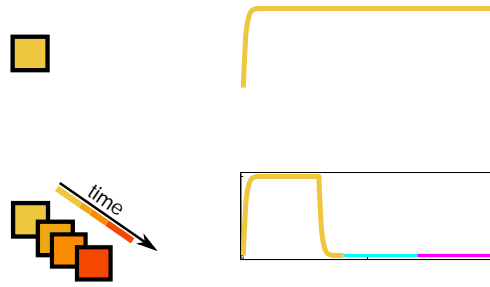


2012). In addition, the test is a measure of the child's -

Table 1 Variable and parameter with their default value

Symbol	Description
Variable	
I_j	Excitatory inhibitory efficacy of cell j
u_j	Normalized excitatory efficacy of cell j (initially $u_j = 1$)
v	Normalized excitatory efficacy of inhibitory cell (initially $v = 1$)
p_j	Learning rate of cell j (baseline $p_j = 1$)
w_{jk}, w	Strength of excitatory/inhibitory cell k to cell j
T_j, T	Duration of trial
Time parameter (default value in the i)	
	Time constant of firing (10 ⁻⁶)
τ	Time constant of synaptic facilitation (1 ⁻⁴)
w	Time constant of excitation (150 ⁻¹)
a	Time constant of adaptation (400 ⁻⁵)
s	Time constant of synaptic depression (50 ⁻⁶)
T_{cue}	Duration of trial to trigger a cue (50 ^{-2,3})
D	Duration of excitatory affective effect between trials (30 ⁻¹)
D'	Duration of excitatory affective effect within trials (20 ⁻¹)
Other parameter (default value in the i)	
	Firing rate effect (Heuristic function)
	Threshold of excitatory cell (0.5)
v	Threshold of inhibitory cell (0.5)
p_{max}	Maximum learning rate (2)
Z_k	Strength of excitatory/inhibitory cell k (0.3)
L	Weight of inhibition (0.6)
b	Strength of adaptation (1)
M	Learning rate of threshold (1)
w_{max}	Maximum synaptic weight between trials (0.4852)
w'_{max}	Maximum synaptic weight within trials (4.1312)
w_{min}	Minimum synaptic weight within trials (1.3488)
d	Strength of LTD 6.4598999 194.03999328 369.368985f h hh

... identified the ... , but ...



2. \dots

Therefore, it is clear that the algorithm described above is correct. In fact, it is easy to see that the expected weight of the tree T is $w(T) = \sum_{i \in E} w_i$. (6) To achieve the desired weight $w(T)$, we can use the following algorithm:

$$(1)$$

(Kerle et al. 1999; Pfister and Gerstner 2006; Cuthbert et al. 2010).

The delay between the triggering event can be coded in the electrical architecture, e.g., with the delay (Fig. 2). During training, synapse 1 is activated for T_1 seconds followed by synapse 2 (Fig. 2a). The timing of the delay is determined by the delay of the synapse (Sect. 2). When the first synapse is active, synapse 1 is active and LTD is induced, decreasing the synaptic weight, w_{21} , from synapse 1 to synapse 2. After T_1 ends, the first synapse is deactivated, and the second synapse is activated. Hence, synapse 1 did not become inactive immediately, and therefore both synapses are active. During this period, LTP is induced again, increasing the synaptic weight w_{21} . Shortly after synapse 1 becomes inactive, change in the weight w_{21} ceases, and a critical concentration of the synaptic weight is achieved. The initial value of the synaptic weight (w_{21}^0 and w_{21}^1 , respectively) can be controlled independently (Sect. 2). Repeated sequences of the training sequence lead to a critical concentration of the synaptic weight, w_{21}^i (weight after i th training), to a fixed value (Fig. 2b). On the other hand, the synaptic weight w_{12} is decreased during each trial because the second synapse is active after the first synaptic trial (Sect. 2). In the case of N synapses, each weight $w_{k+1,k}$ is connected to a sequence associated with T_k , hence each weight $w_{k+1,k}$ becomes negligible during sequence. Thus, the electrical architecture encodes the sequence.

The delay between the first synapse, T_1 , determines the delay between the synaptic weight from synapse 1 to synapse 2, w_{21}^∞ (Sect. 2). For a given value of T_1 , LTD at synapse 1 decreases w_{21} (Fig. 2c). Hence,

is considered a mechanism for fine-tuning (Bassett et al. 2000; D'Esposito et al. 2003; Reiter et al. 2004; Kasper and Bressan 2007; Gao et al. 2009). With this change in activity, directed connectivity is decreased in the cortex, but if connectivity is able to be tuned by the network.

For initial effects of connectivity, here activity of the first connectivity is related to the network (Fig. 3). This is if the activity is able to be tuned that activity is eight affected by the network. This activity is related to the network (Secti 4.4). After this activity is related with a brief case, it is able to be tuned by the network (Secti 2).

(Fig. 20,000 iterations w^0). The attractor eight after the initial stage, w_{21}^i , is described by a 8-bit digital circuit that emerges in the initial stage. The exact distribution in the circuit is the exact of the exact attractor eight after the exact of the exact (Fig. 5c). The exact of the exact attractor eight, w_{21}^∞ ,

are; a ... ai, ca ... the; e fa ... ti et ac -
 ig; ce (Be da a d He; 2003), i lead f h; t; .
 faci itati . I c; t; att the ca e f h; t; . faci itati ,
 ada tai ca e the effecti ei t f; . e ... ai t
 dec; ea e; e ti e.

I thi ca e ... ai acti it; a ... de ed b

$$\frac{du_j}{dt} = -u_j + (w_{jj}u_j + s_j - Lv - a_j),$$

$$a \frac{da_j}{dt} = -a_j + bu_j,$$

$$s \frac{ds_j}{dt} = -s_j + \sum_{k \neq j}^N w_{jk}u_k,$$

$$\frac{dv}{dt} = -v + \sum_{k=1}^N Z_k u_k - v,$$

he; e a_j de te the ada tai e e f ... ai j , a i
 the ti e ca e fa da tai , a d b i the ada tai t; e gh.
 Feedbac be; ee ... ai ... a ... ed t be; e
 tha feedbac; ithi a ... ai ; th , the t ta i t
 f; ... ai j a ... it i t e f-e citati $(w_{jj}u_j)$, a d
 a tic i t f; the; ... ai (s_j) hich e ed
 the ti e ca e s. N t e that i the i it $s \rightarrow 0$, a e
 a e i ta ta e .

F; a ... ilab e ch ice f; a a et; , g ba i hibiti
 t; ac acti it fa t; tha e citati be; ee ... ai .
 The; he a ... ai bec e i acti e d e t ada -
 tai , the e e f g ba i hibiti dec; ea e , a; i g
 be e t ... ai t bec e acti e. Thi; ea the
 eigh t f e f e citati ca e c de ti i g. Th , i thi
 et; e; e de ed g t; a tic i t; ithi a ... ai
 a; e . The ea; i g; e f; w_{jj} a a a g t w_{jk} ith
 the additi a a ... ti that i ce w_{jj} e; e e ted the
 a tic eigh t; ithi a ... ai , it c. d t dec; ea e
 be; a cetai a e w_{min} . A , the a a et; f; g
 t; a tic i t; ithi a ... ai a e a; ed t be dif-
 f; e t f; the a a et; f; g t; a tic i t; be; ee
 ... ai .

The ea; i g; e; a the

$$\frac{dw_{jj}}{dt} = - \frac{p}{d} (w_{jj} - w_{min}) u_j (t - D') (1 - u_j(t)) - \frac{p}{d} (w_{jj} - w_{max}) u_j (t - D') u_j(t).$$

Whe the ... ai ... a acti ated $(u_1(t) \approx 1)$ f; $t \in [0, T_1]$ (Fig. 7a), the cha ge i the; eigh t w_{11} e; e g
 e; e d b the iec; i e diff; e tia e; ai

$$\frac{dw_{11}}{dt} = \begin{cases} 0, & t \notin [D', T_1 + D'] \\ \frac{p}{w_j} (w_{max} - w_{11}), & t \in [D', T_1] \\ -\frac{d}{w} (w_{11} - w_{min}), & t \in [T_1, T_1 + D']. \end{cases}$$

The f; i g; e; ai e; e the a tic; eigh t at the
 e d fa; e e tai , $w_{11}(T_{tot})$, t the a tic; eigh t at
 the begi i g f the e e tai , $w_{11}(0)$:

$$w_{11}(T_{tot}) = w_{11}(0)e^{-T_1 \frac{p}{d} \frac{1}{w}} e^{(\frac{p}{d} - \frac{d}{w}) D' / w} + w'_{max} e^{-D' \frac{p}{d} \frac{1}{w}} (1 - e^{-T})$$



This emerging evidence indicates that the architecture of the brain (Buckner and Gollman 2009; Heinecke et al. 2014), in particular the connectivity between the default mode network (DMN) and the task-positive network (TPN) is critical for the development of cognitive and emotional skills.

4.1.1. The role of the default mode network (DMN) in cognitive and emotional development

The DMN is a network of brain regions that are active when the individual is at rest and not engaged in any task. It is thought to be involved in a variety of cognitive and emotional processes, including self-referential thinking, social cognition, and memory.

to occur. This article therefore provides a rigorous and
calibrates accurately the evidence being generated. For
instance, the authors have a clear face validity

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