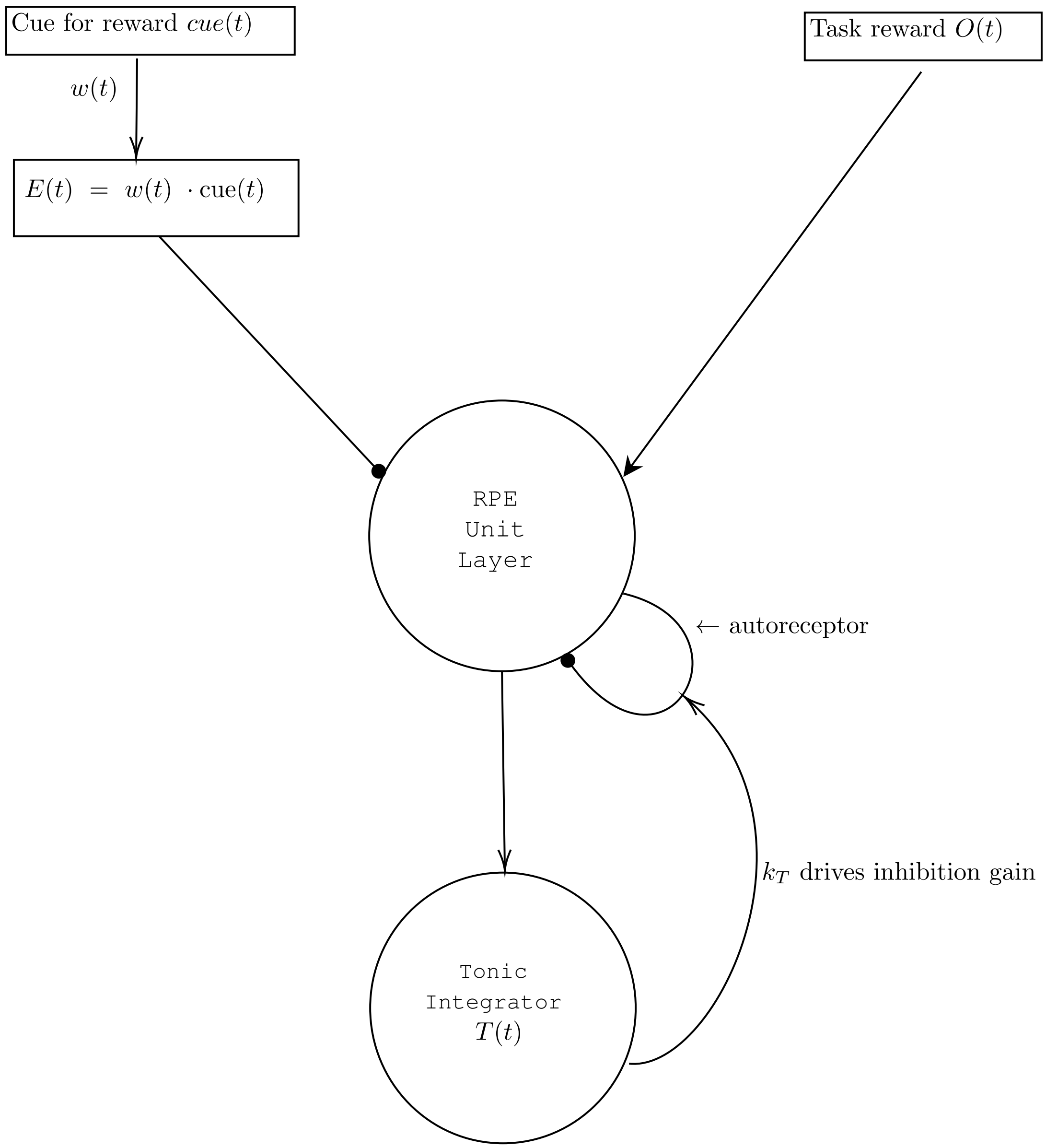
Computational Model of RPE Dynamics with Tonic Dopamine Modulation



$$\frac{dV_i}{dt} = I_i(t) - (k_0 + k_T T(t))\, V_i(t) + \left(\sigma \cdot \sqrt{dt} \cdot \mathcal{N}(u,1)\right) \tag{1}$$

$$I_i(t) = O_i(t) - E_i(t) \tag{2}$$

$$E_i(t) = w(t) \cdot \mathrm{cue}(t) \tag{3}$$

$$\frac{dw}{dt} = \eta \cdot V_i(t) \cdot \mathrm{cue}(t) \tag{4}$$

$$\frac{dT}{dt} = \frac{-T(t) + I_T(t)}{\tau_T} \tag{5}$$

$$I_T(t) = \sum_{\forall i} V_i \tag{6}$$

RPE Update Rule Key

- $V_i(t)$ Membrane variable of RPE neuron i; $I_i(t)$ is its corresponding input.
- $w(t)$ is the weighted sum of active cues.
- η is the learning rate of the RPE weight update.
- $T(t)$ Integrator of the RPE unit layer, intended to represent tonic dopamine.
- k_0 Baseline leak constant.
- k_T Tonic feedback gain that determines how strongly tonic dopamine modulates self-inhibition.
- σ Noise amplitude.
- $\mathcal{N}(u,1)$ Additive Gaussian noise over u units. In MATLAB, this would be

```
numUnits = u
randn(numUnits,1) % N(u,1)
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Essentially, when tonic dopamine $T(t)$ is low, phasic bursts from each RPE unit can persist. When tonic dopamine is high, the leak term $(k_0 + k_T T(t))$ increases and sustained phasic RPE activity is suppressed.