



University of
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The logo of the University of Waterloo, featuring a yellow shield with a red lion and a red chevron.

CNRG — 
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A hallmark of biological systems is the ability to develop expertise through practice. At first, system performance is poor and reliant on constant corrective feedback signals. Through practice proficiency develops, reflected in an increased volume of the associated cortical area (Pascual-Leone, 1995).

(Ashby et al, 2007) proposed that expertise develops through two pathways: A fast loop through direct cortico-cortico connections, and a slower subcortical loop through the basal ganglia. The slow loop uses feedback to converge on a solution and trains the fast loop to respond correctly automatically.

To build a biologically plausible spiking neuron model of the development of expertise that matches experimental data from single-cell recordings to behavior.

- ▶ The infra-limbic cortex stores learned control signals. Presented with a target it projects modulatory weights (blue lines) to the action set.
- ▶ The basal ganglia evaluates system output using feedback signals and modulates contribution to the output signal (red lines).
- ▶ With repetition the infra-limbic cortex learns to generate the correct action automatically whenever the target signal is presented.
- ▶ This transference allows the system to phase out the subcortical loop, and more quickly and consistently execute the task, showing development of expertise.

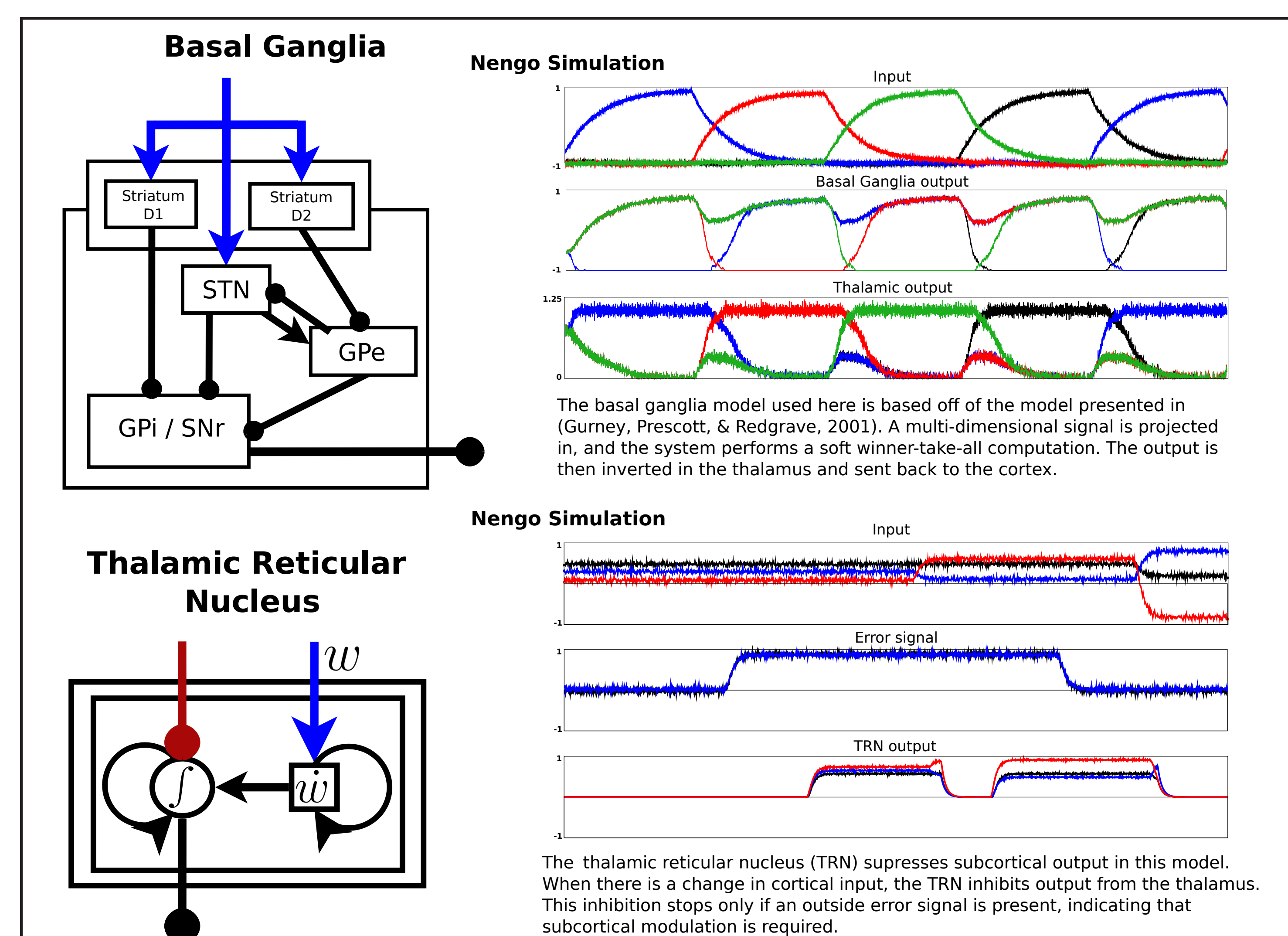
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Figure 3: Lever Press and Discharges.

Top Panel: Raster Plots of Lever Presses. The y-axis shows sessions 4, 5, 6, 9, and 12. The x-axis shows time in seconds (-0.5 to 0.5). A vertical red line marks the time of lever press. Asterisks indicate significant differences.

Bottom Panel: Raster Plots of Discharges. The y-axis shows sessions 4, 5, 6, 9, and 12. The x-axis shows time in seconds (-0.5 to 0.5). A vertical red line marks the time of lever press.

Right Panel: Bar Graphs.

Data: Proportion of Trials Missed vs. Day of Injection (3, 7, 17). Legend: Vehicle (white), 0.04 SCH (light gray), 0.08 SCH (dark gray), 0.16 SCH (black).

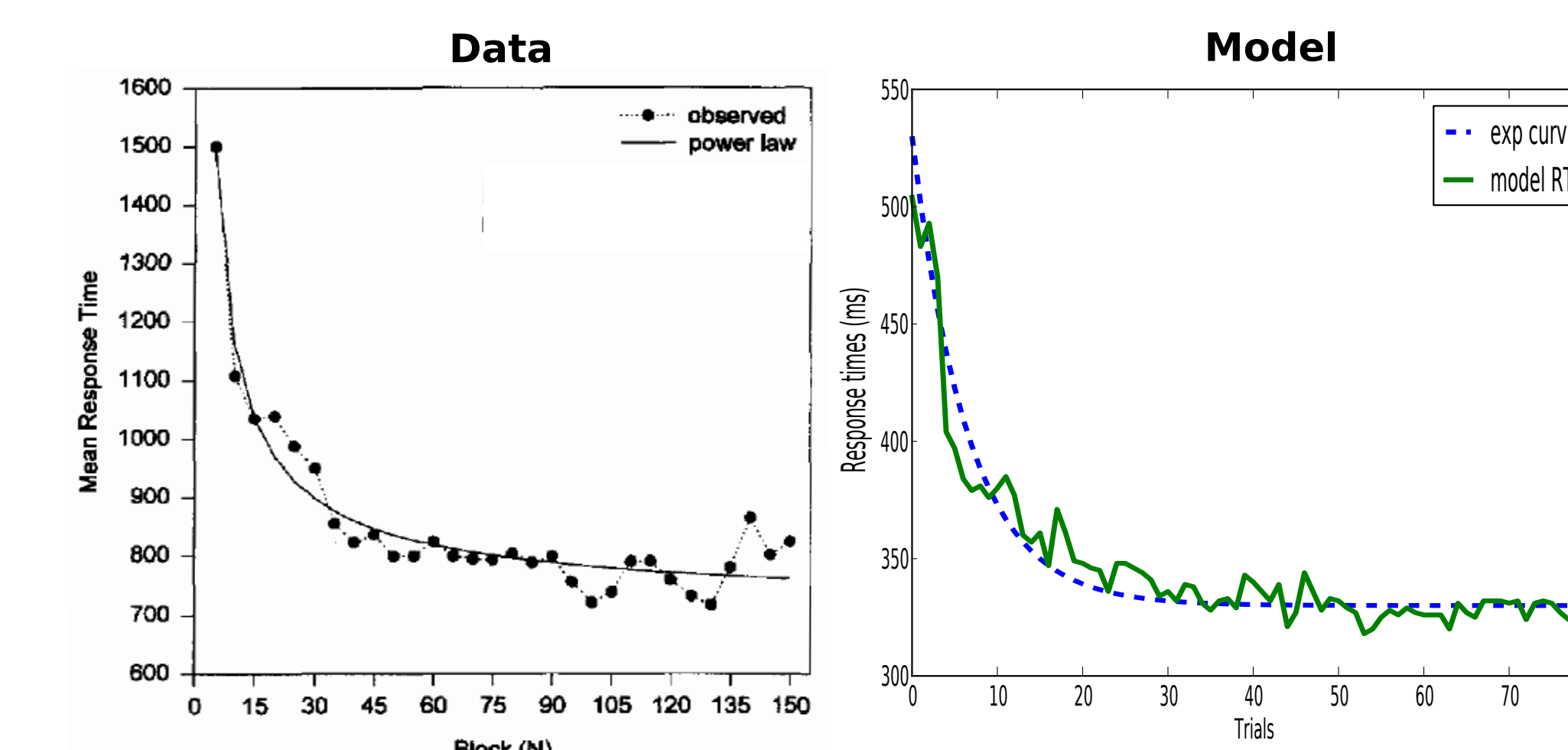
Day of Injection	Vehicle	0.04 SCH	0.08 SCH	0.16 SCH
3	~0.02	~0.04	~0.06	~0.16
7	~0.01	~0.02	~0.03	~0.03
17	~0.01	~0.02	~0.02	~0.02

Model: Difference in RMS of total error vs. Trials (40, 130, 175). Legend: $r=0.0100$ (black), $r=0.0175$ (dark gray), $r=0.0250$ (light gray), $r=0.0500$ (white).

Trials	$r=0.0100$	$r=0.0175$	$r=0.0250$	$r=0.0500$
40	~0.27	~0.17	~0.11	~0.04
130	~0.07	~0.03	~0.02	~0.02
175	~0.04	~0.02	~0.02	~0.02

Striatal dropout: At the beginning of learning there is substantial neural activity in the striatum just before the lever press. With practice, the timing of the neural activity shifts to after the press, and eventually disappears (Carelli, Wolske, & West 1997).

Effect of DA throughout learning: During early trials, injecting dopamine (DA) into the striatum causes a significant increase in error. However, as expertise develops and the subcortical system contributes less and less to execution of the task, the effect is reduced (Choi et al. 2005).



Response time profile: Humans have a highly stereotyped response time (RT) profile over the course of learning a skill, where the mean RT exponentially decreases as a function of the amount of practice (Nosofsky & Palmeri, 1997). Here we show the model RT across trials fit to an exponential curve, as seen in humans.

We have presented a biologically plausible model of the development of expertise. The model learns to perform tasks with response time profiles that match human data, and shows the same striatal dropout and DA injection effects seen in rat recordings. We are aware of no other model at this level of complexity.