SUPPLEMENTARY MATERIALS

COGNITIVE NEURODYNAMICS

Hebbian Consolidation during Sleep Drives the Semantization of Episodic Sequences: A Neurocomputational Model

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Keywords: Sleep-dependent memory consolidation | Hippocampus | Semantic generalization | Replay | Hebbian plasticity | Computational neuroscience | Non-REM sleep | REM sleep | Theta–gamma oscillations | Complementary learning systems

Supplementary Materials: Additional Figures

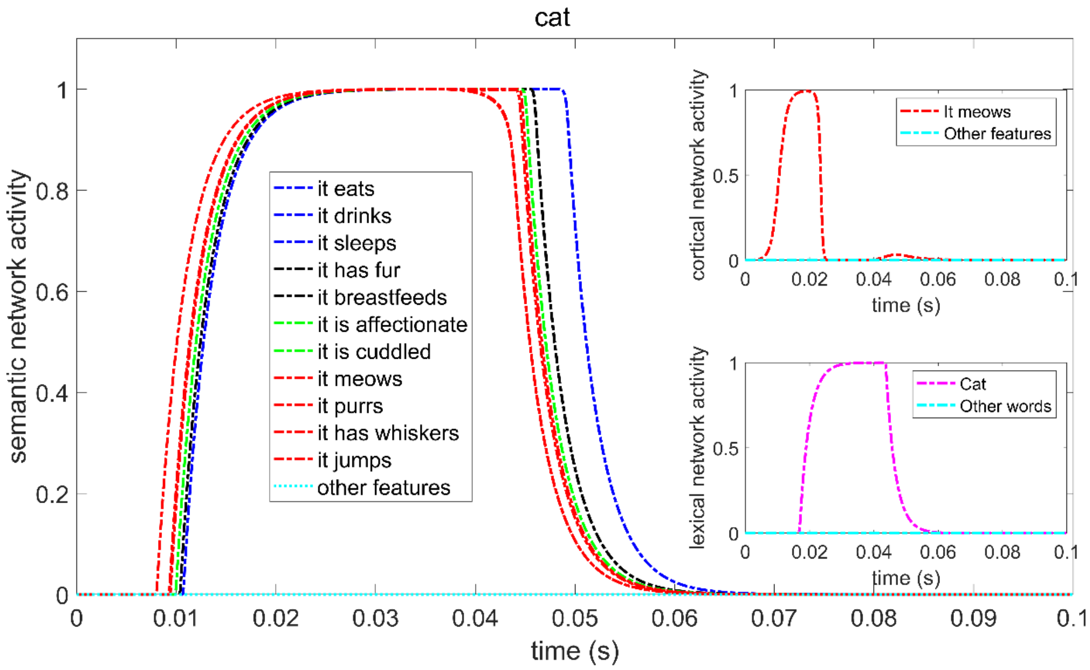


Figure S1 – Simulation of the model response to a sensory feature of the CAT (the feature "It meows", n. 98) provided to the sensory cortex in the interval 0 – 0.03 s, before slow-wave training. Panel A represents the activity of all features in the sensory cortex. Panel B represents the activity in the semantic cortex, where blue lines represent features shared by all ANIMALS, black lines represent features shared by MAMMALS, green lines represent features shared by PETS, and red lines represent distinctive features of the CAT. All remaining features are silent (cyan lines). All cat features are correctly activated. Finally, panel C represents the activity in the lexical net, where the word-form CAT is correctly activated.

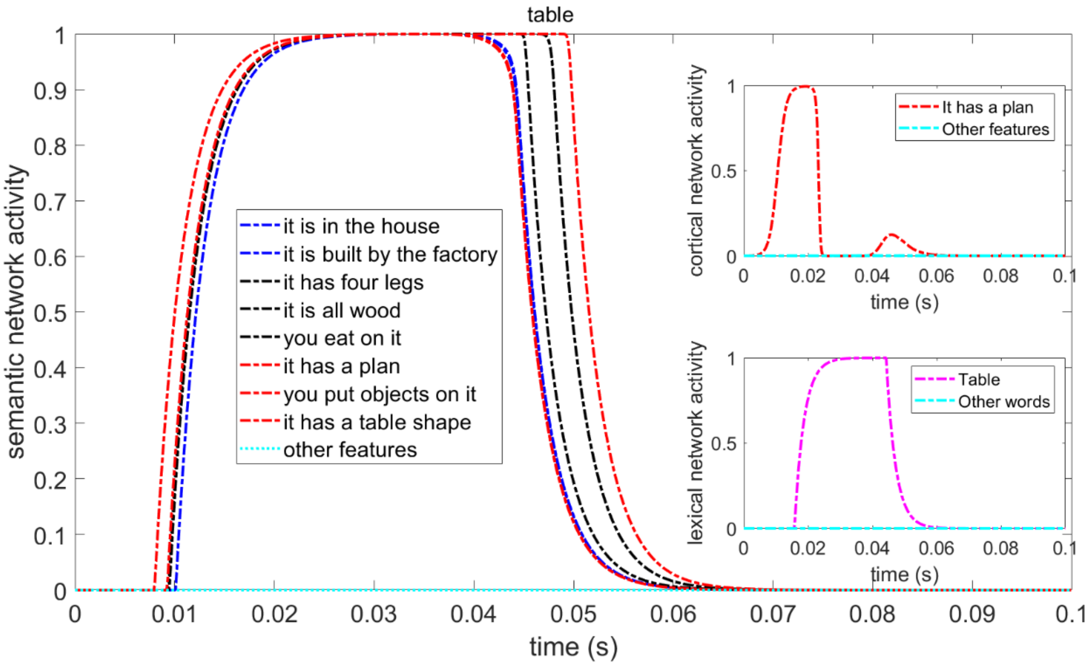


Figure S2 – Simulation of the model response to a sensory feature of the TABLE (the feature "It has a plane", n. 5) provided to the sensory cortex in the interval 0 – 0.03 s, before slow-wave training. Panel A represents the activity of all features in the sensory cortex. Panel B represents the activity in the semantic cortex, where blue lines represent features shared by all PIECES OF FURNITURE, black lines represent features shared by FOUR-LEG FURNITURES, and red lines represent distinctive features of the TABLE. All remaining features are silent (cyan lines). All table features are correctly activated. Finally, panel C represents the activity in the lexical net, where the word-form TABLE is correctly activated.

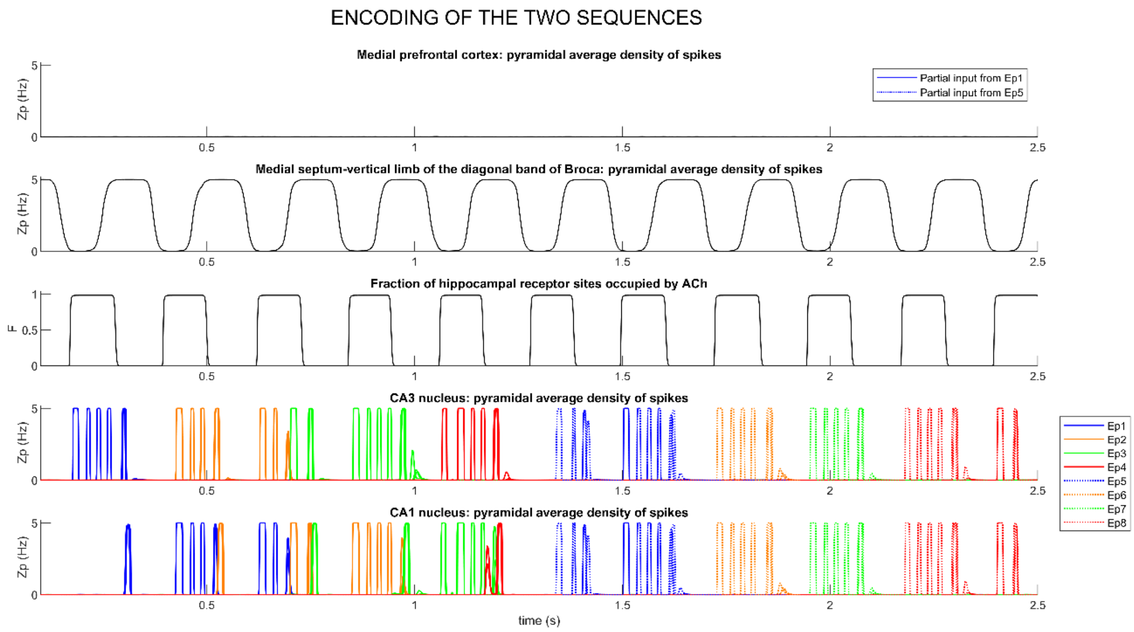


Figure S3 – Activity of the different neurons in the Hippocampus during the encoding phase. The medial prefrontal cortex is silent, and all inputs arrive at CA3 and CA1 neurons from the entorhinal cortex. Inputs of the first sequences (from Episode 1 to Episode 4) are given in sequence during the interval 0-1.25 s, while inputs of the second sequences (from Episode 5 to Episode 8) are given in sequence during the interval 1.25- 2.5 s. Heteroassociative synapses are formed through long-term potentiation from neurons coding for a previous episode in CA1 and neurons coding for the subsequent episode in CA3 when the Achetylcholine level is high.

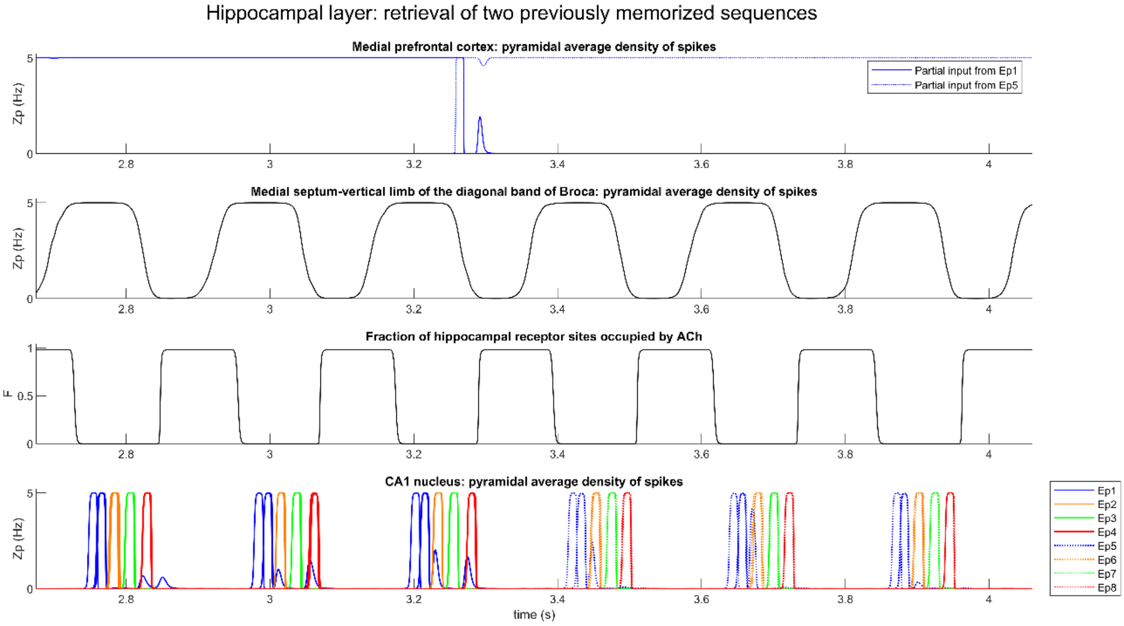


Figure S4 – Activity of the different neurons in the Hippocampus during the recovery phase after training. A cue of the first episode of the first sequence ("My daughter has braids", n. 78, of DAUGHTER) is given to the mPFC during the interval 2.65-2.705 s and then maintained in the prefrontal cortex memory until a new cue arrives. Then, the overall first sequence is reconstructed in the Hippocampus and oscillates with the theta-gamma code (features appear when Ach levels are low). Subsequently, a cue of the first episode of the second sequence ("My dog is faithful", n. 97 of the DOG) is given to the mPFC during the interval 3.25 – 3.305 s and maintained in memory in the prefrontal cortex. Then, the second sequence is reconstructed. Only activity in CA1 neurons is shown for brevity.

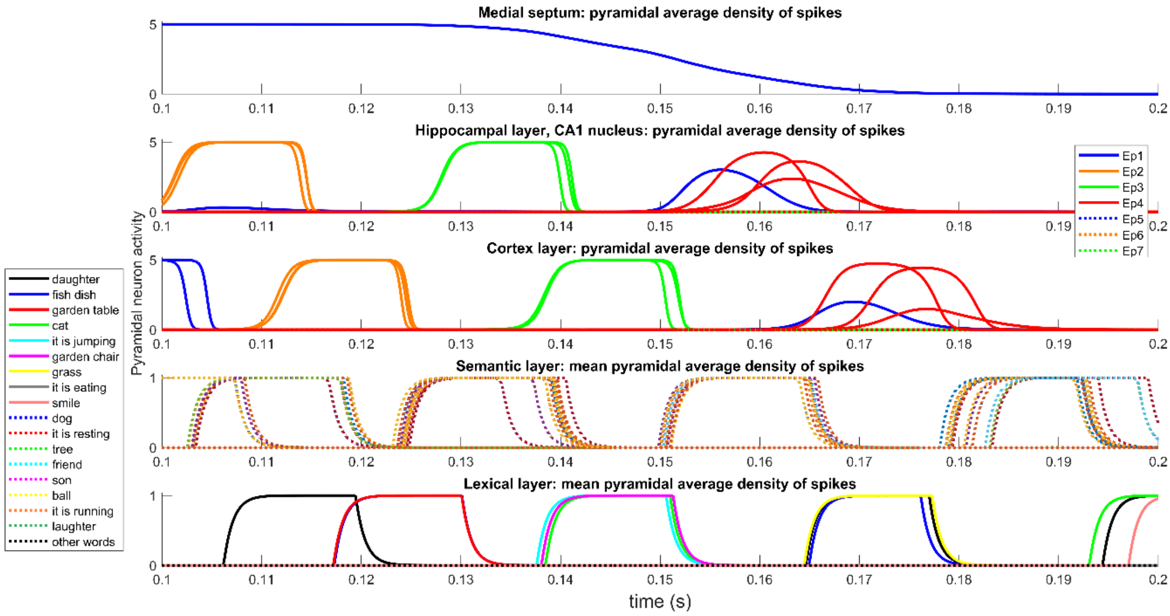


Figure S5 - Temporal pattern of the main neural activities in the model during a recovery phase, before slow sleep training. The simulation is the same as in Fig. 2, but a zoomed portion from 0.1 to 0.15 s is shown to better highlight the single-neuron activity. In particular, the simulation shows the response to one feature of the first episode, in the first sequence ("My daughter has braids"), delivered to the prefrontal cortex between 0.03 and 0.085 s. All features of the corresponding objects are evoked in the semantic net thanks to the autoassociative synapses, and the corresponding word-forms are evoked in the lexical net. Colors in the HC and cortex represent features in the same episode; colors in the semantic network are automatically generated (we have 144 different features), while colors in the lexical network represent individual words in the sequences.

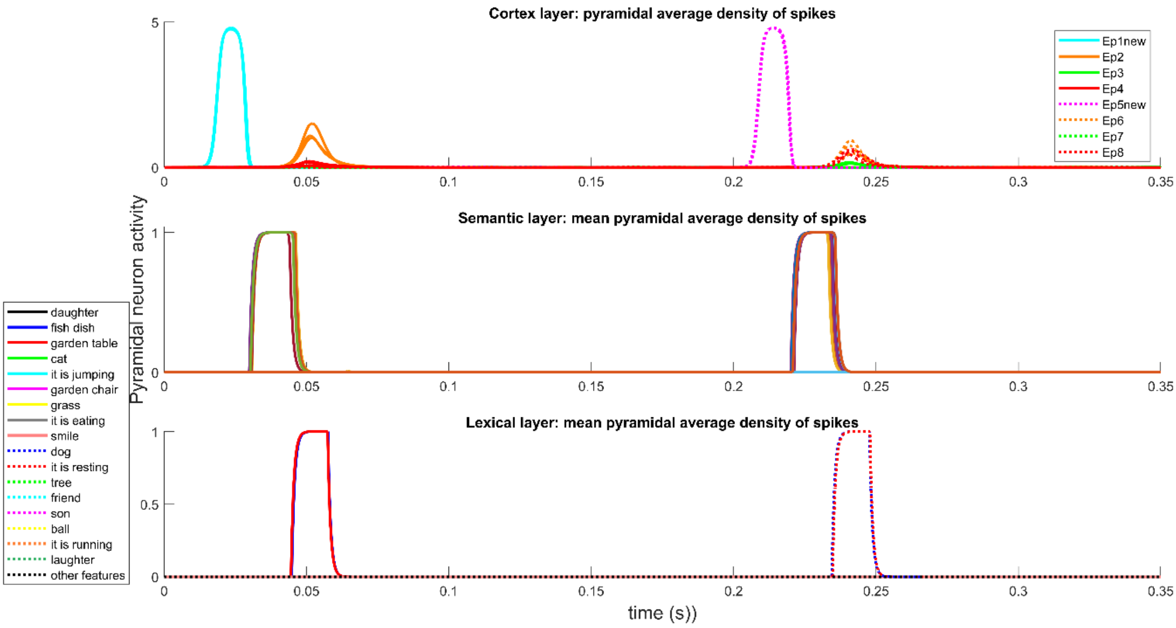


Figure S6 – The same simulation as in Fig. 5 (An example of recovery and generalization from the cortex without the participation of the hippocampus after slow-wave sleep). However, in this case, *only two features* of the first episode of the first sequence have been sent to the sensory cortex in the interval 0.01-0.02 s (feature "It has scales", n. 29 from the FISH DISH, and "It is foldable", n. 53 from the GARDEN TABLE). In contrast, the feature of the other object (feature "She does gymnastics", n. 79, from the DAUGHTER) is maintained at zero. Similarly, *only two features* of the second episode of the second sequence have been sent in the interval 0.2-0.21 s (feature "It barks", n. 95 from the DOG; feature "It relaxes", n. 148 from HE IS RESTING), whereas the feature of the other object ("It has branches", n. 65 from the TREE) is maintained at zero. The presence of only two object features does not allow the overall sequence to be recovered (compare this figure with Fig. 5), i.e., features from the total list of objects are necessary.

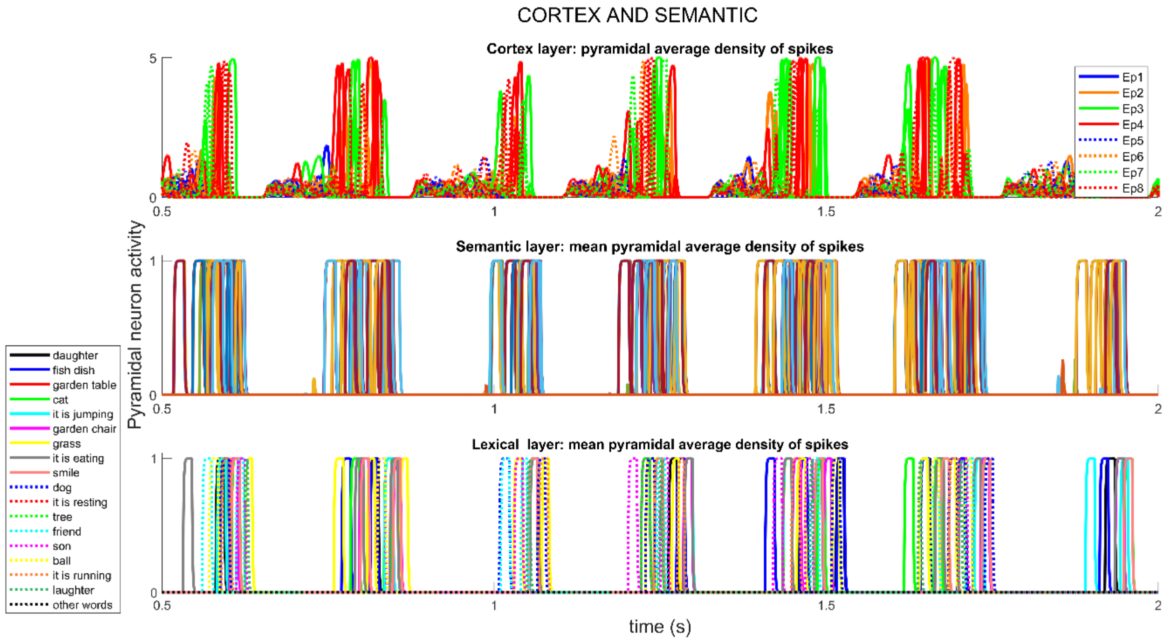
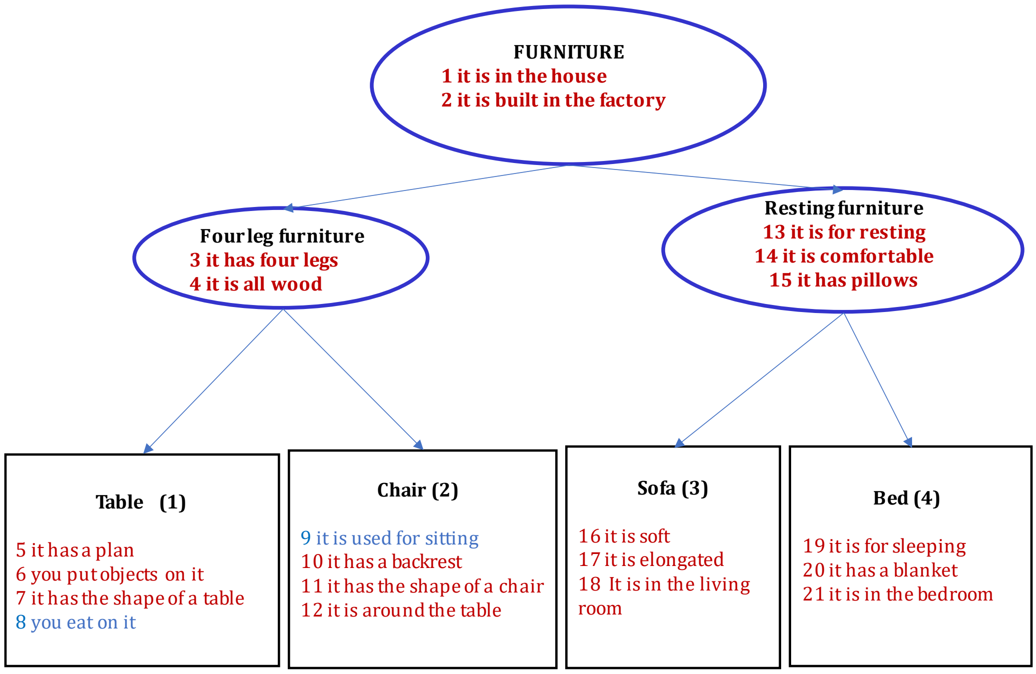
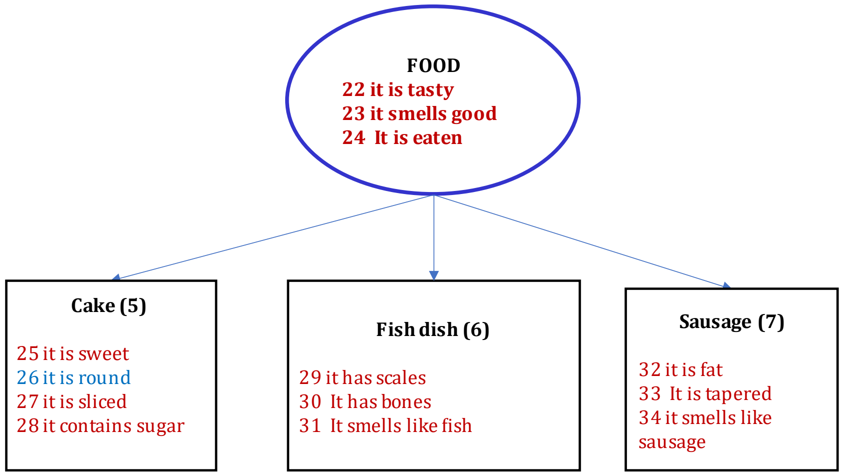
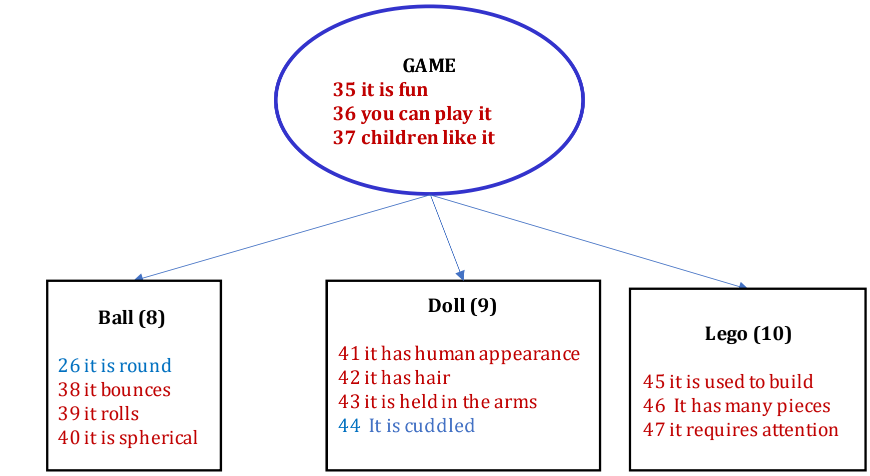


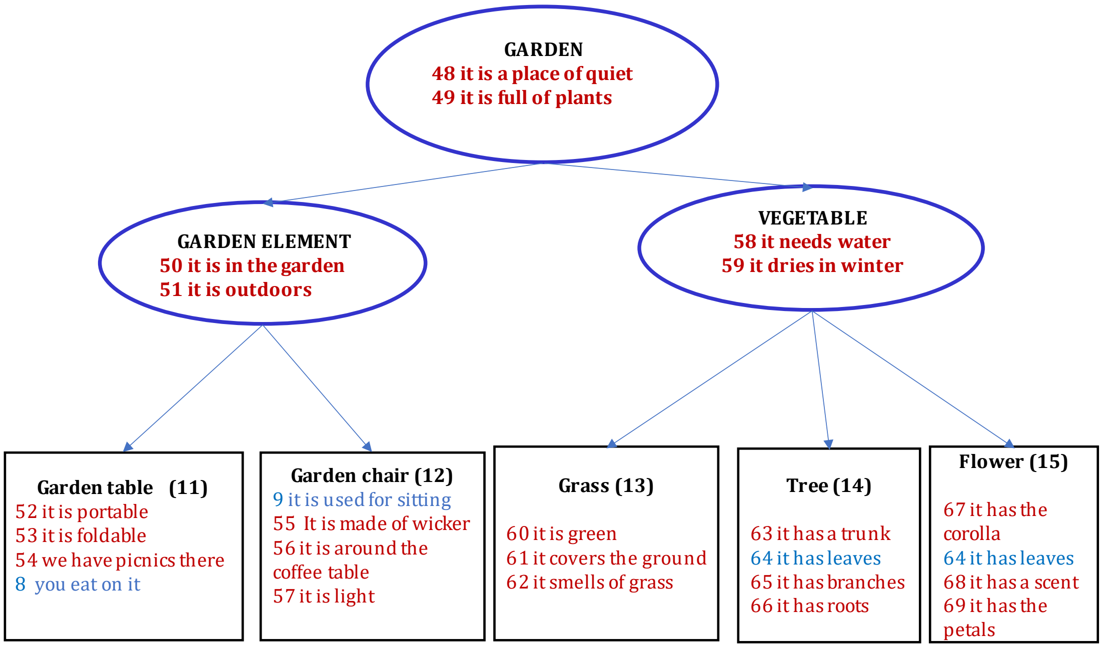
Figure S7 – The same simulation as in Fig. 6, but showing a large temporal interval, to highlight the presence of theta oscillations during REM sleep simulations.

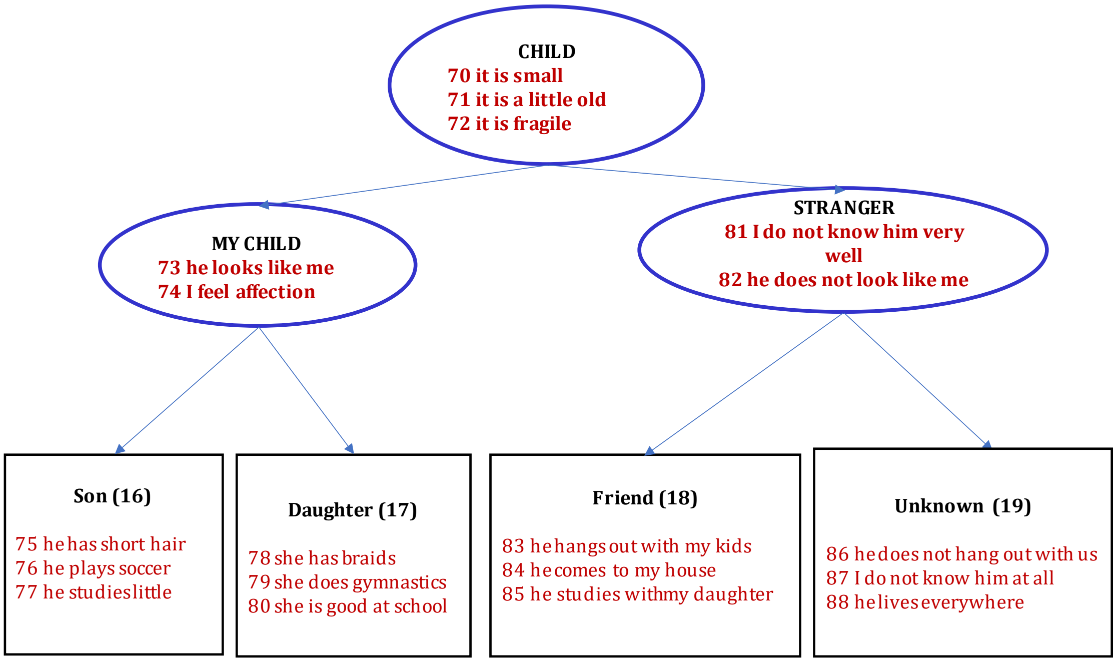
Supplementary Materials: Concept Taxonomy

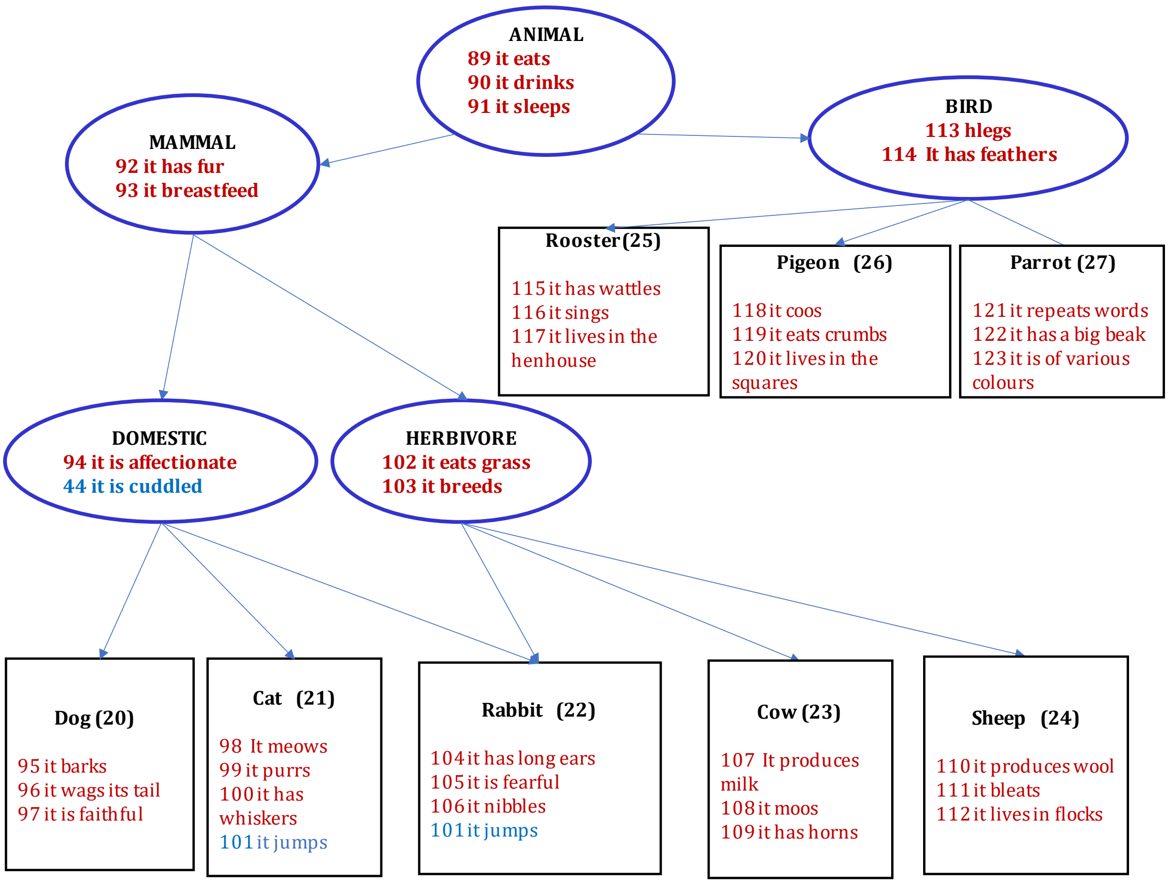





GAME
35 it is fun
36 you can play it
37 children like it
Ball (8)
26 it is round
38 it bounces
39 it rolls
40 it is spherical
Doll (9)
41 it has human appearance
42 it has hair
43 it is held in the arms
44 It is cuddled
Lego (10)
45 it is used to build
46 It has many pieces
47 it requires attention


GARDEN
48 it is a place of quiet
49 it is full of plants
GARDEN ELEMENT
50 it is in the garden
51 it is outdoors
VEGETABLE
58 it needs water
59 it dries in winter
Garden table (11)
52 it is portable
53 it is foldable
54 we have picnics there
8 you eat on it
Garden chair (12)
9 it is used for sitting
55 It is made of wicker
56 it is around the coffee table
57 it is light
Grass (13)
60 it is green
61 it covers the ground
62 it smells of grass
Tree (14)
63 it has a trunk
64 it has leaves
65 it has branches
66 it has roots
Flower (15)
67 it has the corolla
64 it has leaves
68 it has a scent
69 it has the petals


CHILD
70 it is small
71 it is a little old
72 it is fragile
MY CHILD
73 he looks like me
74 I feel affection
STRANGER
81 I do not know him very well
82 he does not look like me
Son (16)
75 he has short hair
76 he plays soccer
77 he studies little
Daughter (17)
78 she has braids
79 she does gymnastics
80 she is good at school
Friend (18)
83 he hangs out with my kids
84 he comes to my house
85 he studies with my daughter
Unknown (19)
86 he does not hang out with us
87 I do not know him at all
88 he lives everywhere


ANIMAL
89 it eats
90 it drinks
91 it sleeps
MAMMAL
92 it has fur
93 it breastfeed
BIRD
113 hlegs
114 It has feathers
Rooster (25)
115 it has wattles
116 it sings
117 it lives in the henhouse
Pigeon (26)
118 it coos
119 it eats crumbs
120 it lives in the squares
Parrot (27)
121 it repeats words
122 it has a big beak
123 it is of various colours
DOMESTIC
94 it is affectionate
44 it is cuddled
HERBIVORE
102 it eats grass
103 it breeds
Dog (20)
95 it barks
96 it wags its tail
97 it is faithful
Cat (21)
98 It meows
99 it purrs
100 it has whiskers
101 it jumps
Rabbit (22)
104 it has long ears
105 it is fearful
106 it nibbles
101 it jumps
Cow (23)
107 It produces milk
108 it moos
109 it has horns
Sheep (24)
110 it produces wool
111 it bleats
112 it lives in flocks

FEELING
124 he feels joy
125 he is affectionate
126 he is tender

Laughter (28)

127 heopens the mouth
128 it has the sound of a laughter
129 hemoves the head

Smile (29)

130 hestretches lips
131 hehalf closes eyes
132 hearouses sympathy

Caress (30)

133 hemoves the hand
134 it has tactile perception
135 it touches the skin

ACTION
136 it does something
137 it changes its state

It is eating (31)

127 heopens the mouth
138 it chews
139 it tastes
140 heuses cutlery

It is resting (34)

147 it lies down
148 it relaxes
149 it closes his eyes

It is jumping (32)

141 it is moving vertically
142 it is rising the air
143 hegives himself a push

It is running (33)

144 it is moving quickly
145 it is changing position along the ground
146 he liftshis knees

Supplementary Materials: Sequence Description

Sequence 1:

1. *I see the braids of my daughter while she places an odorous fish dish on the garden table to have a picnic.*

Daughter – she has braids (**78**); *fish dish* – it smells like fish (**31**); *garden table* – we have picnics there (**54**)

2. *The interested cat meows and gives himself a push to reach the light chair with a jump to look out.*

Cat – it meows (**98**); *it is jumping* – he gives himself a push (**143**); *garden chair* – it is light (**57**)

3. *My daughter, who is smart both at school and at home, to prevent the cat from jumping on the table, breaks off a small piece of the fish plate, avoiding the bones, and places it on the green grass of our house.*

Daughter – she is good at school (**80**); *fish dish* – it has bones (**30**); *grass* – it is green (***60***)

4. *The cat reaches his piece of food and starts chewing it to eat it. In the meantime, he started to purr, he was clearly happy with that meal.*

Cat – it purrs (**99**); *it is eating* – it chews (**138**); *smile* – he arouses sympathy (**132**)

Sequence 2:

5. *My son's friend's faithful dog is lying next to a tree trunk.*

Dog – it is faithful (**97**); *It is resting* – it lies down (**147**); *tree* – it has a trunk (**63**)

6. *Meanwhile, I see my son's short hair as he bounces a ball for his friend he's been hanging out with lately.*

Son – he has short hair (**76**); *friend* – he hangs out with my kids (**83**); *ball* – it bounces (**38**).

7. *The dog, seeing the ball, begins to wave his tail enthusiastically and then runs quickly onto the green grass of the friend's house to reach it.*

Dog – it wags his tail (**96**); *it is running* – it is moving quickly (**144**); *grass* – it is green (***150***).

8. *They are having fun! I am able hear the sound of their laughter, but I have to stop the game anyway because my son must study. Maybe his friend can come to our home to help him.*

Son – he studies little (**77**); *friend* – he comes to my house (**84**); *laughter* – it has the sound of a laughter (**128**)

Supplementary Materials: Model Equations

A quantitative description of the model is given here, with equations, training rules, and all related parameters.

1) Neural Mass Model Units (used in WM, CA1, CA2, and SC)

Synapses –All synapses in the model are described by the following second-order differential equation:

$$\frac{d^2y_n(t)}{dt^2} = \frac{G_n}{\tau_n}z_n(t) - \frac{2}{\tau_n}\frac{dy_n(t)}{dt} - \frac{y_n(t)}{\tau_n^2} \tag{A 1}$$

where G_n is the gain, τ_n is the time constant, and z_n is the input to the synapse, i.e. the presynaptic spike density. The subscript *n* is a generic one; it stands for either *p*, *e*, *s,* or *f*, depending on the neural population the equation is referring to: *p* for pyramidal neurons, *e* for excitatory interneurons, *s* for slow inhibitory interneurons, or *f* for fast inhibitory interneurons. There is a fifth population of neurons *c* to represent cholinergic neurons in the "Theta generator" *(A7)*. All second-order differential equations of type *(A1)* are equivalent to the two first-order differential equations that follow.

$$\begin{cases} \dfrac{dy_n(t)}{dt} = x_n(t) \\ \dfrac{dx_n(t)}{dt} = \dfrac{G_n}{\tau_n}z_n(t) - \dfrac{2}{\tau_n}x_n(t) - \dfrac{y_n(t)}{\tau_n^2} \end{cases}$$

Model of a single computational Unit – For each neuronal population, we first computed the mean membrane potential *v(t)*, which is influenced by synaptic connections. Then we computed the population average firing rate, *z(t)*, through a sigmoidal activation function, *S(v(t))*. Finally, a normalized post-synaptic potential, *y(t)*, can be computed using equations *(A2)*; the latter must be multiplied by the synaptic weight to determine the actual contribution to the post-synaptic membrane potential.

Both pyramidal neurons, fast inhibitory interneurons, and cholinergic neurons can receive an external input – labelled u_p, u_c, and u_f, respectively. These are random variables with normal distribution, mean value m_p (m_c or m_f), and standard deviation σ_p (σ_c or σ_f). Furthermore, to simulate sleep conditions, an additional uniform noise has been added, as specified below. Both reach the target population through an excitatory synapse. In the case of u_p, we implemented a common mathematical procedure to reduce the number of differential equations (and therefore, the number of state variables). Specifically, we processed u_p through the excitatory synapse from excitatory interneurons to pyramidal neurons (see Eq. *(A4)* below), rather than processing the input separately. The other external inputs, u_c and u_f, reach their target population through a dedicated synapse (Eqs. *(A6)* and *(A7)*).

The membrane potential of pyramidal neurons and fast inhibitory interneurons is also influenced by long-range synapses, which connect different Units. Such contributions are labelled *E*(*t*) and *I*(*t*) and will be discussed in the next paragraph (see section 4. "Connections among layers").

Equations for all populations.

Pyramidal neurons:

$$\begin{cases} v_p(t) = C_{pe}y_e(t) + C_{pp}y_p(t) - C_{ps}y_s(t) - C_{pf}y_f(t) + E(t) \\ S\left(v_p(t)\right) = z_p(t) = \dfrac{2e_0}{1+ e^{r(s_0 - v_p)}} \\ \dfrac{dy_p(t)}{dt} = x_p(t) \\ \dfrac{dx_p(t)}{dt} = \dfrac{G_e}{\tau_e} z_p(t) - \dfrac{2}{\tau_e} x_p(t) - \dfrac{y_p(t)}{\tau_e^2} \end{cases} \tag{A 2}$$

It is worth noting that the self-loop '*Cpp*' of pyramidal neurons has been used only in the "WM" layer and is set to zero in the other layers.

Excitatory interneurons:

$$\begin{cases} v_e(t) = C_{ep}y_p(t) \\ S\left(v_e(t)\right) = z_e(t) = \dfrac{2e_0}{1+ e^{r(s_0 - v_e)}} \\ \dfrac{dy_e(t)}{dt} = x_e(t) \\ \dfrac{dx_e(t)}{dt} = \dfrac{G_e}{\tau_e}\left(z_e(t) + \dfrac{u_p}{C_{pe}}\right) - \dfrac{2}{\tau_e} x_e(t) - \dfrac{y_e(t)}{\tau_e^2} \end{cases} \tag{A 3}$$

Slow inhibitory interneurons:

$$\begin{cases} v_s(t) = C_{sp}y_p(t) \\ S\left(v_s(t)\right) = z_s(t) = \dfrac{2e_0}{1+ e^{r(s_0 - v_s)}} \\ \dfrac{dy_s(t)}{dt} = x_s(t) \\ \dfrac{dx_s(t)}{dt} = \dfrac{G_s}{\tau_s} z_s(t) - \dfrac{2}{\tau_s} x_s(t) - \dfrac{y_s(t)}{\tau_s^2} \end{cases} \tag{A 4}$$

Fast inhibitory interneurons:

$$\begin{cases} v_f(t) = C_{fp}y_p(t) - C_{fs}y_s(t) - C_{ff}y_f(t) + y_l(t) + I(t) \\ S\left(v_f(t)\right) = z_f(t) = \dfrac{2e_0}{1 + e^{r\left(s_0 - v_f(t)\right)}} \\ \dfrac{dy_f(t)}{dt} = x_f(t) \\ \dfrac{dx_f(t)}{dt} = \dfrac{G_f}{\tau_f} z_f(t) - \dfrac{2}{\tau_f} x_f(t) - \dfrac{y_f(t)}{\tau_f^2} \\ \dfrac{dy_l(t)}{dt} = x_l(t) \\ \dfrac{dx_l(t)}{dt} = \dfrac{G_e}{\tau_e}(u_f(t)) - \dfrac{2}{\tau_e} x_l(t) - \dfrac{y_l(t)}{\tau_e^2} \end{cases} \tag{A 5}$$

The external inputs are composed of a deterministic portion and noise:

$$u_p(t) = m_p(t) + \sigma_p(t)$$
$$u_f(t) = m_f(t) + \sigma_f(t) \tag{A 6}$$

All parameters' values are listed in the tables below. Note that the variance of the noise is divided by the integration step, *dt*. In this way, we obtain a white noise with power density equal to $\sigma^2\, dt$ = 5.

Table A 1: *Parameters describing the dynamics of the populations within the Neural Mass Model*

Synapses				**Fuction S(*v(t)*)**	
G_e (mV)	5.17	τ_e (ms)	8	e_0 (Hz)	2.5
G_s (mV)	4.45	τ_s (ms)	33.3	r (mV^{-1})	0.56
G_f (mV)	57.1	τ_f (ms)	3.33 (2.5)	s_0 (mV)	12
Inputs		**Intra-unit connections**		C_{pp}	2000 or 0*
m_p (Hz)	***See Description below***	C_{ep}	54	C_{fp}	108
m_f (Hz)	0	C_{pe}	54	C_{fs}	27
σ_p^2 (s^{-2})	5/dt	C_{sp}	54	C_{pf}	300
σ_f^2 (s^{-2})	5/dt	C_{ps}	67.5	C_{ff}	10

C_{pp} is different from zero only in the Working Memory

Description of the external inputs (mp and mf) in different conditions

Working Memory

Autobiographical Retrieval: mp = 5000 to the neuron representing one feature of the first episode of the sequence 0 elsewhere

Hippocampus (from the enthorinal cortex)

Encoding: mp = 2000*Ach(t) mf = 200*Ach(t) to the neurons that code features of an episode (both in L1 and L2; in L2 the inputs are delayed).

Retrieval: mp = 0

SWS training: mp in L1 = random uniform distribution 50 – 400

Sensory Cortex

Cortex retrieval without the HC: mp = 1000 for 10ms to the neurons representing three features belonging to the semantic of the first episode (not necessarily the features memorized in the hippocampus)

REM: mp = random uniform distribution 200-250

2) The MS Unit (theta generator)

The "**Theta generator**" is composed of the same four populations described above (pyramidal neurons, excitatory interneurons, slow and fast GABAergic interneurons) plus a fifth population describing the activity of Cholinergic neurons.

Cholinergic neurons:

$$\begin{cases} v_c(t) = y_c(t) - \ C_{cf}\, y_f(t) \\ S\big(v_c(t)\big) = z_c(t) = \dfrac{2e_0}{1 + \ e^{r(s_0 - v_c(t))}} \\ \dfrac{dy_c(t)}{dt} = x_c(t) \\ \dfrac{dx_c(t)}{dt} = \dfrac{G_e}{\tau_e} u_c(t) - \dfrac{2}{\tau_e} x_c(t) - \dfrac{y_c(t)}{\tau_e^2} \end{cases}$$

$$u_c(t) = m_c(t) + \sigma_c(t)$$

where m_c is the external input and σ_c the noise SD.

Acetylcholine binding – for each neuron of the MS cholinergic population, the synthesis of acetylcholine by cholinergic neurons is simulated through first-order dynamics with unit gain:

$$\frac{dy_{ACh}(t)}{dt} = \frac{1}{\tau_{atc}}\big(-\mathrm{y_{ACh}(t) + z_c(t)}\big) \tag{A 7}$$

where $y_{ACh}(t)$ is the concentration of acetylcholine, τ_{atc} the time constant of acetylcholine release by cholinergic neurons, and $z_c(t)$ the average density of spikes of cholinergic neurons.

$y_{ACh}(t)$ determines the fraction of receptor sites for acetylcholine, $ACh(t)$, occupied at the hippocampal level. This is described through the Hill's equation.

$$ACh(t) = \frac{y_{ACh}(t)^{n_c}}{{k_d}^{n_c} + y_{ACh}(t)^{n_c}}$$

$$n_c = 2, k_d = 0.7$$

(A 8)

where n_c is the degree of Acetylcholine cooperativity; k_d is the dissociation constant (i.e., the y_{ACh} concentration for which 50% of the maximum effect is obtained). In the present work, ACh_{max} was set to 1. Hence, $ACh(t)$ corresponds to the fraction of receptor sites occupied at a given instant t (*Pirazzini et Al, 2025*).

Table A 2: *Parameters describing the dynamics of the populations within the MS or "Theta generator" Unit*

Synapses				Fuction S(*v(t)*)	
G_e (mV)	5.17	τ_e (ms)	12.3	e_0 (Hz)	2.5
G_s (mV)	4.45	τ_s (ms)	44.4	r (mV^{-1})	0.56
G_f (mV)	57.1	τ_f (ms)	3.70	s_0 (mV)	12
		τ_{atc} (ms)*	2.78		
Inputs		**Intra-unit connections**		C_{cf}	67.5*0.9
m_p and m_c (Hz)	500	C_{ep}	54	C_{fp}	81
m_f (Hz)	0	C_{pe}	54	C_{fs}	0
σ_p^2 (s^{-2})	5/dt	C_{sp}	54 54*0.9 – during sws	C_{pf}	0
σ_f^2 (s^{-2})	5/dt	C_{ps}	67.5 67.5*0.5 - during sws	C_{ff}	9

**The value of τ_{atc} (ms) is really small. This very rapid dynamics was assumed to test the hypothesis that Ach works with a timescale compatible with the peaks and throughs of the theta wave. This is a strong model assumption still not verified experimentally but which may be at least partially justified by the absence of sufficiently rapid experimental techniques for detecting spatiotemporal variations in Ach (Pirazzini et Al, 2025).*

The changes in values during non-REM sleep are due to the influence of the thalamus in modulating the connections during sleep. These changes lead to saturation of the neurons and a constant peak in the theta oscillation during SWS, and consequently to a value of acetylcholine close to zero.

3) The semantic and Lexical Units

The semantic and the lexical layers have a simpler, non-oscillating structure. Each Unit is composed of only one neuronal population ($x_S(t)$ for the semantic and $x_l(t)$ for the lexical). The activity is described through a first order dynamics and a sigmoidal relationship.

Semantic neurons:

$$\begin{cases} \dfrac{dx_s(t)}{dt} = \dfrac{1}{\tau_s}\big(-x_s(t) + I_s(t)\big) \\ z_s(t) = S\big(x_s(t)\big) = \dfrac{1}{1 + e^{-\frac{1}{T_s}(x_s(t)-\varphi_x)}} \end{cases} \tag{A 9}$$

Lexical neurons:

$$\begin{cases} \dfrac{dx_l(t)}{dt} = \dfrac{1}{\tau_l}\big(-x_l(t) + I_l(t)\big) \\ z_l(t) = S\big(x_l(t)\big) = \dfrac{1}{1 + \mathrm{e}^{-\frac{1}{T_s}(x_l(t)-\varphi_{xl})}} \end{cases} \tag{A 10}$$

The inputs I_s and I_l represent synaptic connections from other Units (see section 4. “Connections among Layers”).

Table A 3: *Parameters describing the dynamics of the populations within “Semantic” Unit*

Time constants and multiplicative constants				Fuction S(*v(t)*)	
$\propto_d$ (ms^{-1})	1/ τ_d	τ_s (ms)	1	T_s	0.01
β_d(ms^{-1})	6*$\propto_d$	τ_d (ms)	30	$\varphi_{x,s}$	0.55

Table A 4: *Parameters describing the dynamics of the populations within “Lexical” Unit*

Time constants and multiplicative constants		Fuction S(*v(t)*)	
τ_l (ms)	1	T_s	0.01
		$\varphi_{x,s}$	3.5

4) Connections among layers

Each layer in the model consists of several individual Units of the type described above (with the exception of the MS, which is described by a single Unit). These Units are connected via long-range connections that typically link pyramidal neurons in the pre-synaptic layer to pyramidal neurons (monosynapticexcitation) or to fast GABAergic interneurons (disynaptic inhibition) in the post-synaptic layer.

Number of Units – In the hippocampus, all features have a different neural representation, even if the same feature is repeated in different contexts. This is because the hippocampus codes for autobiographic memories that are context specific. Therefore, in the hippocampus all the sequences are perfectly orthogonal. For example, the representation of the feature "It is green" for the grass in two different episodes is different and needs two different neurons. Consequently, "WM", "L1", "L2", have N_{ep} neurons representing all autobiographic features in the episodes. Conversely, features in the "cortex" and "semantic" are more general, i.e., the same Unit codes for the same feature in different contexts. We denote with N_{sem} the quantity of features used in the semantic network. N_{ep} is N_{sem} plus the quantity of shared features between sequences. The "lexical" layer has N_{obj} neurons, that is the number of objects (or concepts) trained in the semantic layer.

$$N_{ep} = 150 \quad ; \quad N_{sem} = 149 \quad ; \quad N_{obj} = 34.$$

Long range connections – Long-range synapses connect two different Units, either belonging to the same layer or to different layers. We denote with *Wp glutamatergic* connections to post-synaptic pyramidal neurons, and with *Wf* glutamatergic connections to post-synaptic fast inhibitory interneurons. Af denotes very fast (maybe due to gap-junctions) connections to fast interneurons. In the following, we will use subscripts (*i* or *j*) to represent the position of a Unit within a layer, and superscripts (either WM, Theta, L1, L2, cortex, semantic) to represent a layer. Generally, the first subscript (or superscript) will be used to represent the post-synaptic Unit (or the post-synaptic layer) whereas the second subscript (or superscript) will represent the pre-synaptic Unit (or the pre-synaptic layer). For instance, the symbol Wp_{ij}^{L1WM} in the following represents an excitatory synapse from a pre-synaptic neuron at position *j* in layer "WM" to a post-synaptic neuron at position *i* in layer "L1". Instead, when a long-range synapse is used to connect Units belonging to the same layer, only one superscript is used (e.g., Wp_{ij}^{L1}).

For each layer, E(t) and I(t) ((E(t) is the input of the pyramidal neurons and I(t) is the input of the fast inhibitory interneurons, see Eqs. *(A3)* and *(A6)*) are therefore calculated as follows:

.

WM:

$$E_i^{WM}(t) = 0$$

L1:

$$E_i^{L1}(t) = \left(1 - ACh(t)\right)\left(W_p^{L1WM} {y_{p,i}}^{WM}(t - D^{L1WM}) + \sum_{j=1}^{N_{ep}} Wp_{ij}^{L1L2}\, {y_{p,j}}^{L2}(t - D^{L1L2})\right)$$
$$+ \left(1 - ACh(t)\right)\left(\sum_{j=1}^{N_{ep}} Wp_{ij}^{L1}\, {y_{p,j}}^{L1}(t - D^{L1}) + Disinhibitor\right)$$
$$I_i^{L1}(t) = \left(1 - \mathrm{ACh(t)}\right)\left(\sum_{j=1}^{N_{ep}} Wf_{ij}^{L1}\, {y_{p,j}}^{L1}(t - D^{L1}) + \sum_{j=1}^{N_{ep}} Af_{ij}^{L1}\, {z_{p,j}}^{L1}(t - D^{L1})\right)$$

(A 11)

where:

$$Disinhibitor = \mathrm{gaintheta}\left({y_{p,j}}^{Theta}(t - D^{L1Theta}) - T_{theta}\right)$$

(A 12)

L2:

$$E_i^{L2}(t) = \left(1 - \mathrm{ACh(t)}\right) W_p^{L2L1} {y_{p,i}}^{L1}(t - D^{L2L1})$$

(A 13)

Cortex:

$$E_i^{CORTEX}(t) = \sum_{j=1}^{N_{ep}} Wp_{ij}^{CORTEXL2}\, {y_{p,j}}^{L2}(t - D^{CORTEXL2}) + \sum_{j=1}^{N_{SEM}} Wp_{ij}^{CORTEXSEM}\, x_{s,j}(t - D^{CORTEXSEM})$$
$$I_i^{L1}(t) = \sum_{j=1}^{N_{SEM}} Af_{ij}^{CORTEXCORTEX}\, {z_{p,j}}^{CORTEX}(t - D^{CORTEXCORTEX})$$

(A 14)

where *D* represents the delay in the connectivity among the layers. Specifically, the values of parameters pertaining to the equations above, as well as the values of fixed synapses, are reported in the following tables.

The input of the semantic and lexical layer $I_s(t)$ and $I_l(t)$ are described in the following.

Semantic:

$$W_{d_{ij}}^{SEMSEM}(t) = Wp_{ij}^{SEMSEM} depl_j(t)$$

$$\frac{ddepl_j(t)}{dt} = \alpha_d \left(1 - depl_j(t)\right) - \beta_d x_{sj}(t) depl_j(t)$$

$$I_{s,i}(t) = W_p^{SEMCORTEX} z_{pc,i}(t - D^{SEMCORTEX}) + \sum_{j=1}^{N_{SEM}} W_{d_{ij}}^{SEMSEM} x_{s,j}^{SEM}$$

(A 15)

Where $W_p^{SEMCORTEX}$ is a scalar value, and the second term of the last equation computes the sum of the inputs from the semantic layer neurons entering the i-th semantic layer neuron. Since, $if\ i = j \ \ => \ W_{i,j}^{SEMSEM} = 0$, the self-ring is zero and each neuron receives no input from itself.

The variable $depl_j(t)$ has a decreasing rate proportional to the value of $x_{sj}(t)$. Therefore, all the synapses which exit from neuron x_{sj} (i.e., synapses $W_{i,j}^{SEMSEM}$) exhibit a fatigue phenomenon where the neuron is active.

Lexical:

$$I_{l,i}(t) = \left(\sum_{j=1}^{N_{SEM}} Wp_{ij}^{LEXSEM} x_{s,j}^{SEM}(t - D^{LEXSEM}) \right)$$

(A 16)

Table A 5: *Delays between layers*

Intralayer delay	0.1 ms
D^{L1WM} *and* D^{WML1}	3 ms
D^{L1L2} *and* D^{L1L2}	1 ms

D^{MSBDL1}	1 ms
$D^{CORTEXL2}$	5 ms
$\boldsymbol{D^{SEMCORTEX}}$ **and** $\boldsymbol{D^{CORTEXSEM}}$	12 ms
$\boldsymbol{D^{LEXSEM}}$	12 ms

The first term of Eq. (*A14, A16*) implements the role of acetylcholine in modulating input signals to the hippocampus.

Eq. *(A15)* explains the global disinhibition we implemented by the “Theta generator” layer on “L1” layer. The term ‘Disinhibitor’ receives the overall activity from “Theta generator” and compares it with a threshold (T_{theta}). If the global activity in “Theta generator” is below T, the inhibitor silences all Units in “L1” by acting on the inputs of the excitatory interneurons. This inhibition is then retracted as soon as the global activity in “Theta generator” rises to the threshold.

Table A 6: *Fixed connections between units. Arrays diagonal in type except for Af.*

Wp^{L1WM}	$(1x1)$	*125 or 0*	$gain_{theta}$	*100*
Wp^{L2L1}	$(1x1)$	*250 or 0*	T_{theta}	*5*
$Wp^{CORTEXL2}$	$(N_{sem}xN_{ep})$	*250 or 0*	$Af^{CORTEXCORTEX}$ $(N_{sem}xN_{sem})$	*0.75*
$Wp^{SEMCORTEX}$	$(1x1)$	*0.33*		

$\boldsymbol{Wp^{CORTEXL2}}$ *– This matrix is not exactly diagonal. Infact its dimension is* $N_{sem}\ x\ N_{ep}$*. Its values are different from zero)value = 250) if one autobiographical feature in L2 is connected to a corresponding general feature in the Sensory Cortex. .*

$\boldsymbol{Af^{CORTEXCORTEX}}$ *-This matrix is used to implement competition among the neurons of the cortex. The values are set at zero in the principal diagonal.*

These fixed connections are reset or modified depending on the brain state.

- Wp^{L1WM} is zero during the *SWS training* and during the *only cortex retrieval,* i.e. the WM is disconnected from the hippocampus.
- $Wp^{CORTEXL2}$ is zero during *REM sleep*, i.e. the cortex is disconnected from the hippocampus.
- During REM we hypnotize that extra-unit connections are increased of the 20%. Therefore, $Wp^{SEMCORTEX}$ and $Wp^{CORTEXSEM}$ (*Eq A25*) are multiplied by 1.2.

5) Synapse training

Training rules – All excitatory and inhibitory connections are trained by means of Hebbian rule, while desynchronizing synapses are trained with an anti-Hebbian mechanism. Semantic training uses a different version of the Hebb rule in order to obtain a hierarchical structure to model the semantic memory (Ursino et al. 2023). For a more detailed description of the training procedures, we refer to the section "*Training of the network*" of the article.

Here is a list of the training procedures of the model with the respective trained parameters:

(a) Semantic training: It trains the reciprocal connections between the features to make them recall the whole concept starting from a single feature: W_p^{SEMSEM}
(b) Lexical training: It trains the feedforward connections from the semantic to the lexical layer to reconstruct one item if all its features are firing in the semantic layer: W_p^{LEXSEM}
(c) Hippocampus training: It trains the feedback loop among L1: $W_p^{L1L1}, A_f^{L1L1}, W_f^{L1L1}$ and the feedback from L2 to L1: W_p^{L1L2}
(d) Slow wave sleep training: it trains $W_p^{CORTEXSEM}$ to ensure that the semantics of each episode can recall the semantics of the following one.

Normalization of the sum to a maximum

After application of the Hebb rule, we checked that the sum of the synapses entering into a Unit cannot overcome a global maximum, named W_{maxsum} (different for the excitatory, inhibitory and desynchronizing synapses). This avoids that an excessive input leads a Unit to saturation, eliminating the oscillatory activity (in case of excessive excitation) or moving the activity to zero (in case of excessive inhibition). The presence of a maximal synapse sum also warrants that all objects in an episode are present in the semantic layer for a future episode to be evoked in the Sensory Cortex, and that all features are present in the Semantic Cortex for a corresponding word-form to be evoked in the Lexical Network.

We have (this example is related to a generic synapse array W, but the same principle applies to all the matrices of synapses trained with the Hebb rule)

$$S_i = \sum_j W_{ij} \, .$$

$$If \; S_i > \; W_{maxsum} \quad \Longrightarrow \quad W_{ij} \leftarrow \; W_{ij} \cdot \frac{W_{maxsum}}{S_i} \tag{A 17}$$

The values of the maximum entering sums of synapses for each training are given at Tables *A11-14*.

Numerical algorithm:

The differential equations were numerically solved with the Euler method, with an integration step dt. All parameters' values are shown in the following tables.

Semantic layer training

Synapses within “semantic” layer:

Hebb rule (long term potentiation)

$$gate = \left(x_{s,i}(t) - \theta_{post}\right) > 0 \; or \; \left(x_{s,j}(t) - \theta_{pre}\right) > 0$$

$$\Delta W_{ij}^{SEMSEM} = \gamma^{SEM} \; gate \; \left(x_{s,i}(t) - \theta_{post}\right)\left(x_{s,j}(t) - \theta_{pre}\right)\left(W_{max} - W_{ij}(t)\right)$$

$$W_{ij}^{SEMSEM}(t + T_s) = W_{ij}^{SEMSEM}(t) + \Delta W_{ij}^{SEMSEM}(t)$$

(A 18)

here γ represents a learning factor, $x_{s,i}(t)$ is the activity of the neuron in unit *i* and $x_{s,j}(t)$ is the activity of the neuron in unit *j*. It is worth noting that the synapse is modified only if the pre-synaptic activity or the post-synaptic activity is above threshold.

The diagonal of the matrix W^{SEMSEM} is forced at zero, i.e. the self-ring is set at zero.

Lexical layer training

Synapses within “lexical” layer:

Hebb rule (long term potentiation)

$$gate = \left(x_{l,i}(t) - \theta_{post}\right) > 0 \; or \; \left(x_{s,j}(t) - \theta_{pre}\right) > 0$$

$$\Delta W_{ij}^{SEMLEX} = \gamma^{LEX} \; gate \; \left(x_{l,i}(t) - \theta_{post}\right)\left(x_{s,j}(t) - \theta_{pre}\right)\left(W_{max} - W_{ij}(t)\right)$$

$$W_{ij}^{SEMLEX}(t + T_s) = W_{ij}^{SEMLEX}(t) + \Delta W_{ij}^{SEMLEX}(t)$$

(A 19)

here γ represents a learning factor, $x_{L,i}(t)$ is the activity of the *i-th* neuron of the lexical layer and $x_{s,j}(t)$ is the activity of the *j-th* neuron of the semantic layer. It is worth noting that the synapse is modified only if the pre-synaptic activity or the post-synaptic activity is above threshold.

Finally, the last term in Eqs. *(A21-27*) means that the synapses cannot overcome a maximum saturation value, W_{max} and so that the overall learning rate decreases approaching saturation.

Hippocampus episodic memory training

Synapses within layer “L1”:

Hebb rule (long term potentiation)

$$\Delta Wp_{ij}^{L1} = {\gamma_{Wp}}^{L1}\left(\frac{{z_{p,i}}^{L1}(t)}{2e_0} - \theta_{Wp}^{L1}\right)^{+}\left(\frac{{z_{p,j}}^{L1}(t)}{2e_0} - \theta_{Wp}^{L1}\right)^{+}\left(Wp_{max}^{L1} - Wp_{ij}^{L1}(t)\right)$$

$$Wp_{ij}^{L1}(t + T_s) = Wp_{ij}^{L1}(t) + \Delta Wp_{ij}^{L1}(t)$$

(A 20)

$$\Delta Wf_{ij}^{L1} = {\gamma_{Wf}}^{L1}\left(\frac{{z_{f,i}}^{L1}(t)}{2e_0} - \theta_{Wf}^{L1}\right)^{+}\left(\frac{{z_{p,j}}^{L1}(t)}{2e_0} - \theta_{Wf}^{L1}\right)^{+}\left(Wf_{max}^{L1} - Wf_{ij}^{L1}(t)\right)$$

$$Wf_{ij}^{L1}(t + T_s) = Wf_{ij}^{L1}(t) + \Delta Wf_{ij}^{L1}(t)$$

(A 21)

Anti-Hebb rule (long term potentiation)

$$\Delta Af_{ij}^{L1} = {\gamma_{Af}}^{L1}\left(\theta_{Af}^{L1} - \frac{{z_{f,j}}^{L1}(t)}{2e_0}\right)^{+}\left(\frac{{z_{p,i}}^{L1}(t)}{2e_0} - \theta_{Wp}^{L1}\right)^{+}\left(Af_{max}^{L1} - Af_{ij}^{L1}(t)\right)$$

$$Af_{ij}^{L1}(t + T_s) = Af_{ij}^{L1}(t) + \Delta Af_{ij}^{L1}(t)$$

(A 22)

Synapses from “L2” layer to “L1” layer:

Hebb rule (long term potentiation)

$$\Delta Wp_{ij}^{L1L2} = {\gamma_{Wp}}^{L1L2}\left(\frac{{z_{p,i}}^{L2}(t)}{2e_0} - \theta_{Wp}^{L1L2}\right)^{+}\left(\frac{{z_{p,j}}^{L1}(t)}{2e_0} - \theta_{Wp}^{L1L2}\right)^{+}\left(Wp_{max}^{L1L2} - Wp_{ij}^{L1L2}(t)\right)$$

$$Wp_{ij}^{L1L2}(t + T_s) = Wp_{ij}^{L1L2}(t) + \Delta Wp_{ij}^{L1L2}(t)$$

(A 23)

Slow wave sleep training

Synapses from “semantic” layer to “cortex” layer:

Hebb rule (long term potentiation)

$$\begin{aligned}\Delta Wp_{ij}^{CORTEXSEM} &= {\gamma_{Wp}}^{CORTEXSEM}\left(\frac{{z_{p,j}}^{CORTEX}(t)}{2e_0} - \theta_{Wp}^{CORTEXSEM}\right)^{+}\left(x_{s,i}(t)\right.\\ &\quad \left.- \theta_{Wp}^{CORTEXSEM}\right)^{+}\left(Wp_{max}^{CORTEXSEM} - Wp_{ij}^{CORTEXSEM}(t)\right)\end{aligned}$$

$$Wp_{ij}^{CORTEXSEM}(t + T_s) = Wp_{ij}^{CORTEXSEM}(t) + \Delta Wp_{ij}^{CORTEXSEM}(t)$$

(A 24)

here γ represents the learning factor, $z_{p,i}(t)$ is the activity of the pyramidal neuron in Unit *i*, $z_{f,i}(t)$ is the activity of the fast inhibitory neuron in Unit *i*, $x_{s,i}(t)$ is the activity of the semantic neuron in Unit i, $2e_0$ is the maximum firing rate (hence, all activities are normalized to the maximum). The function $()^+$ stands for the operator 'positive part'.

Table A 7: *Parameters describing the Hippocampus Training procedure*

Parameter	Value
dt (ms)	0.1
t_{end} (ms) (length of the procedure)	4125
m_p^{L1}/ m_p^{L2} (Hz)	$2000 * Ach * yEC1$ (current episodes) or 0 (others)
m_f^{L1}/ m_f^{L2} (Hz)	$200 * Ach * yEC2$ (current episodes) or 0 (others)
See Eq *(A11)* for $yEC1$ *and* $yEC2$	
$\theta_{low\_Wp}^{L1}$	0.91
$\theta_{low\_Wf}^{L1}$	0.86
$\theta_{up\_Wf}^{L1}$	0.08
$\theta_{low\_Wp}^{L1L2}$	0.95
γ_{Wp}^{L1}	0.8
γ_{Wf}^{L1}	0.4
γ_{Af}^{L1}	0.4
γ_{Wp}^{L1L2}	0.95
Wp_{max}^{L1}	170
Wf_{max}^{L1}	10
Af_{max}^{L1}	1.2
Wp_{max}^{L1L2}	150
Wp_{maxsum}^{L1}	510
Wf_{maxsum}^{L1}	30
Af_{maxsum}^{L1}	175.2
Wp_{maxsum}^{L1L2}	600

Table A 8: *Parameters describing the Semantic Training procedure*

Parameter	Value
Number of permutations	1000
$m_p{}^s$	1 with 80% probability (to all the features of the selected object)
θ_{post}	0.67
θ_{pre}	0.10
γ_s	0.02
W_{max}^{SEMSEM}	1.65
W_{maxsum}^{SEMSEM}	5*1.65

Table A 9: *Parameters describing the Lexical Training procedure*

Parameter	Value
Number of permutations	1000
$m_p{}^s$	1 with 80% probability (to all the features of the selected object)
$m_p{}^l$	4 (to the selected object)
θ_{post}	0.67
θ_{pre}	0.10
γ_l	0.05
W_{max}^{LEXSEM}	2
W_{maxsum}^{LEXSEM}	4

Table A 10: *Parameters describing the Slow Wave Sleep Training procedure*

Parameter	Value

dt (ms)	0.1
t_{end} (ms) (length of the procedure)	25000
m_p^{L1}	*random uniform noise distribution* 150 – 400
θ_{low_Wp}	0.95
γ_{Wp}	0.2
$Wp_{max}^{CORTEXSEM}$	35
$Wp_{maxsum}^{CORTEXSEM}$	2000