Supplementary materials 2

The present study used MATLAB for the simulations of RTs. The connectionist model used in the present work is a simple recurrent neural network (RNN), consisting of four artificial neurons that represent four features (the crime-relevant (CR) event, the crime-irrelevant (CI) event, True, and False). The link strengths among the neurons are the connection weights learned based on the Hebbian learning rule [**?**].

Assuming a fully-connected recurrent network, the firing rate output r_i of neuron i is controlled by a linear activation function which transforms total input to a firing rate output, with a peak firing rate of $r_{max} = 10$ Hz and a time constant of $\tau_r = 10$ ms (Eqs. (1) and (2)). The total input to each neuron ($I_{tot,i}$) is a sum of external sensory input ($I_{ext,i}$) = 1.3 and recurrent synaptic currents ($I_{rec,i}$) (Eq. (3)). External sensory inputs occurs when the agent received the corresponding stimulus.

As is shown in Eq.(4), recurrent synaptic currents are defined as the product of firing rates of connected neurons r_j and synaptic weights w_{ij}. These recurrent synaptic currents contribute to the variations in the synaptic connection strength; that is, the updated weights are the sum of pre-updated weights and recurrent synaptic currents (Eq.(5)). Here we set the learning rate $k = 2 \times 10^5$. All synaptic connections w_{ij} and firing rates r_i are initially set to zero.

Besides, we presume an abstract neuromodulatory signal e that distinguishes between periods of encoding ($e = 1$) and retrieval ($e = 0$). In the encoding period, the network builds associations between features belonging to the agent(the crime-relevant event & True) and the recurrent synaptic currents do not exist. Here, the external sensory input $I_{ext,i} = 0.8 + 0.5 \times$ scale(Past Negative Score) ranged from 0.8 to 1.3. During the period of retrieval, recurrent synaptic currents are activated and passed to the next neuron as input when the agent receives the features same to their own.

This dynamic system will finally reach a stable state (Eq.(2)), with firing rates as the input of the drift-diffusion model.

$$I_{tot,i} = \begin{cases} I_{tot,i} & \text{for} \quad I_{tot,i} \leq r_{max} \\ r_{max} & \text{for} \quad I_{tot,i} > r_{max} \end{cases} \tag{1}$$

$$\tau_r \frac{dr_i}{dt} = -r_i + I_{tot,i} \tag{2}$$

$$I_{tot,i} = I_{ext,i} + I_{rec,i} \tag{3}$$

$$I_{rec,i} = (1 - e) \sum_{n=1}^{j} r_j w_{ij} \tag{4}$$

$$w_{ij} = w_{ij} + e k r_i r_j \tag{5}$$

The drift-diffusion models (DDM) are established based on the two-alternative forced choice tasks. In the DDM, two competing neuronal pools accumulate evidence of motor responses on the left and right, respectively. When evidence in one of the populations reaches the pre-determined firing rate threshold, the motor response is enacted and the decision is made. In this study, we apply the two-variable network model reported by ?] and ?]. We obtained the stimuli-driven input of the DDM from the connectionist model once firing rates reached an equilibrium condition. We acquired each neuron's firing rate output from the connectionist model and subsequently calculated the total firing rate output of each one of the motor populations. Then the level of sensory evidence s' is proportional to the difference in total firing rate input for each motor population, not including the firing rate activity produced by external stimulation I_{ext} (Eq. (8)). We made use of the sensory evidence s' [?] to gain the input I_{stim} caused by stimuli for each neuron population, which is proportional to the sensory evidence s' adjusted by a gain factor $f = 0.45$ and a mean value of $0 = 30$ Hz (Eq. (7)).

$$I_{fix} = \begin{cases} J_{A,ext}(50 + 100 exp[-(t - t_{fix})/\tau_{ad}]) & \text{for} \quad t_{fix} \leq t < t_{stim} \\ J_{A,ext}(6 + 44 exp[-(t - t_{stim})/\tau_{ad}]) & \text{for} \quad t > t_{stim} \end{cases} \tag{6}$$

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$$I_{stim,i} = J_{A,ext}\mu_0(1 + fs')$$ (7)

$$s' = (\sum r_L - \sum r_R) - I_{ext} + 0.05$$ (8)

Fixation on the cross before every trial contributes to a small excitatory input I_{fix} defined in Eq.(6). It is adjusted by a gain factor $J_{A,ext} = 1.1 \times 10^3$ nA/Hz and shows an adaptation with a time constant $ad = 40$ ms. Each population also receives noisy synaptic inputs with a mean value of $I_0 = 0.3297$ nA and a white noise component $\eta_i(t)$ with an amplitude of $\sigma_{noise} = 0.009$ nA filtered by a synaptic time constant of $\tau_{noise} = 2$ ms (Eq. (12)).

Each population's firing rate r_i (where $i = L, R$) is a function of the synaptic current input $I_{tot,i}$ described in Eq.(2) [see **?**], with parameters $a = 270$ Hz/nA, $b = 108$ Hz and $d = 0.154$ s.

Together with stimuli-driven input, fixation excitatory input and noise, the excitatory and inhibitory synaptic couplings constitute the total synaptic input to each population with $J_{ii} = 0.3275$ nA and $J_{ij} = 0.1137$ nA (Eq. (10)). NMDA currents S_i are manipulated by a dynamic system described in Eq. (11), in which the $tau_s = 55+ 10 \times \text{scale(AUC)}$ ranged from 55 to 65, representing different levels of evidence accumulation speed.

At last, we obtained the lower firing rate of two populations as the simulated reaction time through Eq(9) with $a = 270$ Hz/nA, $b = 108$ Hz and $d = 0.154$ s.

$$r_i = f(I_i) = \frac{aI_i - b}{(1 - exp[-d(aI_i - b)])}$$ (9)

$$I_{tot,i} = J_{ii}S_i - J_{ij}S_j + I_{stim,i} + I_{fix} + I_{noise,i}$$ (10)

$$\frac{dS_i}{dt} = -\frac{S_i}{\tau_s} + (1 - S_i)\gamma f(I_i)$$ (11)

$$\tau_{noise}\frac{dI_{noise}(t)}{dt} = -(I_{noise,i}(t) - I_0) + \eta_i(t)\sqrt{\tau_{noise}}\sigma_{noise}$$ (12)