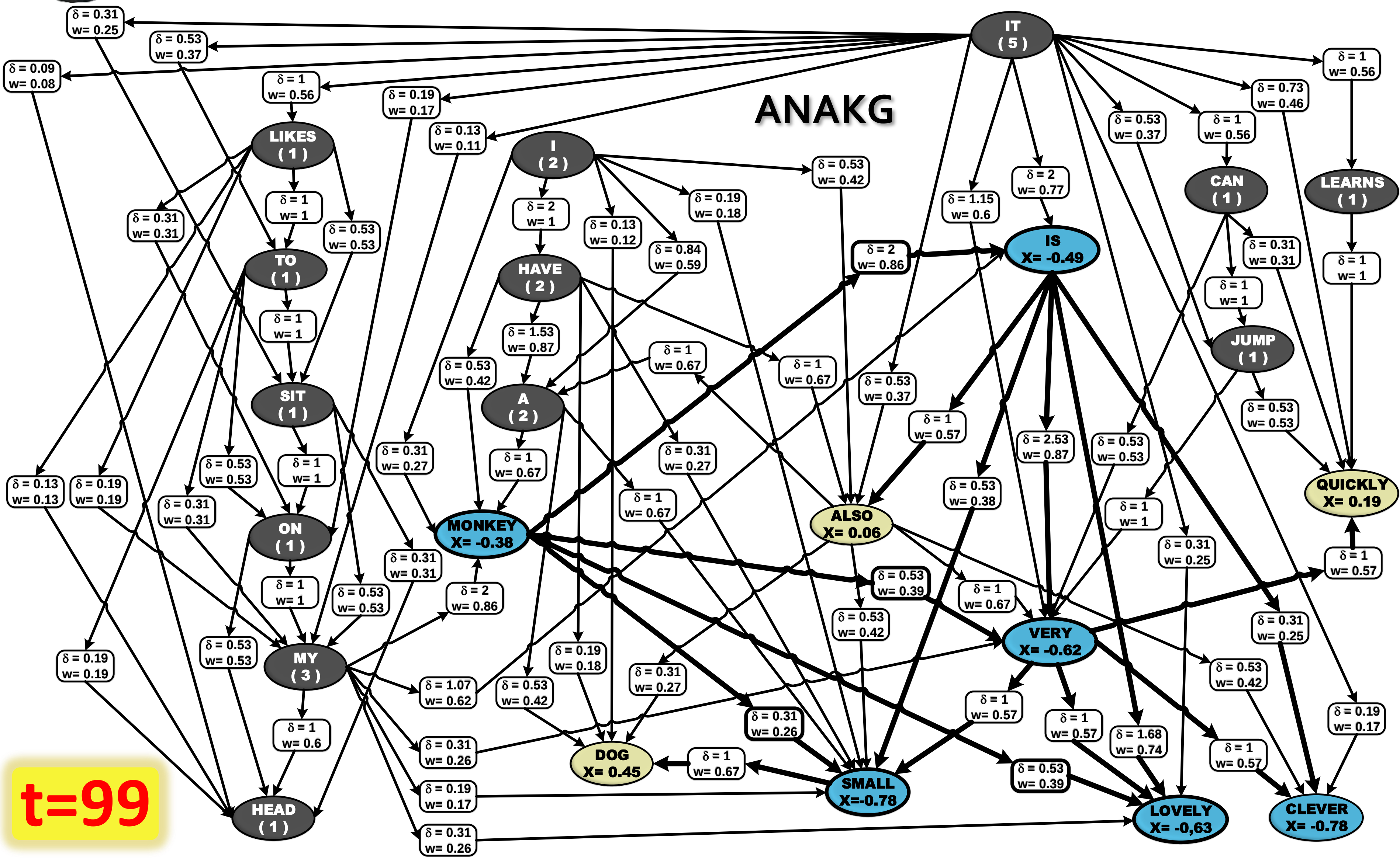


ASSOCIATIVE NEURAL GRAPH ANAKG-2

Neuron SMALL stimulates a connected neuron

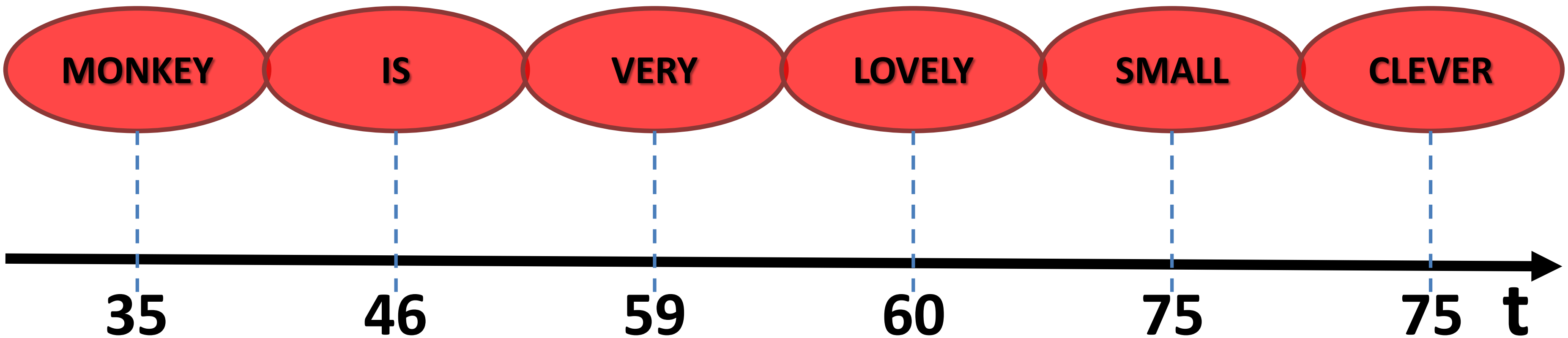


All neurons are relaxing, refracting, and returning back to their resting states.



ASSOCIATIVE NEURAL GRAPH ANAKG-2
What answer we got?

What answer returned this associative neural graph for external stimulation of neuron MONKEY?



I cannot agree more!

What do you think about me?

Has the created associative neural graph gained any knowledge about this MONKEY?

ASSOCIATIVE NEURAL GRAPH ANAKG-2
CONCLUSIONS AND REMARKS

*"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 have also a small dog."*

The training sequence set did not include the summary about this monkey we got:

Monkey is very lovely, small, clever.

CONCLUSION:

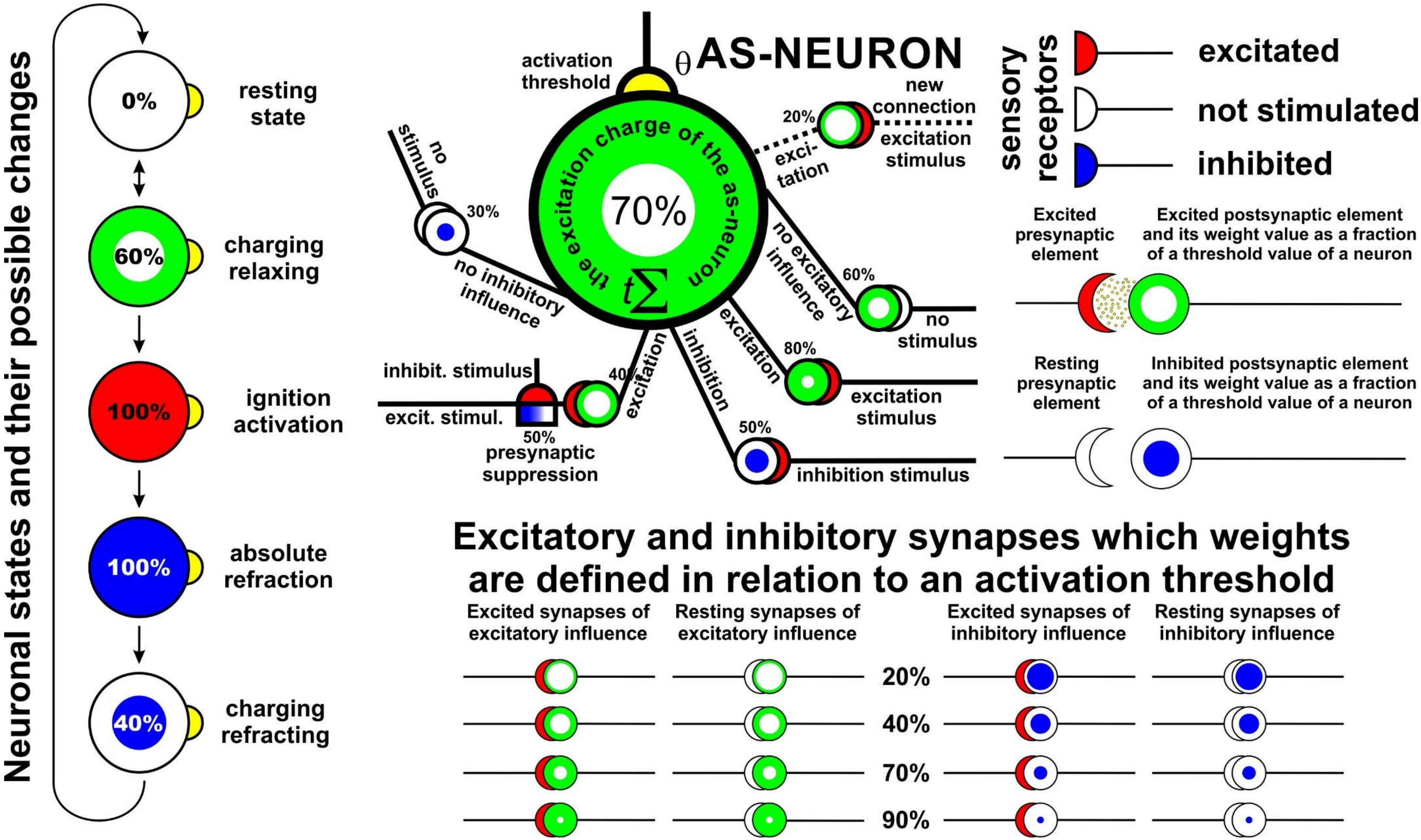
The developed Associative Neural Graph gained some knowledge about this monkey and generalized training sentences.

GENERAL CONCLUSIONS ABOUT ASSOCIATIVE NEURAL GRAPHS

- ✓ Can form, model, and represent knowledge.
- ✓ Use plastic mechanisms to create a structure that reproduces relations between objects.
- ✓ Construction and adaptation is very fast and easy.
- ✓ We can recall artificial associations for reconstruction of training sequences or generalization about them.
- ✓ The associative answer depends on a given context for recalling:
  - Longer contexts will usually reproduce training sequences.
  - Shorter contexts will generalize or return the most frequent training sequences.
- ✓ We can use them for data mining, knowledge exploration, formation, and discovery.

AS-NEURONS NOTATIONS

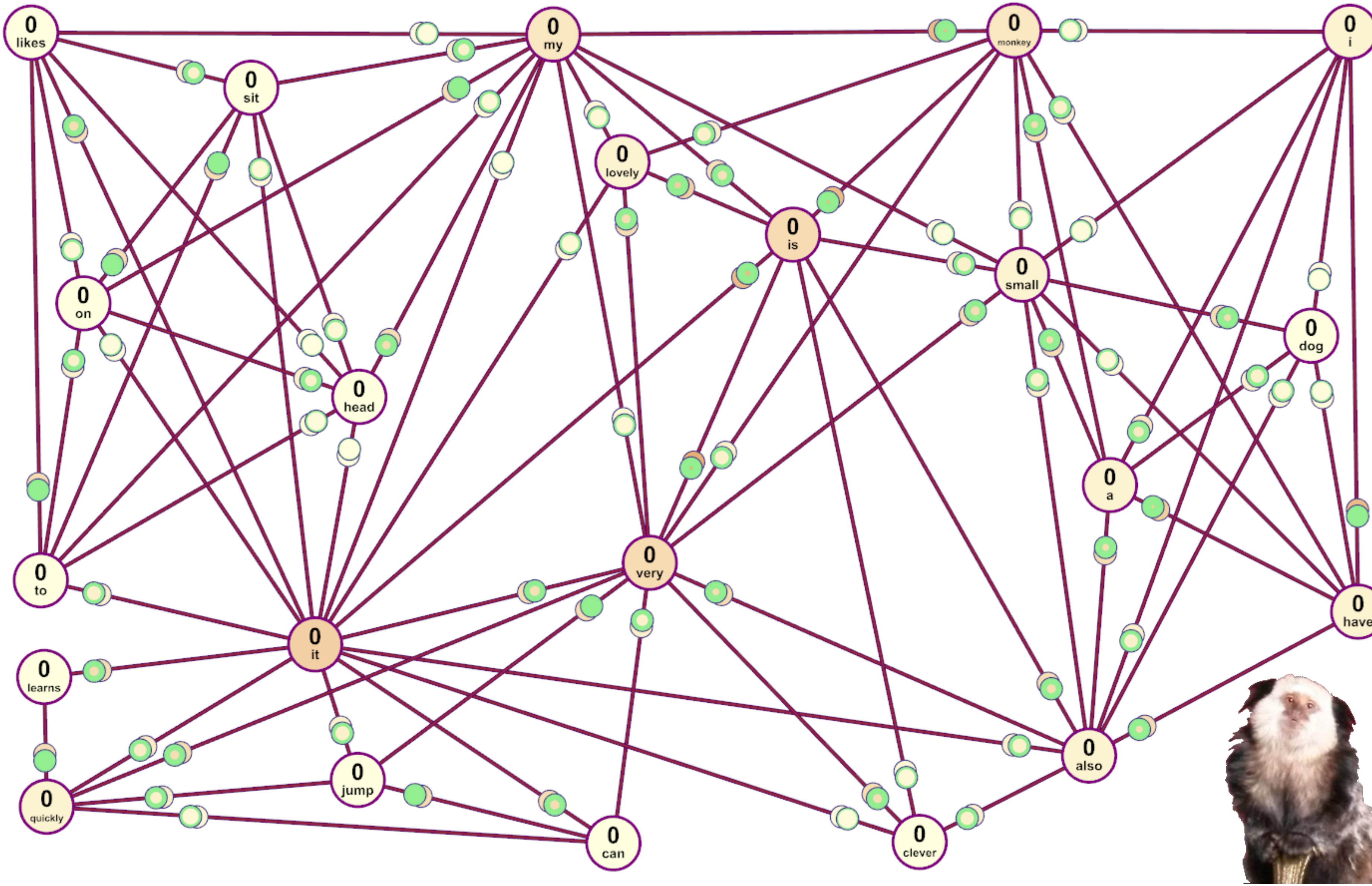
As-neurons change their internal states on stimuli and time lapse.



Weight values are notated as a fraction of a threshold value.

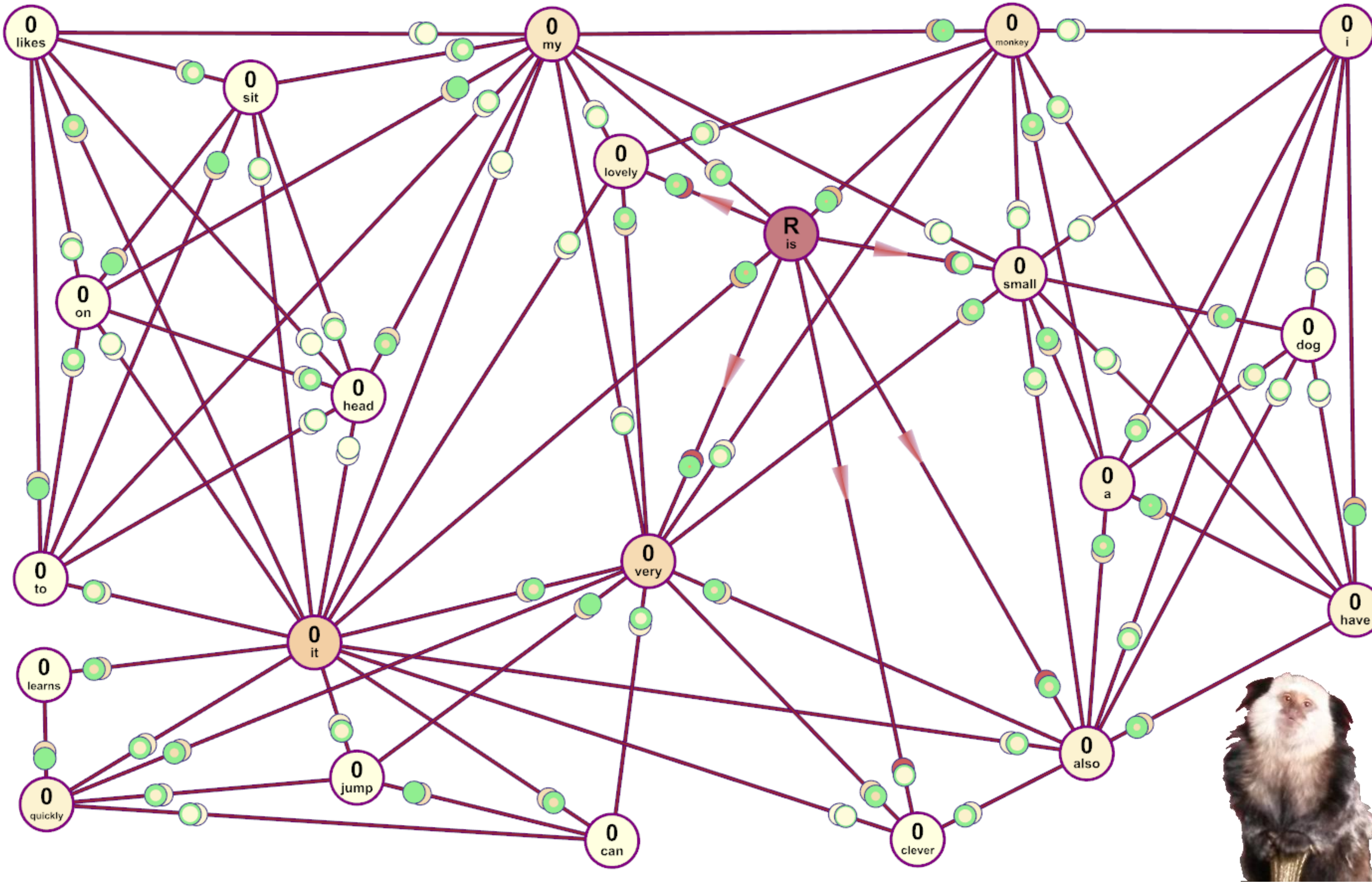
ASSOCIATIVE NEURAL GRAPHS

ANAKG-2 for training sequence set MONKEY in this notation.



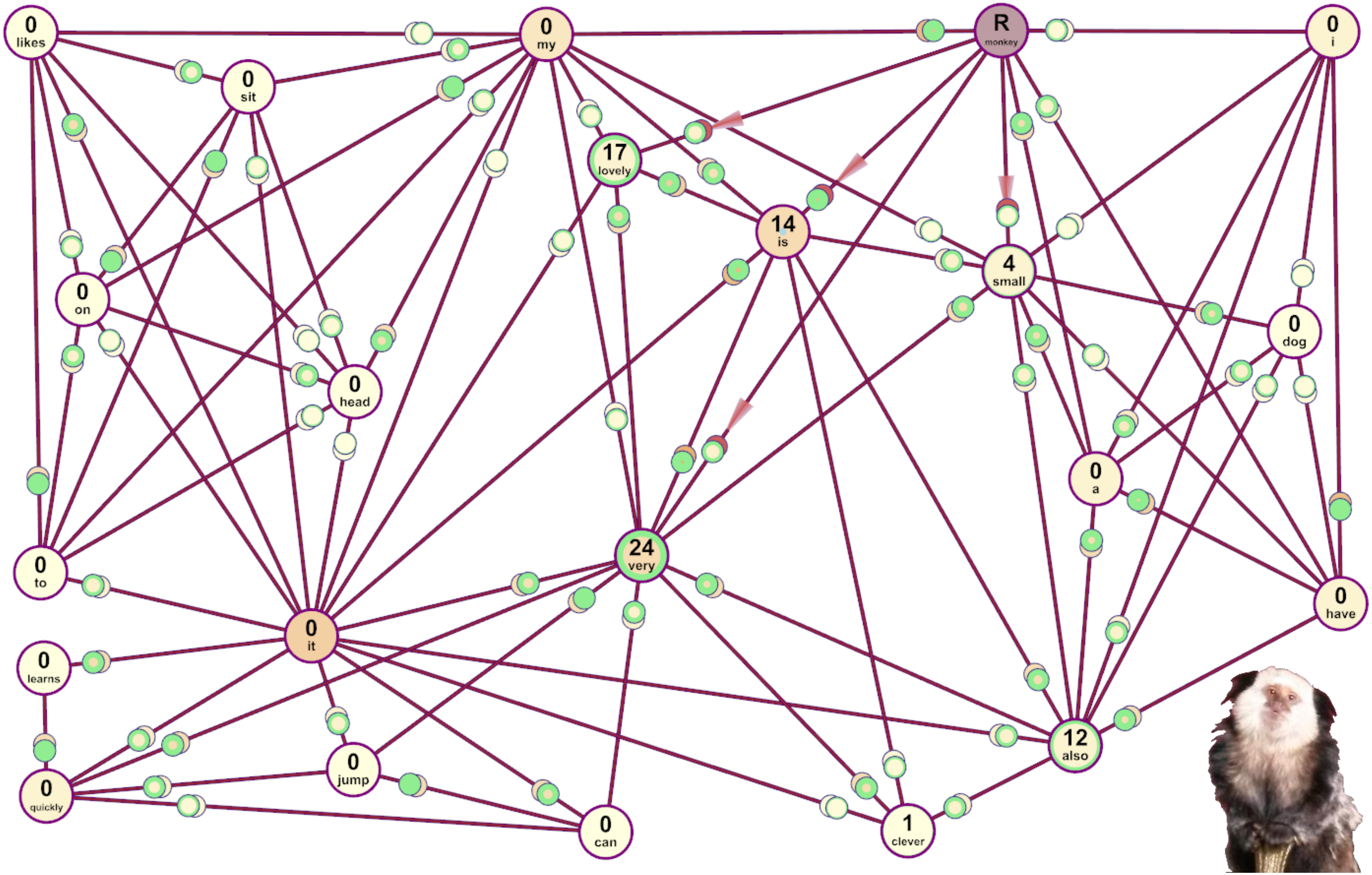
ASSOCIATIVE NEURAL GRAPHS

Activation of neuron MONKEY and stimulation of connected neurons.



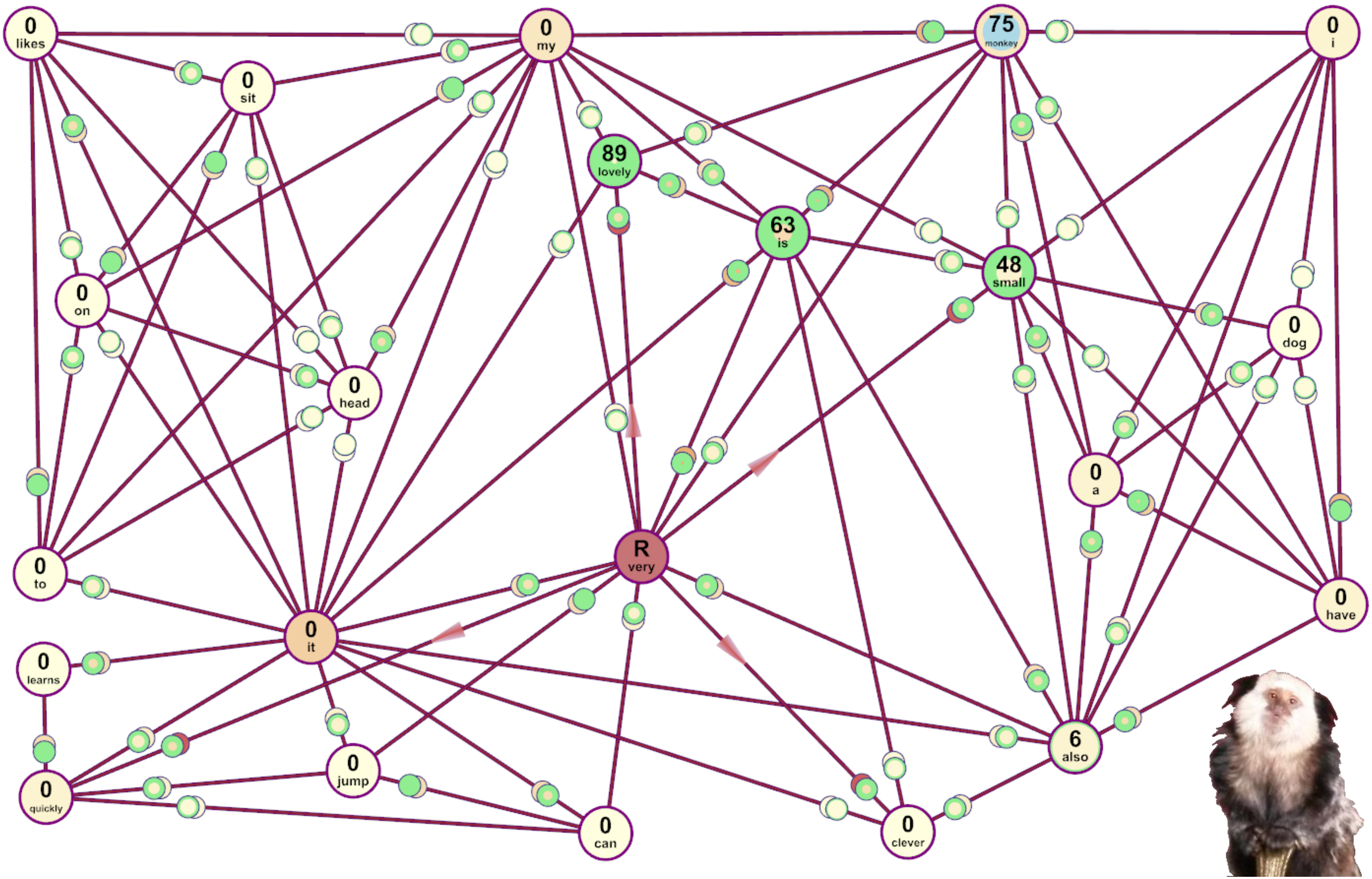
ASSOCIATIVE NEURAL GRAPHS

ANAKG-2 is producing reaction on: „What **is** this **monkey** like?”



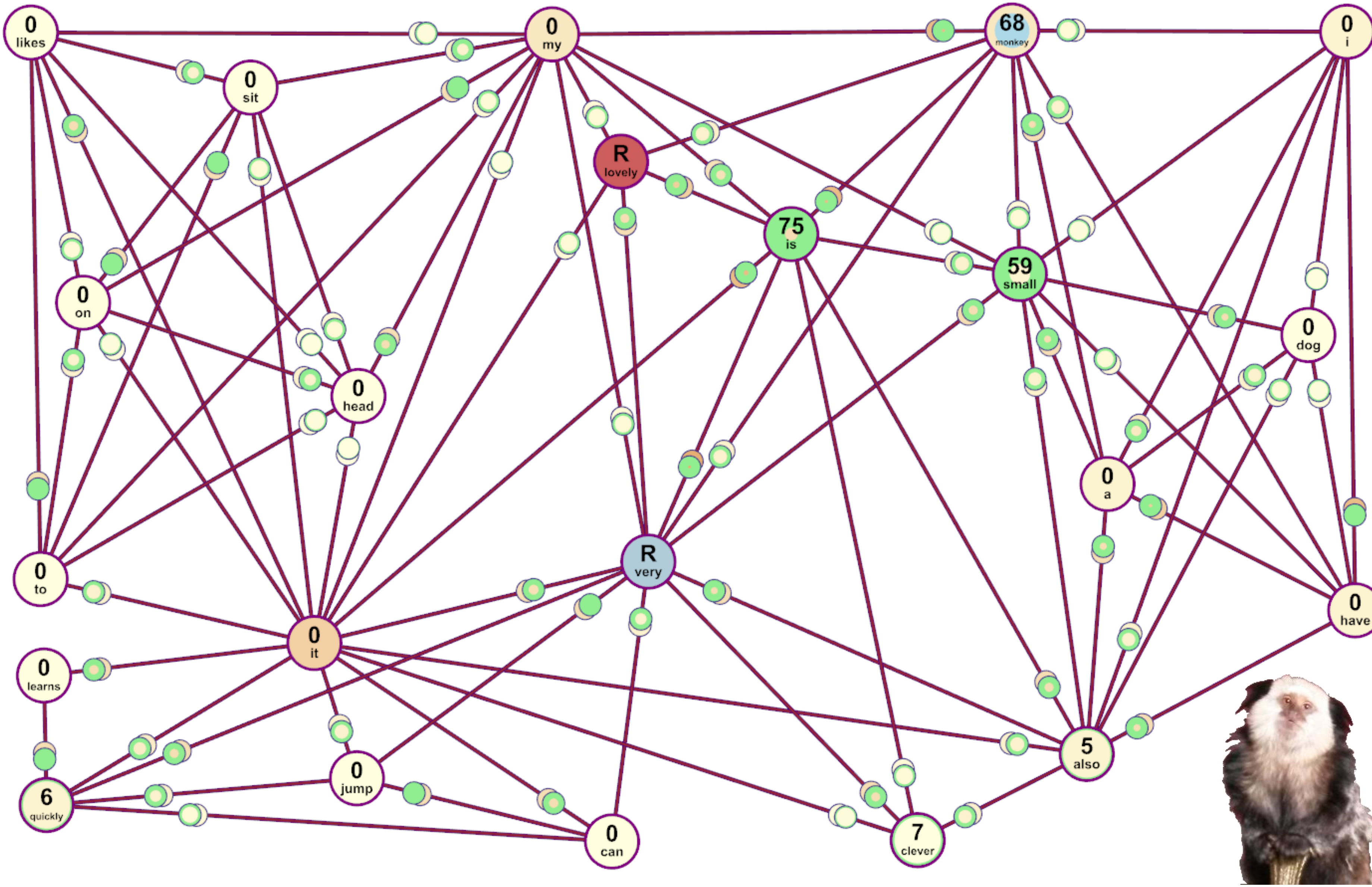
ASSOCIATIVE NEURAL GRAPHS

ANAKG-2 is gradually producing answer: IS – MONKEY – VERY – ...



ASSOCIATIVE NEURAL GRAPHS

ANAKG-2 is gradually producing answer: IS – MONKEY – VERY – LOVELY …



Conclusions and Remarks

1. New model of neurons: AS-NEURONS.
2. New associative mechanisms that are able to operate on graphs of neurons.
3. New method for adapting parameters of associative neural graphs ANAKG
4. New approach to conduct computations using as-neurons and presented graphs
5. New generalization ability of these graphs on a sequence level.

Generalizing of Robot Control Step Sequences

This methodology is universal to manage and generalize various training sequences.

Various Robot Control Step Sequences can be used to construct Associative Neural Graph and take advantages of it.

It provides the possibility to generalize about robot control routines as well as bring the most general back as memories.

Possible Applications

1. Automation and control of robot movemente
2. Correction and translation
3. Gesture and emotion recognition
4. Classifiers
5. Data mining
6. Knowledge representation and discovery
7. Efficient competitive associative structures of data processing

CONCLUSIONS

Associative processes naturally occurring in brains can be used to model and form knowledge that is indispensable to develop real artificial intelligence and intelligent robot controlers.

If you are tired driving a car

you can use natural or artificial intelligence


80
40
20
0

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Artificial Associative Systems

Google: Horzyk horzyk@agh.edu.pl

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