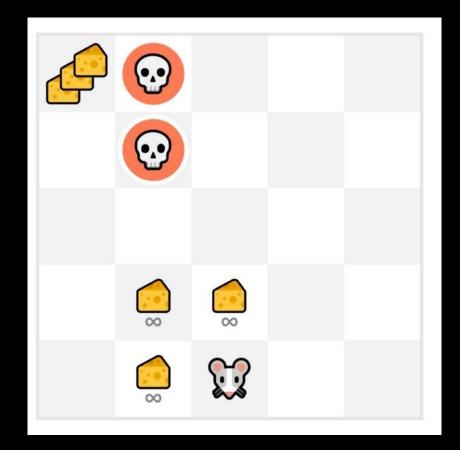
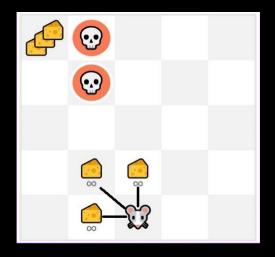
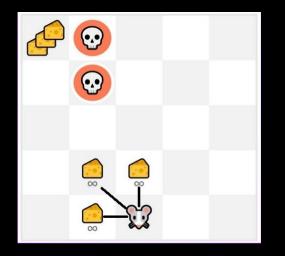
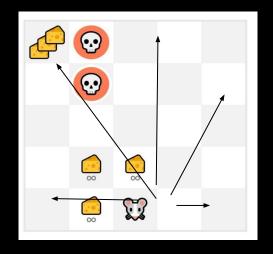
An exploration-exploitation model based on norepinephrine and dopamine activity

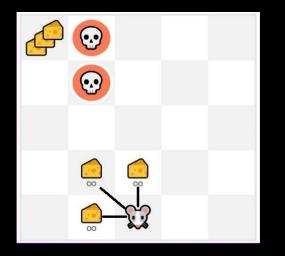
> Yervand Azatian NEU 502A: Systems and Cognitive Neuroscience

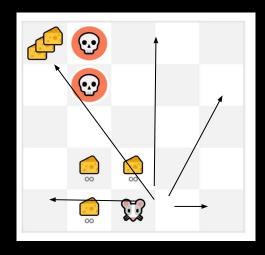


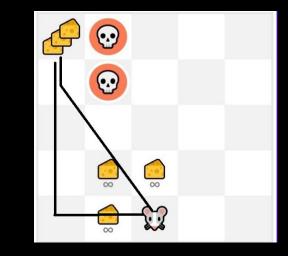


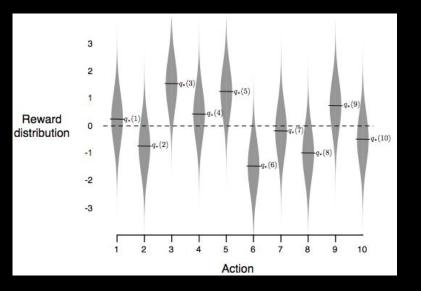


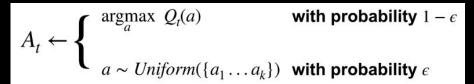


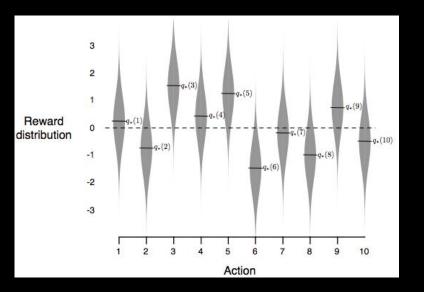


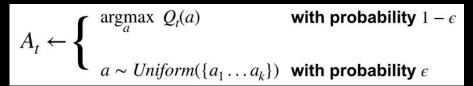


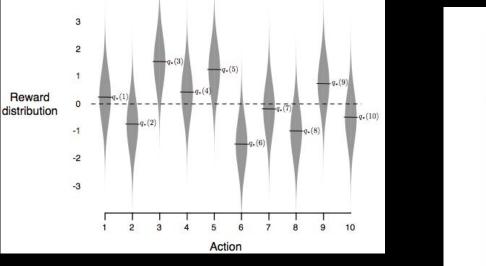


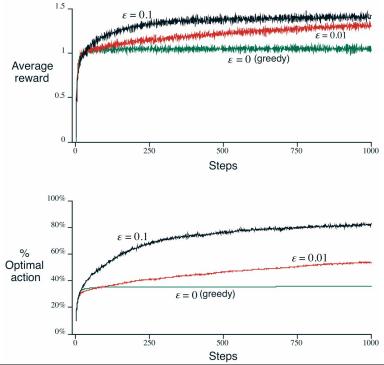


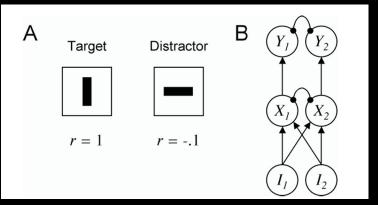


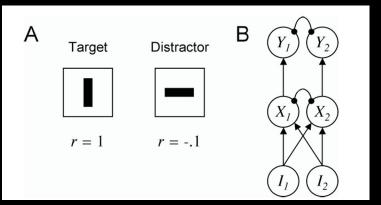






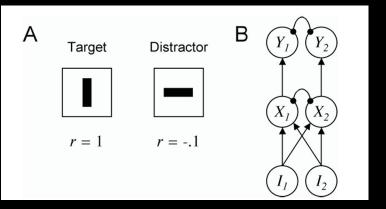


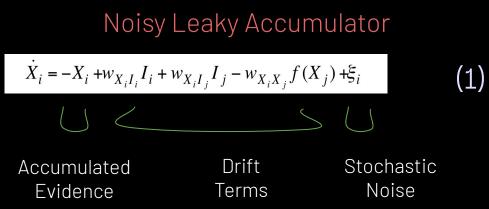


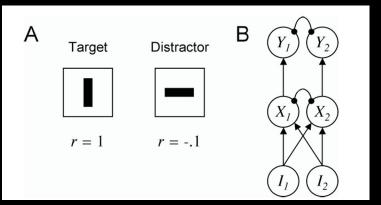


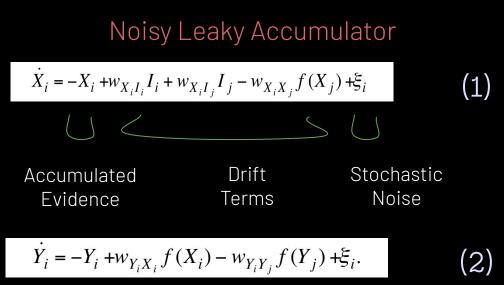
Noisy Leaky Accumulator

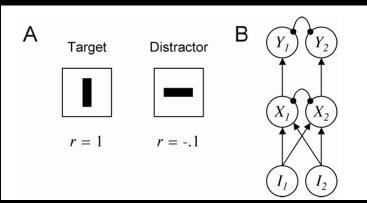
$$\dot{X}_{i} = -X_{i} + w_{X_{i}I_{i}}I_{i} + w_{X_{i}I_{j}}I_{j} - w_{X_{i}X_{j}}f(X_{j}) + \xi_{i}$$

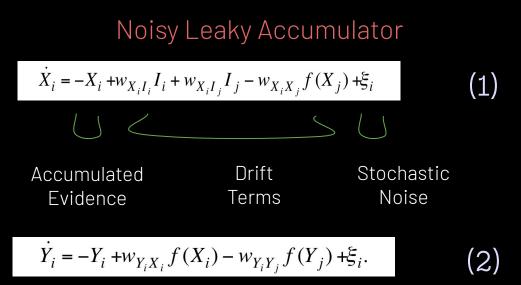




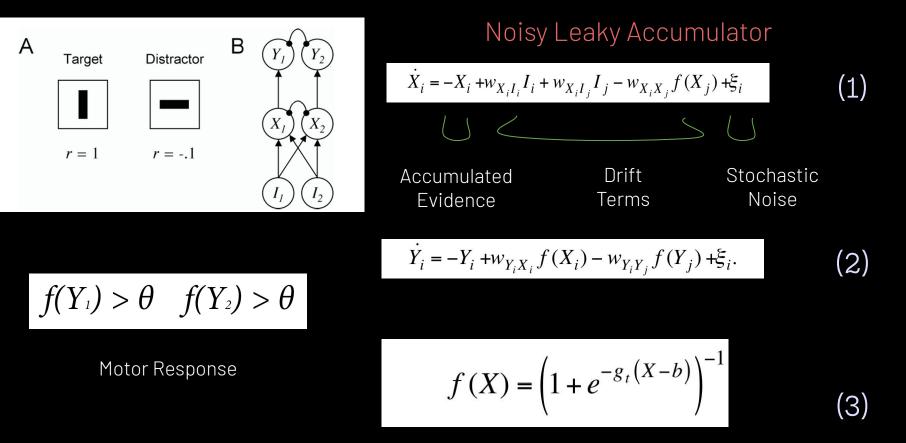


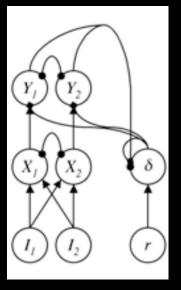






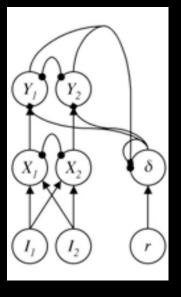
$$f(X) = \left(1 + e^{-g_t(X-b)}\right)^{-1}$$





$$(Y_1)$$
 (Y_2) (X_2) (X_2) (X_2) (X_2) (X_2) (X_2) (X_2) (X_2) (Y_2) $(Y_2$

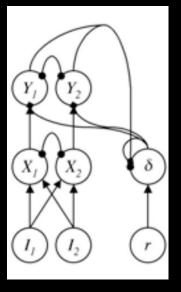
$$\delta(t) = r(t) - w_{\delta Y_1} Z(Y_1(t)) - w_{\delta Y_2} Z(Y_2(t))$$
4



$$\delta(t) = r(t) - w_{\delta Y_1} Z(Y_1(t)) - w_{\delta Y_2} Z(Y_2(t))$$

$$(4)$$
Reward
Reward
received
Expected
reward

Reward Prediction Error (RPE)



$$\delta(t) = r(t) - w_{\delta Y_1} Z(Y_1(t)) - w_{\delta Y_2} Z(Y_2(t))$$
(4)

Reward

received

Expected

reward

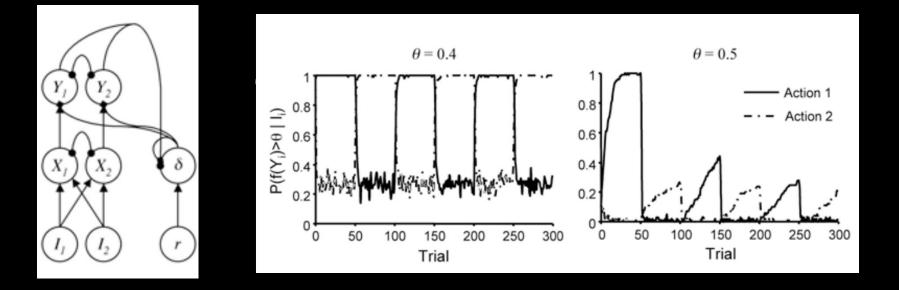
Rewar

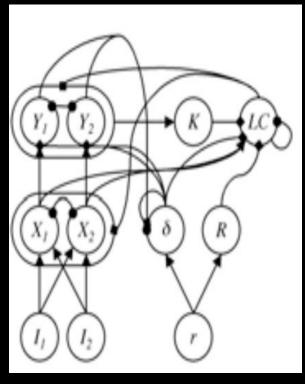
Reward Prediction Error (RPE)

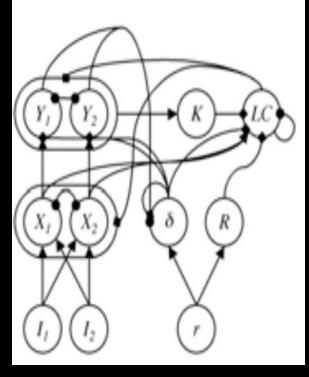
$$w_{\delta Y_i}(t+1) = w_{\delta Y_i}(t) + \lambda \delta(t) Z(Y_i)$$

Update weights based on RPE

Performance of Model with Dopamine Mediated Learning



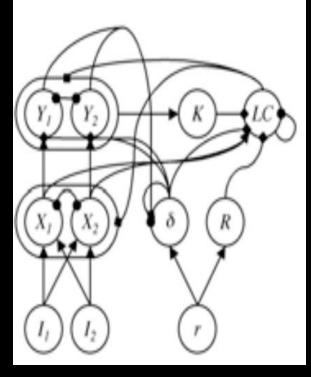




State of the LC is given by the FitzHugh-Nagumo set of differential equations:

$$\tau_v \dot{v} = v(\alpha - v)(v - 1) - u + w_{vX_1} f(X_1) + w_{vX_2} f(X_2)$$

(6)



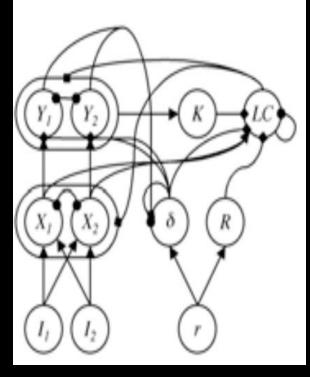
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$$\tau_v \dot{v} = v(\alpha - v)(v - 1) - u + w_{vX_1} f(X_1) + w_{vX_2} f(X_2)$$

(6)

Cubic Dampening Nonlinearity

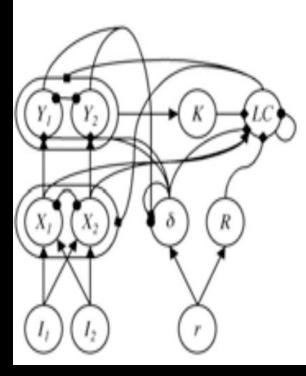
 τ



State of the LC is given by the FitzHugh-Nagumo set of differential equations:

$$\dot{v} = v(\alpha - v)(v - 1) - u + w_{vX_1}f(X_1) + w_{vX_2}f(X_2)$$
Cubic Dampening
Nonlinearity
$$\tau_u \dot{u} = h(v) - u \qquad (7)$$

(6)



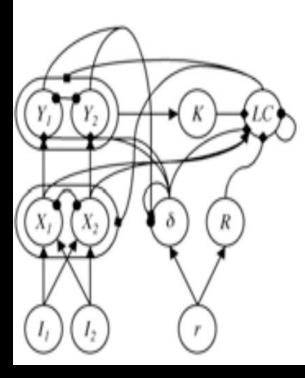
State of the LC is given by the FitzHugh-Nagumo set of differential equations:

$$\tau_{v}\dot{v} = v(\alpha - v)(v - 1) - u + w_{vX_{1}}f(X_{1}) + w_{vX_{2}}f(X_{2})$$
Cubic Dampening
Nonlinearity
$$\tau_{u}\dot{u} = h(v) - u \qquad (7)$$

$$h(v) = Cv + (1 - C)d$$

When C =1: phasic mode When C is small: tonic mode (6)

(8)



State of the LC is given by the FitzHugh-Nagumo set of differential equations:

$$\tau_{v}\dot{v} = v(\alpha - v)(v - 1) - u + w_{vX_{1}}f(X_{1}) + w_{vX_{2}}f(X_{2})$$
Cubic Dampening
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$$\tau_{u}\dot{u} = h(v) - u \qquad(7)$$

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 $g_t = G + ku_t$

When C =1: phasic mode When C is small: tonic mode

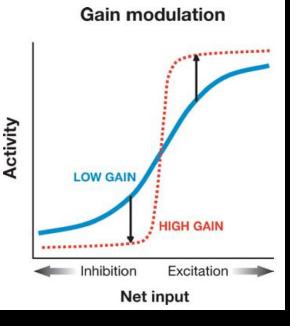
Modification of gain

(9)

(8)

(6)

τ



State of the LC is given by the FitzHugh-Nagumo set of differential equations:

$$v\dot{v} = v(\alpha - v)(v - 1) - u + w_{vX_1}f(X_1) + w_{vX_2}f(X_2)$$
Cubic Dampening
Nonlinearity
$$\tau_u \dot{u} = h(v) - u \qquad (7)$$

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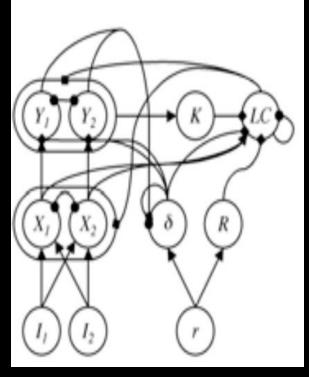
When C =1: phasic mode When C is small: tonic mode

(8)

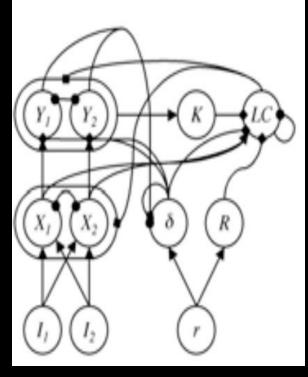
(9)

(6)

Modification of gain

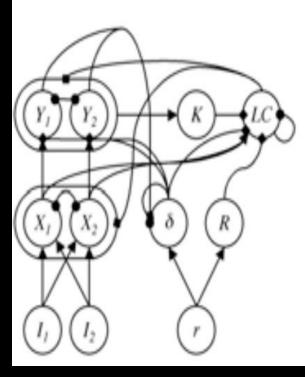


$$\begin{aligned} \tau_v \dot{v} &= v(\alpha - v)(v - 1) - u + w_{vX_1} f(X_1) + w_{vX_2} f(X_2) \\ \tau_u \dot{u} &= h(v) - u \quad h(v) = Cv + (1 - C)d \quad g_t = G + ku \end{aligned}$$



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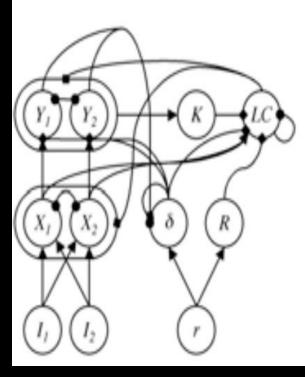
Value of C is updated after every trial by measures of response conflict and reward rate



$$\begin{aligned} \tau_v \dot{v} &= v(\alpha - v)(v - 1) - u + w_{vX_1} f(X_1) + w_{vX_2} f(X_2) \\ \tau_u \dot{u} &= h(v) - u \quad h(v) = Cv + (1 - C)d \quad g_t = G + ku \end{aligned}$$

Value of C is updated after every trial by measures of response conflict and reward rate

$$K = \frac{\mathbf{Y}_1 \cdot \mathbf{Y}_2}{\left\|\mathbf{Y}_1\| \mathbf{Y}_2\right\|}$$



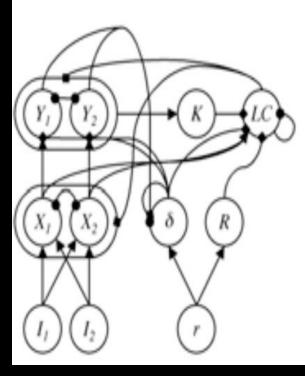
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Value of C is updated after every trial by measures of response conflict and reward rate

(10

$$K = \frac{\mathbf{Y}_1 \cdot \mathbf{Y}_2}{\left|\mathbf{Y}_1\right| \left|\mathbf{Y}_2\right|}$$

$$K_{S}(T+1) = (1 - \varepsilon_{S})K_{S}(T) + \varepsilon_{S}K(T)$$
(11)



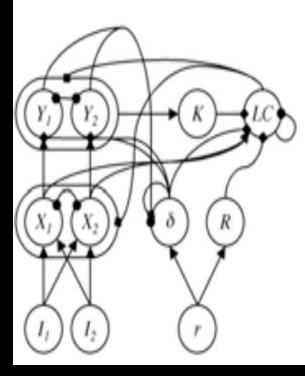
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Value of C is updated after every trial by measures of response conflict and reward rate

(1

$$K = \frac{\mathbf{Y}_1 \cdot \mathbf{Y}_2}{\left\|\mathbf{Y}_1\| \mathbf{Y}_2\right\|}$$

$$K_{S}(T+1) = (1 - \varepsilon_{S})K_{S}(T) + \varepsilon_{S}K(T)$$
(11)
$$R(T+1) = (1 - \varepsilon_{R})R(T) + \varepsilon_{R}r$$
(12)



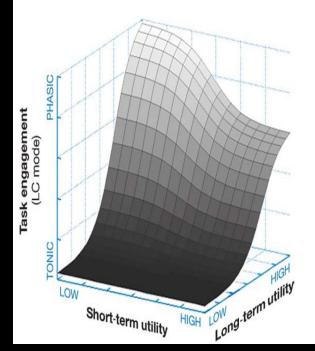
$$\begin{aligned} \tau_v \dot{v} &= v(\alpha - v)(v - 1) - u + w_{vX_1} f(X_1) + w_{vX_2} f(X_2) \\ \tau_u \dot{u} &= h(v) - u \quad h(v) = Cv + (1 - C)d \quad g_t = G + ku \end{aligned}$$

Value of C is updated after every trial by measures of response conflict and reward rate

$$K = \frac{\mathbf{Y}_1 \cdot \mathbf{Y}_2}{\left\|\mathbf{Y}_1\| \mathbf{Y}_2\right\|}$$

10)
$$\frac{K_S(T+1) = (1 - \varepsilon_S)K_S(T) + \varepsilon_S K(T)}{R(T+1) = (1 - \varepsilon_R)R(T) + \varepsilon_R r}$$
(12)

$$C = \sigma(K_S) (1 - \sigma(K_L)) \sigma(R)$$
(13)



$$\tau_{v}\dot{v} = v(\alpha - v)(v - 1) - u + w_{vX_{1}}f(X_{1}) + w_{vX_{2}}f(X_{2})$$

$$\tau_{u}\dot{u} = h(v) - u \quad h(v) = Cv + (1 - C)d \quad g_{t} = G + ku$$

Value of C is updated after every trial by measures of response conflict and reward rate

$$K = \frac{\mathbf{Y}_1 \cdot \mathbf{Y}_2}{\left\|\mathbf{Y}_1\| \mathbf{Y}_2\right\|}$$

(12)

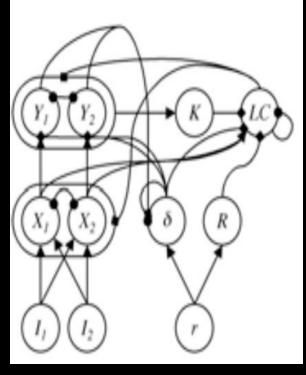
$$K_{S}(T+1) = (1 - \varepsilon_{S})K_{S}(T) + \varepsilon_{S}K(T)$$

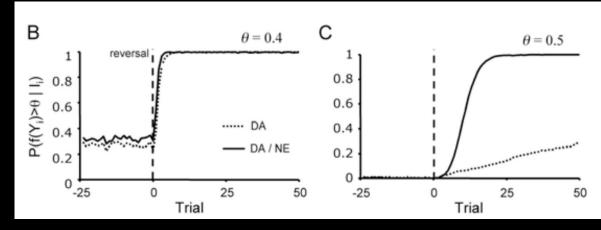
$$R(T+1) = (1 - \varepsilon_{R})R(T) + \varepsilon_{R}r$$

$$(12)$$

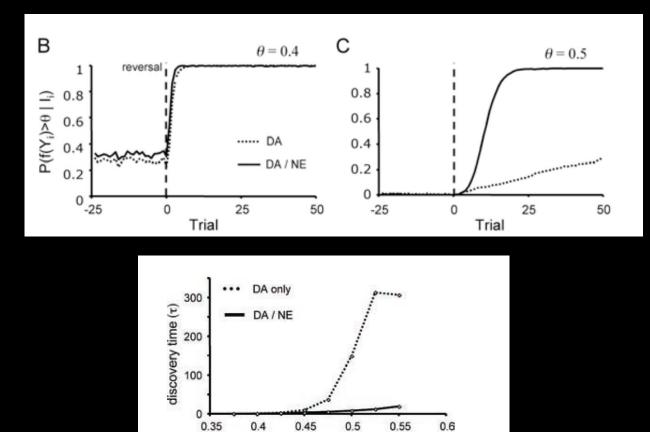
$$C = \sigma(K_S) (1 - \sigma(K_L)) \sigma(R)$$
(13)

Model Performance with **Dopamine** and **Noradrenaline**





Model Performance with **Dopamine** and **Noradrenaline**



threshold (θ)