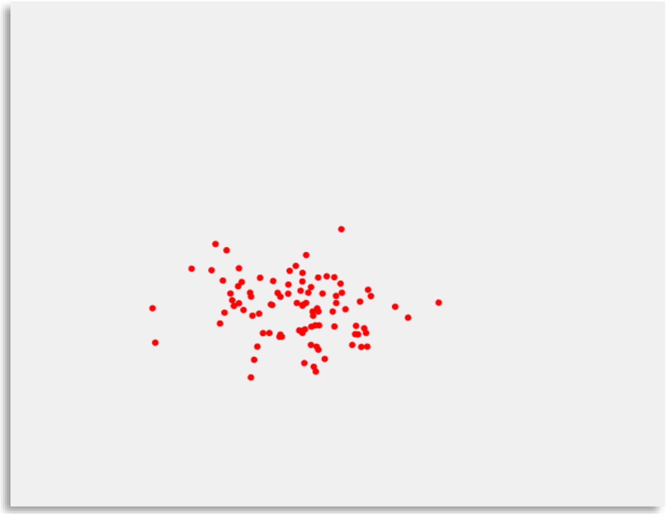
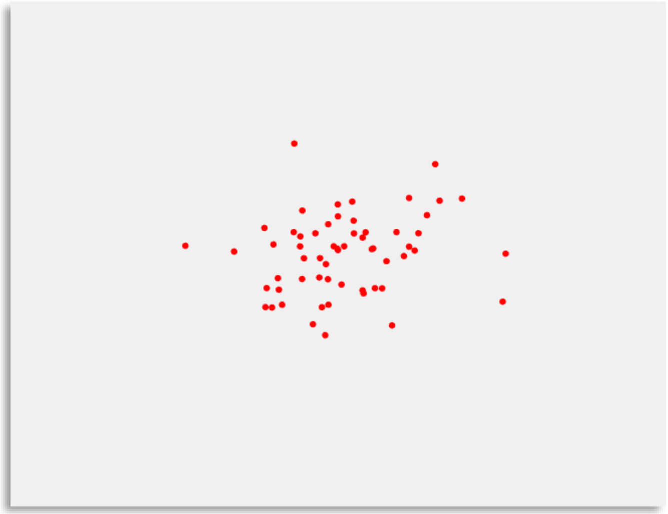
Active inference

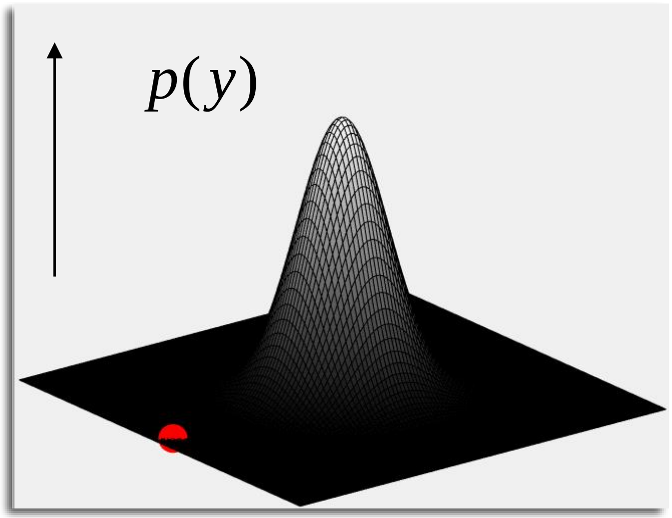
Computational psychiatry course

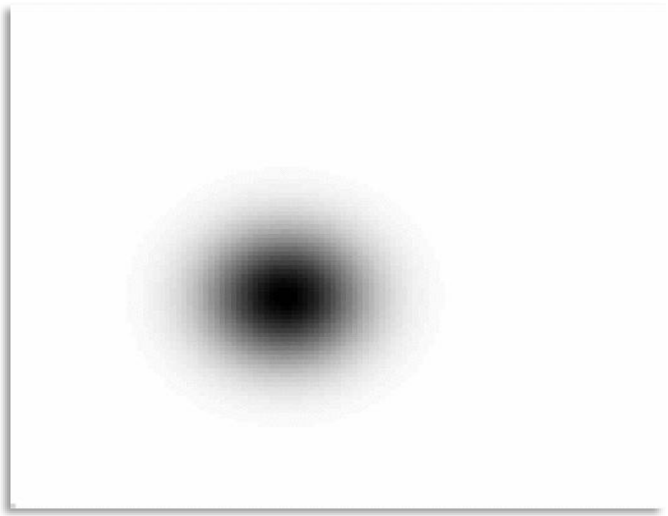
Active inference
Generative models
Exploitation
Exploration
Movement
Hierarchy

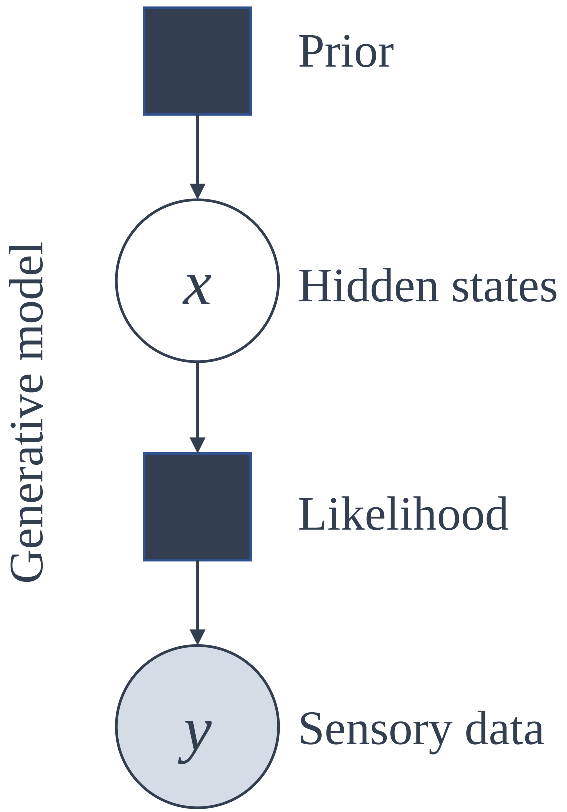
Active inference
Generative models
Exploitation
Exploration
Movement
Hierarchy





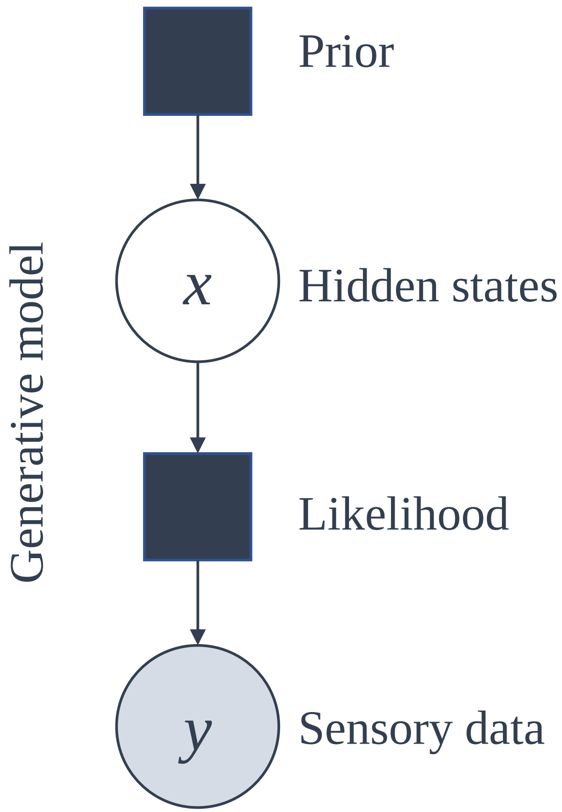

$p(y)$





Model evidence

$$\ln p(y)$$

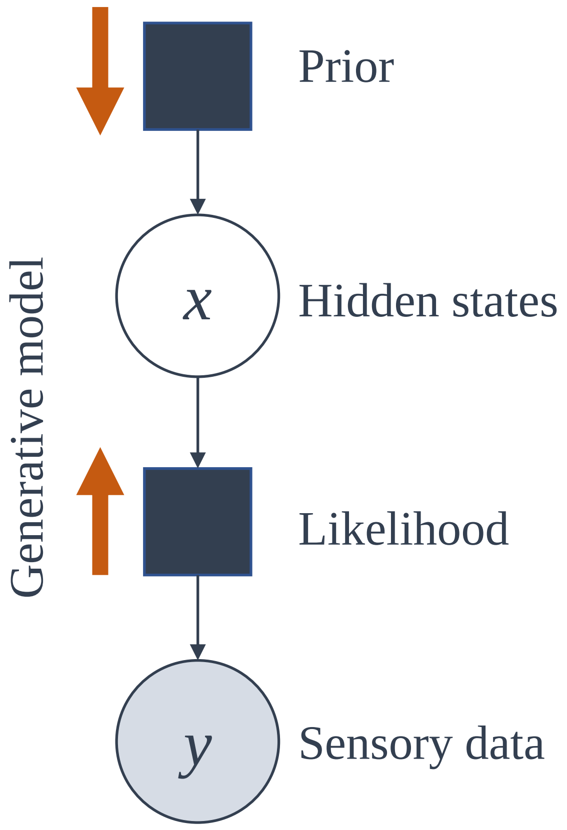


Free energy

$$-F(y) = E_q[\ln p(x, y)] - E_q[\ln q(x)]$$
$$= \ln p(y) + \underbrace{E_q[\ln p(x \mid y) - \ln q(x)]}_{\leq 0}$$

Active inference

$$q(x) = \arg\min_q F[q, y]$$
$$a = \arg\min_a F[q, y(a)]$$



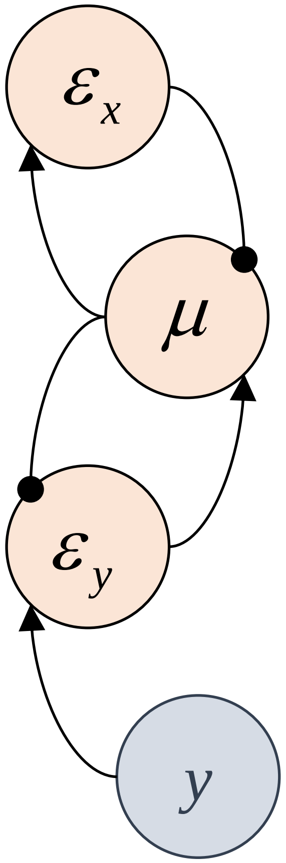
Free energy

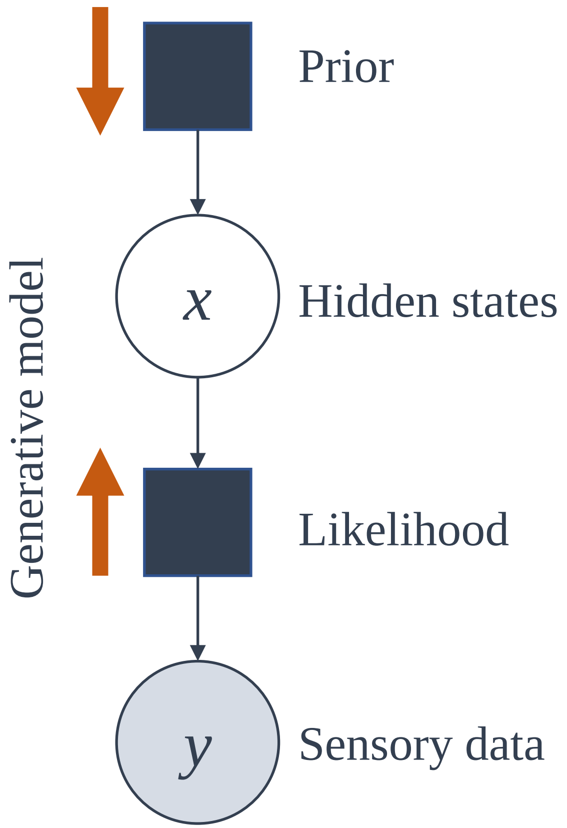
$$
\begin{aligned}
-F(y) &= E_q[\ln p(x,y)] - E_q[\ln q(x)] \\
&= E_q[\ln p(y \mid x)] + E_q[\ln p(x)] \\
&\quad - E_q[\ln q(x)]
\end{aligned}
$$

Message passing

$$\delta_q F = 0 \Leftrightarrow$$

$$\ln q(x) = \ln p(y \mid x) + \ln p(x) + const.$$





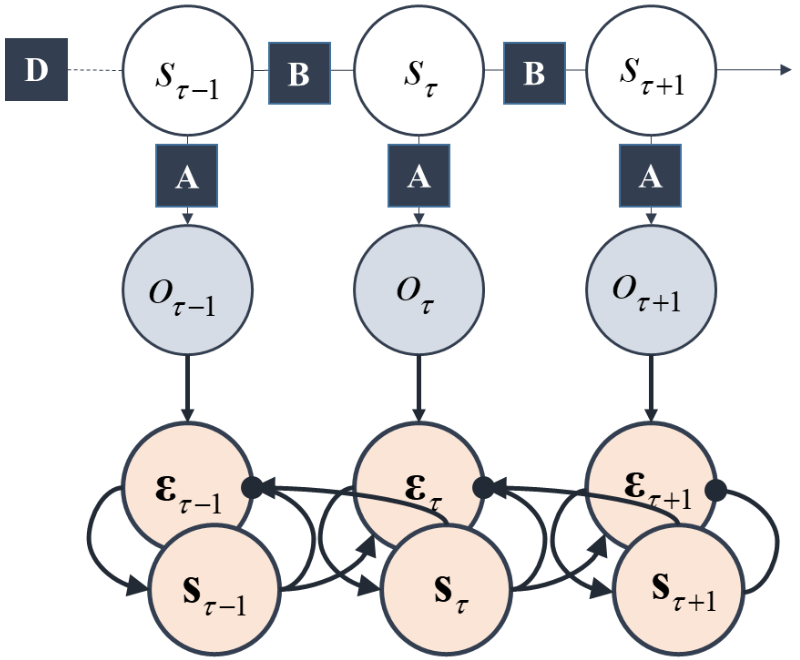
Free energy

$$
\begin{aligned}
-F(y) &= E_q[\ln p(x,y)] - E_q[\ln q(x)] \\
&= E_q[\ln p(y \mid x)] + E_q[\ln p(x)] \\
&\quad - E_q[\ln q(x)]
\end{aligned}
$$

Message passing

$$
\begin{aligned}
\dot{\mu} &= -\nabla_{\mu} F \\
&= \Pi_y \varepsilon_y \quad - \Pi_x \varepsilon_x
\end{aligned}
$$

Active inference
Generative models
Exploitation
Exploration
Movement
Hierarchy



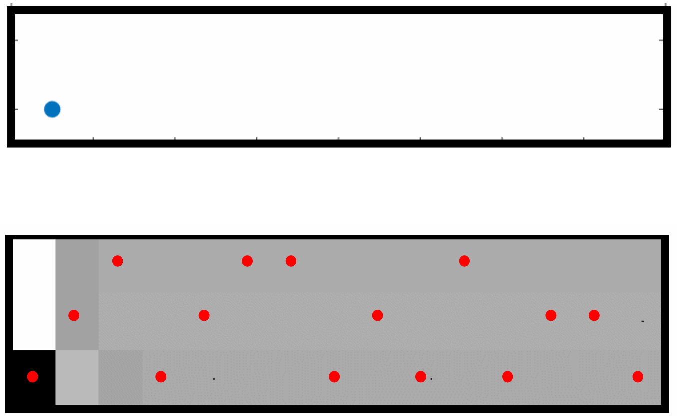
Generative model

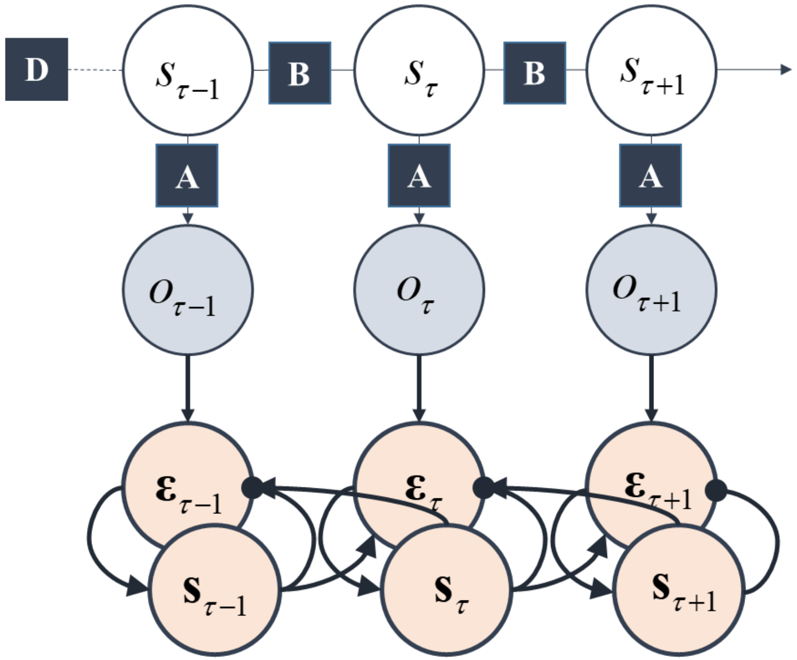
$$P(\tilde{o},\tilde{s}) = P(s_1)\prod_{\tau} P(s_{\tau+1} \mid s_{\tau})P(o_{\tau} \mid s_{\tau})$$

$$P(o_{\tau} \mid s_{\tau}) = Cat(\mathbf{A})$$
$$P(s_{\tau} \mid s_{\tau-1}) = Cat(\mathbf{B})$$
$$P(s_1) = Cat(\mathbf{D})$$

Bayesian message passing

$$\mathbf{s}_{\tau} = \sigma(\mathbf{v}_{\tau});\;\; \dot{\mathbf{v}}_{\tau} = \boldsymbol{\varepsilon}_{\tau}$$
$$\boldsymbol{\varepsilon}_{\tau} = \ln \mathbf{A} \cdot o_{\tau} + \tfrac{1}{2}\ln(\mathbf{B}_{\tau}\mathbf{s}_{\tau}) + \tfrac{1}{2}\ln(\mathbf{B}^{\dagger}_{\tau+1}\mathbf{s}_{\tau+1}) - \ln \mathbf{s}_{\tau}$$





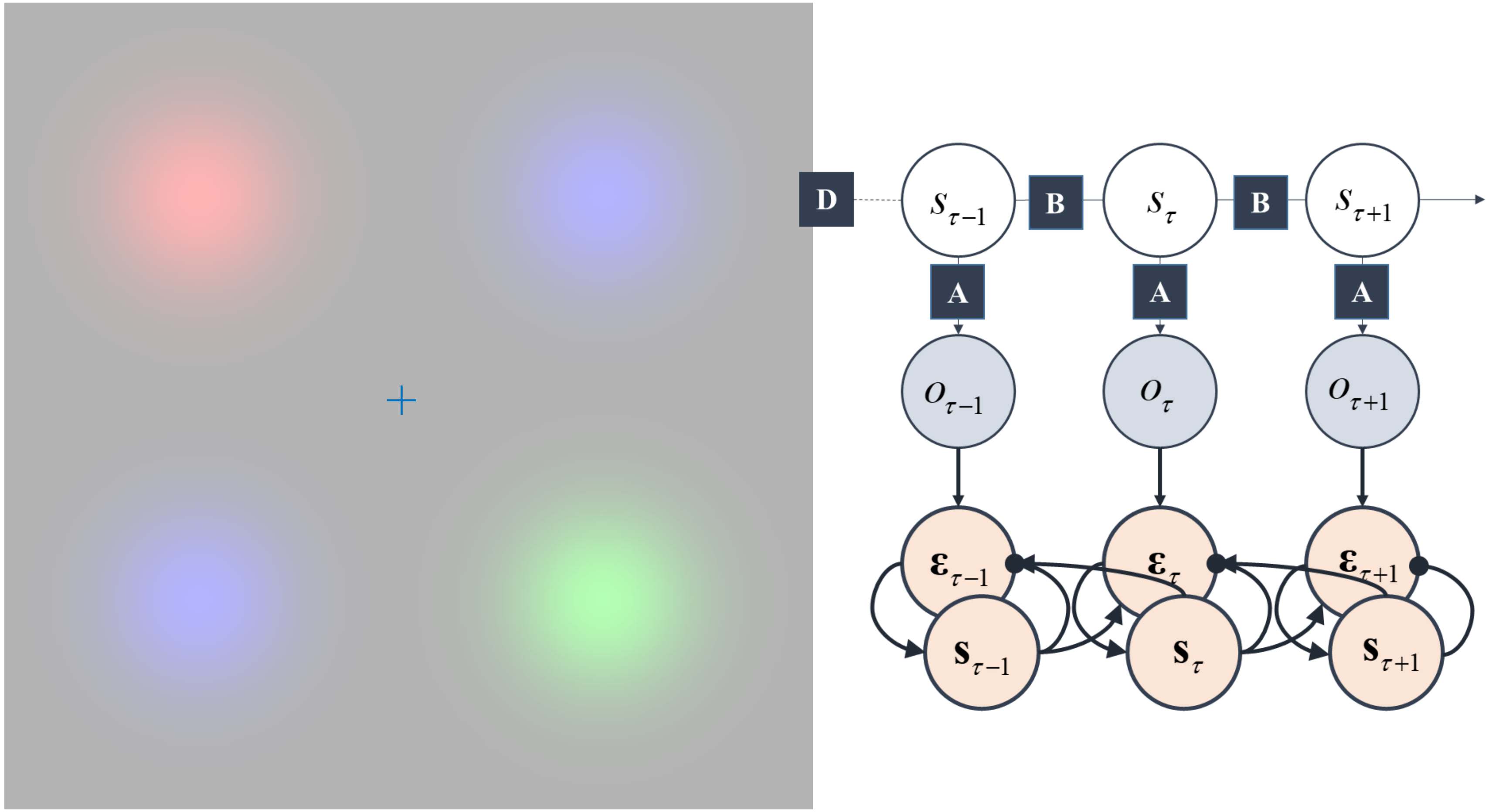
Generative model

$$P(\tilde{o},\tilde{s}) = P(s_1)\prod_\tau P(s_{\tau+1} \mid s_\tau)P(o_\tau \mid s_\tau)$$

$$P(o_\tau \mid s_\tau) = Cat(\mathbf{A})$$
$$P(s_\tau \mid s_{\tau-1}) = Cat(\mathbf{B})$$
$$P(s_1) = Cat(\mathbf{D})$$

Bayesian message passing

$$\mathbf{s}_\tau = \sigma(\mathbf{v}_\tau);\ \dot{\mathbf{v}}_\tau = \boldsymbol{\varepsilon}_\tau$$
$$\boldsymbol{\varepsilon}_\tau = \ln \mathbf{A} \cdot o_\tau + \tfrac{1}{2}\ln(\mathbf{B}_\tau \mathbf{s}_\tau) + \tfrac{1}{2}\ln(\mathbf{B}^\dagger_{\tau+1}\mathbf{s}_{\tau+1}) - \ln \mathbf{s}_\tau$$



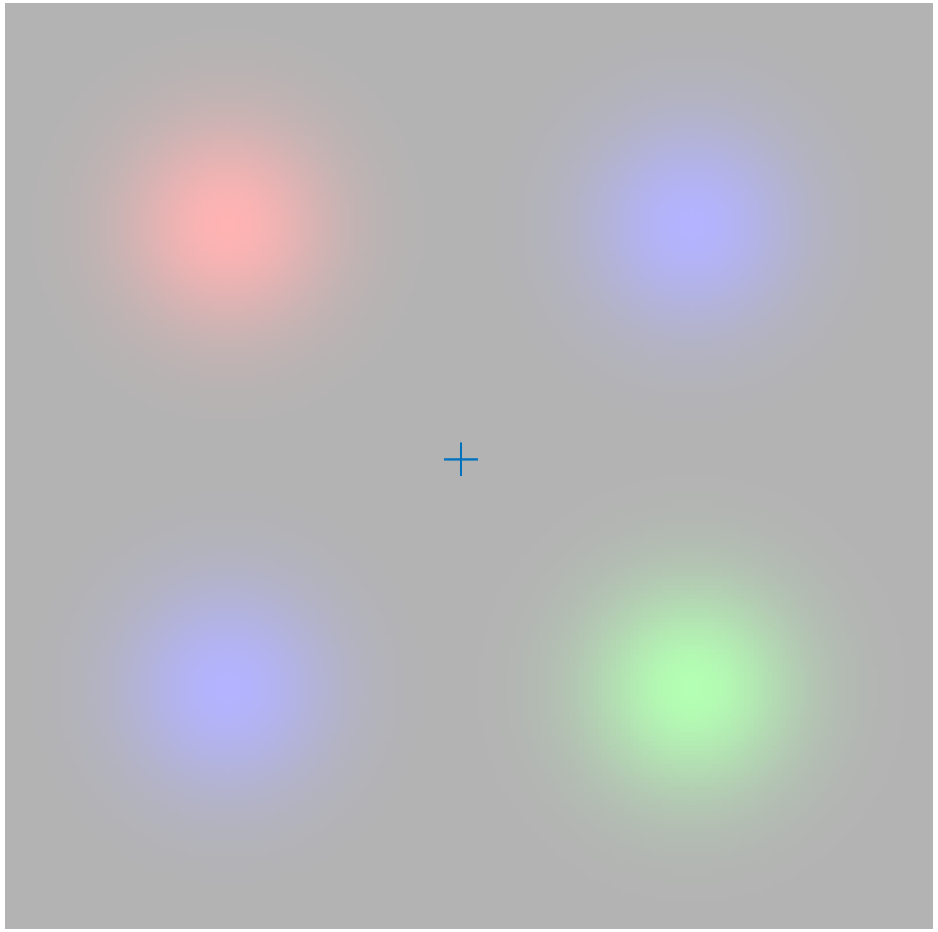
Generative model

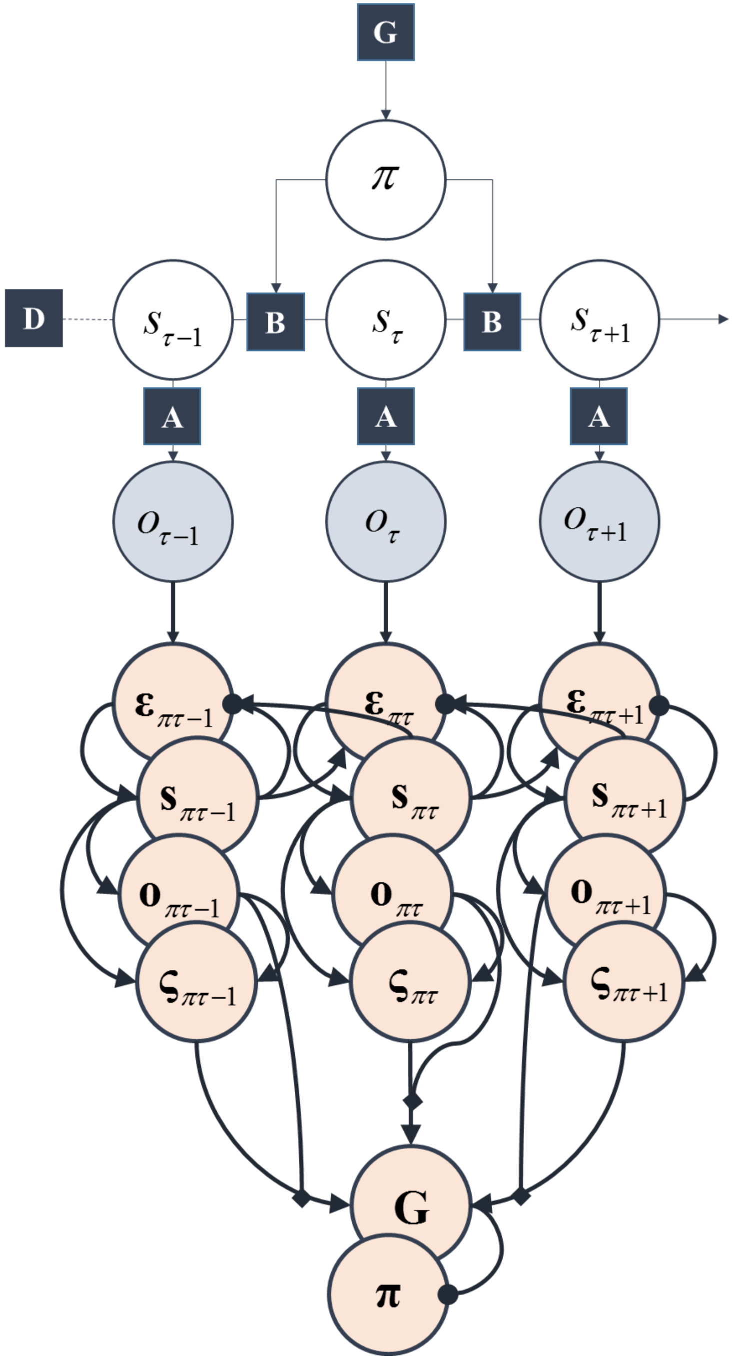
$$P(\tilde{o},\tilde{s}) = P(s_1)\prod_{\tau} P(s_{\tau+1} \mid s_\tau)P(o_\tau \mid s_\tau)$$

$$P(o_\tau \mid s_\tau) = Cat(\mathbf{A})$$
$$P(s_\tau \mid s_{\tau-1}) = Cat(\mathbf{B})$$
$$P(s_1) = Cat(\mathbf{D})$$

Bayesian message passing

$$\mathbf{s}_\tau = \sigma(\mathbf{v}_\tau);\ \dot{\mathbf{v}}_\tau = \boldsymbol{\varepsilon}_\tau$$
$$\boldsymbol{\varepsilon}_\tau = \ln \mathbf{A} \cdot o_\tau + \tfrac{1}{2}\ln(\mathbf{B}_\tau \mathbf{s}_\tau) + \tfrac{1}{2}\ln(\mathbf{B}^{\dagger}_{\tau+1}\mathbf{s}_{\tau+1}) - \ln \mathbf{s}_\tau$$





Generative model

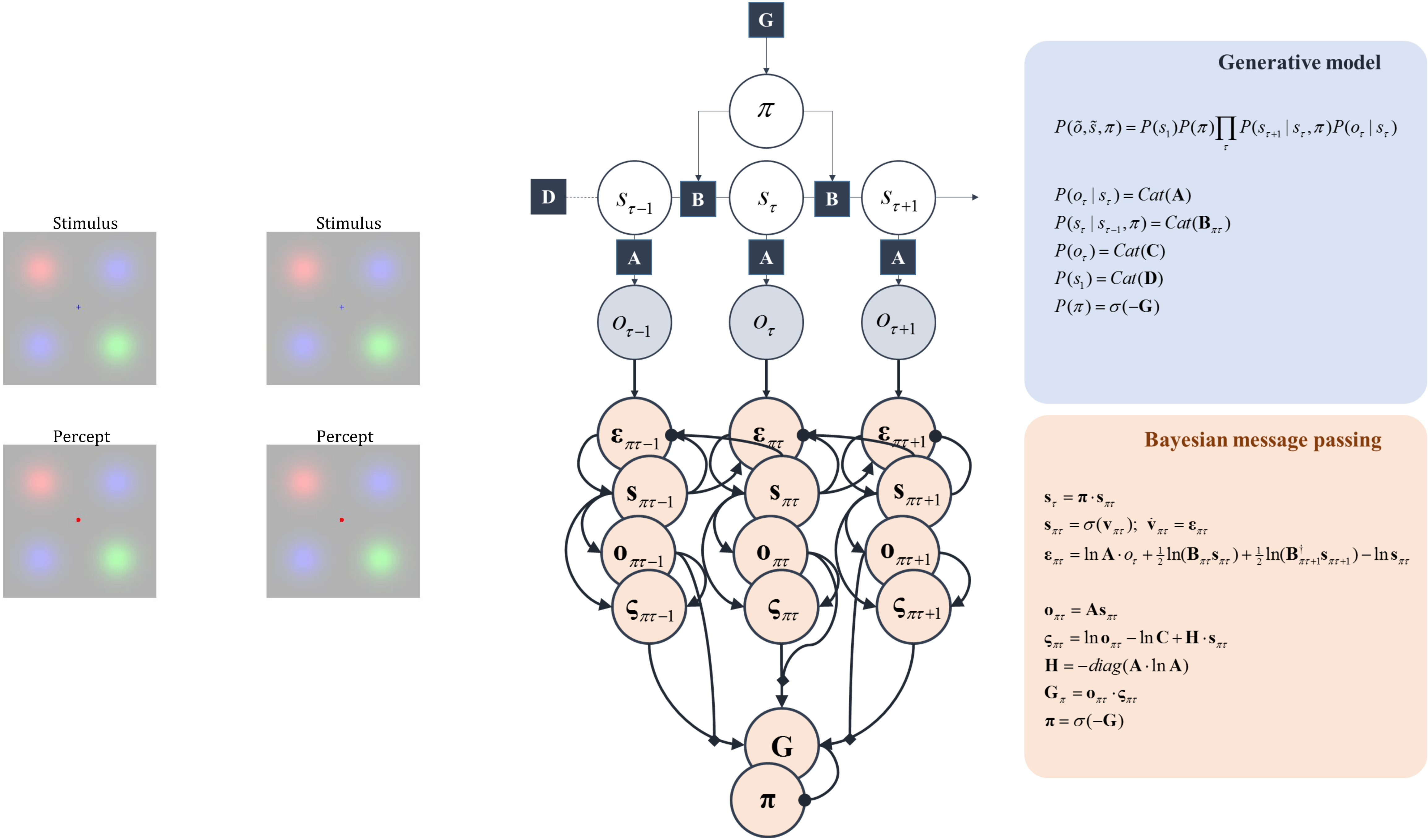
$$P(\tilde{o},\tilde{s},\pi) = P(s_1)P(\pi)\prod_{\tau} P(s_{\tau+1} \mid s_\tau,\pi)P(o_\tau \mid s_\tau)$$

$$\begin{aligned}
&P(o_\tau \mid s_\tau) = Cat(\mathbf{A})\\
&P(s_\tau \mid s_{\tau-1},\pi) = Cat(\mathbf{B}_{\pi\tau})\\
&P(o_\tau) = Cat(\mathbf{C})\\
&P(s_1) = Cat(\mathbf{D})\\
&P(\pi) = \sigma(-\mathbf{G})
\end{aligned}$$

Bayesian message passing

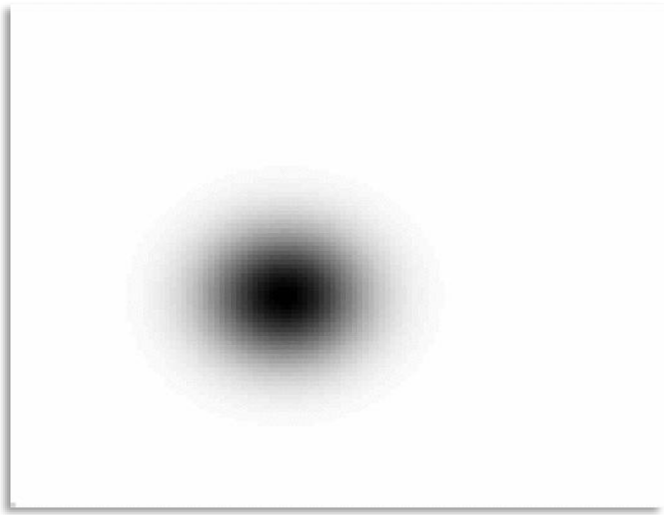
$$\begin{aligned}
&\mathbf{s}_\tau = \boldsymbol{\pi}\cdot\mathbf{s}_{\pi\tau}\\
&\mathbf{s}_{\pi\tau} = \sigma(\mathbf{v}_{\pi\tau});\;\; \dot{\mathbf{v}}_{\pi\tau} = \boldsymbol{\varepsilon}_{\pi\tau}\\
&\boldsymbol{\varepsilon}_{\pi\tau} = \ln\mathbf{A}\cdot o_\tau + \tfrac{1}{2}\ln(\mathbf{B}_{\pi\tau}\mathbf{s}_{\pi\tau}) + \tfrac{1}{2}\ln(\mathbf{B}^{\dagger}_{\pi\tau+1}\mathbf{s}_{\pi\tau+1}) - \ln\mathbf{s}_{\pi\tau}
\end{aligned}$$

$$\begin{aligned}
&\mathbf{o}_{\pi\tau} = \mathbf{A}\mathbf{s}_{\pi\tau}\\
&\boldsymbol{\varsigma}_{\pi\tau} = \ln\mathbf{o}_{\pi\tau} - \ln\mathbf{C} + \mathbf{H}\cdot\mathbf{s}_{\pi\tau}\\
&\mathbf{H} = -diag(\mathbf{A}\cdot\ln\mathbf{A})\\
&\mathbf{G}_\pi = \mathbf{o}_{\pi\tau}\cdot\boldsymbol{\varsigma}_{\pi\tau}\\
&\boldsymbol{\pi} = \sigma(-\mathbf{G})
\end{aligned}$$


Stimulus
Stimulus
Percept
Percept
G
π
D
$s_{\tau-1}$
B
s_τ
B
$s_{\tau+1}$
A
A
A
$o_{\tau-1}$
o_τ
$o_{\tau+1}$
$\boldsymbol{\varepsilon}_{\pi\tau-1}$
$\boldsymbol{\varepsilon}_{\pi\tau}$
$\boldsymbol{\varepsilon}_{\pi\tau+1}$
$\mathbf{s}_{\pi\tau-1}$
$\mathbf{s}_{\pi\tau}$
$\mathbf{s}_{\pi\tau+1}$
$\mathbf{o}_{\pi\tau-1}$
$\mathbf{o}_{\pi\tau}$
$\mathbf{o}_{\pi\tau+1}$
$\boldsymbol{\varsigma}_{\pi\tau-1}$
$\boldsymbol{\varsigma}_{\pi\tau}$
$\boldsymbol{\varsigma}_{\pi\tau+1}$
G
$\boldsymbol{\pi}$
Generative model
$P(\tilde{o},\tilde{s},\pi) = P(s_1)P(\pi)\prod_\tau P(s_{\tau+1} \mid s_\tau,\pi)P(o_\tau \mid s_\tau)$
$P(o_\tau \mid s_\tau) = Cat(\mathbf{A})$
$P(s_\tau \mid s_{\tau-1},\pi) = Cat(\mathbf{B}_{\pi\tau})$
$P(o_\tau) = Cat(\mathbf{C})$
$P(s_1) = Cat(\mathbf{D})$
$P(\pi) = \sigma(-\mathbf{G})$
Bayesian message passing
$\mathbf{s}_\tau = \boldsymbol{\pi} \cdot \mathbf{s}_{\pi\tau}$
$\mathbf{s}_{\pi\tau} = \sigma(\mathbf{v}_{\pi\tau});\ \dot{\mathbf{v}}_{\pi\tau} = \boldsymbol{\varepsilon}_{\pi\tau}$
$\boldsymbol{\varepsilon}_{\pi\tau} = \ln \mathbf{A} \cdot o_\tau + \frac{1}{2}\ln(\mathbf{B}_{\pi\tau}\mathbf{s}_{\pi\tau}) + \frac{1}{2}\ln(\mathbf{B}^\dagger_{\pi\tau+1}\mathbf{s}_{\pi\tau+1}) - \ln \mathbf{s}_{\pi\tau}$
$\mathbf{o}_{\pi\tau} = \mathbf{A}\mathbf{s}_{\pi\tau}$
$\boldsymbol{\varsigma}_{\pi\tau} = \ln \mathbf{o}_{\pi\tau} - \ln \mathbf{C} + \mathbf{H} \cdot \mathbf{s}_{\pi\tau}$
$\mathbf{H} = -diag(\mathbf{A} \cdot \ln \mathbf{A})$
$\mathbf{G}_\pi = \mathbf{o}_{\pi\tau} \cdot \boldsymbol{\varsigma}_{\pi\tau}$
$\boldsymbol{\pi} = \sigma(-\mathbf{G})$

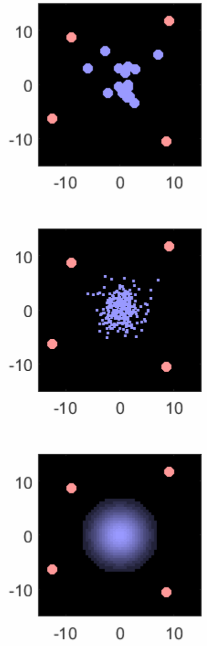
Active inference
Generative models
Exploitation
Exploration
Movement
Hierarchy

Goals and steady state



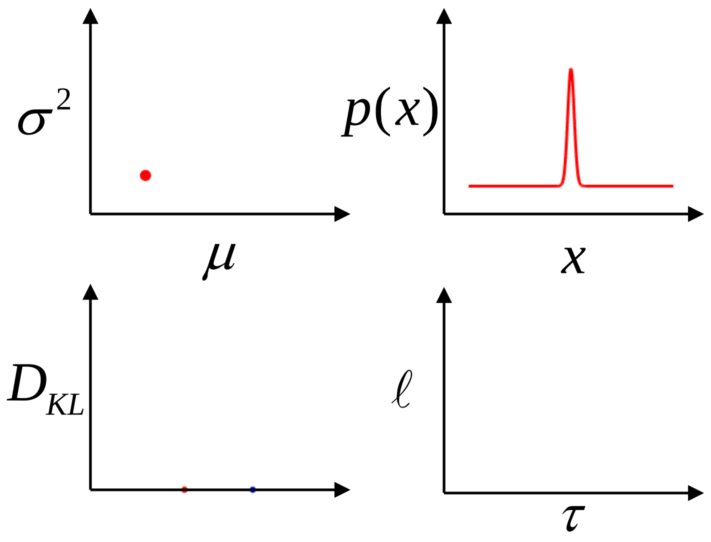
$$D_{KL}\left[P(o\,|\,\pi)\,\|\,P(o\,|\,C)\right]$$

Goals and steady state



$$D_{KL}\left[P(o\,|\,\pi)\,\|\,P(o\,|\,C)\right]$$

Goals and steady state



$$D_{KL}\left[P(o\,|\,\pi)\,\|\,P(o\,|\,C)\right]$$

Goals and steady state

$$-H\left[P\left(o\,|\,\pi\right)\right]-\mathrm{E}_{P(o|\pi)}\left[\ln P\left(o\,|\,C\right)\right]$$

$$\Updownarrow$$

$$D_{KL}\left[P\left(o\,|\,\pi\right)\|\,P\left(o\,|\,C\right)\right]$$

Active inference
Generative models
Exploitation
Exploration
Movement
Hierarchy

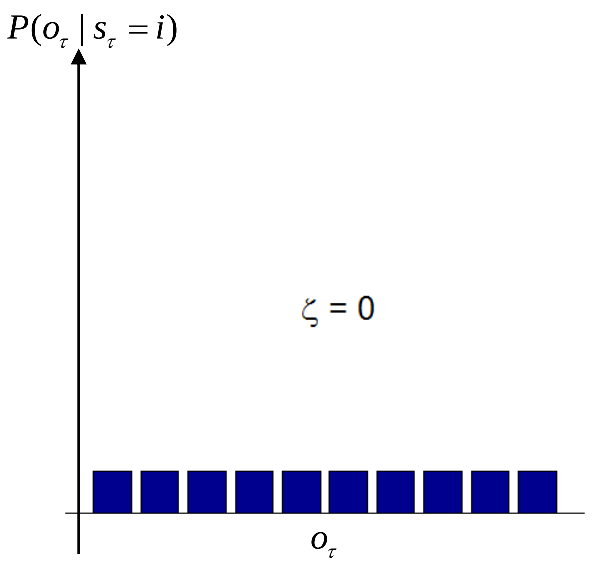
Information gain

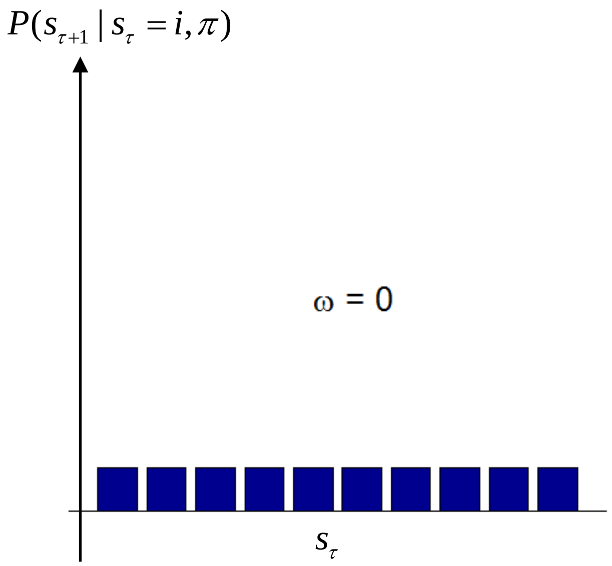
$$\mathcal{I}(\pi) = D_{KL}\left[P(o,s \mid \pi) \parallel P(o \mid \pi)P(s \mid \pi)\right]$$

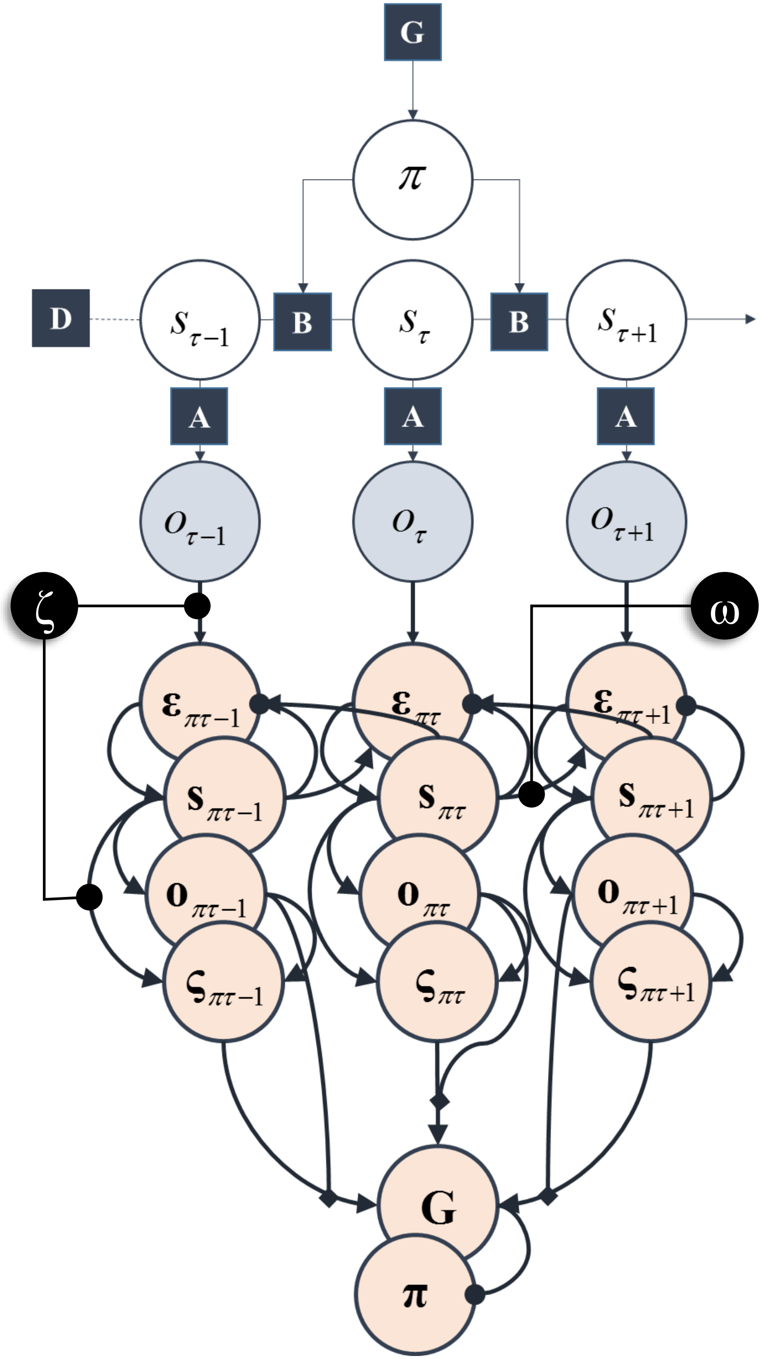
$$= \mathrm{E}_{P(o|\pi)}\left[D_{KL}\left[P(s \mid o,\pi) \parallel P(s \mid \pi)\right]\right]$$

$$= H\left[P(o \mid \pi)\right] - \mathrm{E}_{P(s|\pi)}\left[H\left[P(o \mid s)\right]\right]$$

$$P(o,s \mid \pi) = P(s \mid o,\pi)P(o \mid \pi) = P(o \mid s)P(s \mid \pi)$$







Generative model

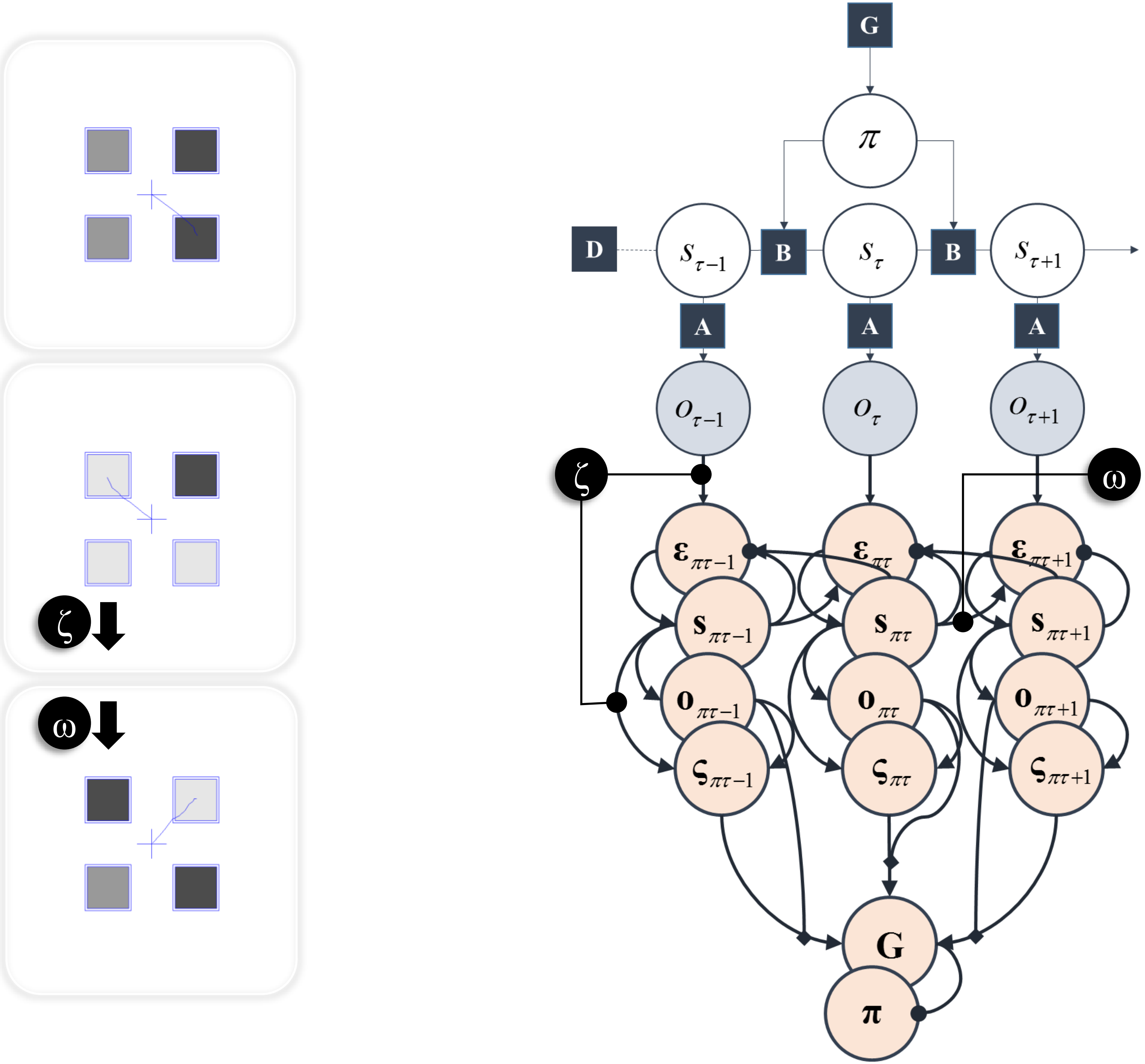
$$P(\tilde{o},\tilde{s},\pi) = P(s_1)P(\pi)\prod_\tau P(s_{\tau+1} \mid s_\tau,\pi)P(o_\tau \mid s_\tau)$$

$$P(o_\tau \mid s_\tau) = Cat(\mathbf{A})$$
$$P(s_\tau \mid s_{\tau-1},\pi) = Cat(\mathbf{B}_{\pi\tau})$$
$$P(o_\tau) = Cat(\mathbf{C})$$
$$P(s_1) = Cat(\mathbf{D})$$
$$P(\pi) = \sigma(-\mathbf{G})$$

Bayesian message passing

$$\mathbf{s}_\tau = \boldsymbol{\pi} \cdot \mathbf{s}_{\pi\tau}$$
$$\mathbf{s}_{\pi\tau} = \sigma(\mathbf{v}_{\pi\tau});\ \ \dot{\mathbf{v}}_{\pi\tau} = \boldsymbol{\varepsilon}_{\pi\tau}$$
$$\boldsymbol{\varepsilon}_{\pi\tau} = \ln \mathbf{A} \cdot o_\tau + \tfrac{1}{2}\ln(\mathbf{B}_{\pi\tau}\mathbf{s}_{\pi\tau}) + \tfrac{1}{2}\ln(\mathbf{B}^\dagger_{\pi\tau+1}\mathbf{s}_{\pi\tau+1}) - \ln \mathbf{s}_{\pi\tau}$$

$$\mathbf{o}_{\pi\tau} = \mathbf{A}\mathbf{s}_{\pi\tau}$$
$$\varsigma_{\pi\tau} = \ln \mathbf{o}_{\pi\tau} - \ln \mathbf{C} + \mathbf{H} \cdot \mathbf{s}_{\pi\tau}$$
$$\mathbf{H} = -diag(\mathbf{A} \cdot \ln \mathbf{A})$$
$$\mathbf{G}_\pi = \mathbf{o}_{\pi\tau} \cdot \varsigma_{\pi\tau}$$
$$\boldsymbol{\pi} = \sigma(-\mathbf{G})$$



Generative model

$$P(\tilde{o},\tilde{s},\pi) = P(s_1)P(\pi)\prod_\tau P(s_{\tau+1}\mid s_\tau,\pi)P(o_\tau\mid s_\tau)$$

$$P(o_\tau \mid s_\tau) = Cat(\mathbf{A})$$
$$P(s_\tau \mid s_{\tau-1},\pi) = Cat(\mathbf{B}_{\pi\tau})$$
$$P(o_\tau) = Cat(\mathbf{C})$$
$$P(s_1) = Cat(\mathbf{D})$$
$$P(\pi) = \sigma(-\mathbf{G})$$

Bayesian message passing

$$\mathbf{s}_\tau = \boldsymbol{\pi}\cdot\mathbf{s}_{\pi\tau}$$
$$\mathbf{s}_{\pi\tau} = \sigma(\mathbf{v}_{\pi\tau});\ \dot{\mathbf{v}}_{\pi\tau} = \boldsymbol{\varepsilon}_{\pi\tau}$$
$$\boldsymbol{\varepsilon}_{\pi\tau} = \ln\mathbf{A}\cdot o_\tau + \tfrac{1}{2}\ln(\mathbf{B}_{\pi\tau}\mathbf{s}_{\pi\tau}) + \tfrac{1}{2}\ln(\mathbf{B}^\dagger_{\pi\tau+1}\mathbf{s}_{\pi\tau+1}) - \ln\mathbf{s}_{\pi\tau}$$

$$\mathbf{o}_{\pi\tau} = \mathbf{A}\mathbf{s}_{\pi\tau}$$
$$\boldsymbol{\varsigma}_{\pi\tau} = \ln\mathbf{o}_{\pi\tau} - \ln\mathbf{C} + \mathbf{H}\cdot\mathbf{s}_{\pi\tau}$$
$$\mathbf{H} = -diag(\mathbf{A}\cdot\ln\mathbf{A})$$
$$\mathbf{G}_\pi = \mathbf{o}_{\pi\tau}\cdot\boldsymbol{\varsigma}_{\pi\tau}$$
$$\boldsymbol{\pi} = \sigma(-\mathbf{G})$$

Expected free energy

Explore $$H\left[P\left(o \mid \pi\right)\right] - \mathrm{E}_{P(s|\pi)}\left[H\left[P\left(o \mid s\right)\right]\right]$$

$$\mathrm{E}_{P(o|\pi)}\left[\ln P\left(o \mid C\right)\right] + H\left[P\left(o \mid \pi\right)\right] - \mathrm{E}_{P(s|\pi)}\left[H\left[P\left(o \mid s\right)\right]\right]$$

$$\mathrm{E}_{P(o|\pi)}\left[\ln P\left(o \mid C\right)\right] + H\left[P\left(o \mid \pi\right)\right]$$ Exploit

Expected free energy

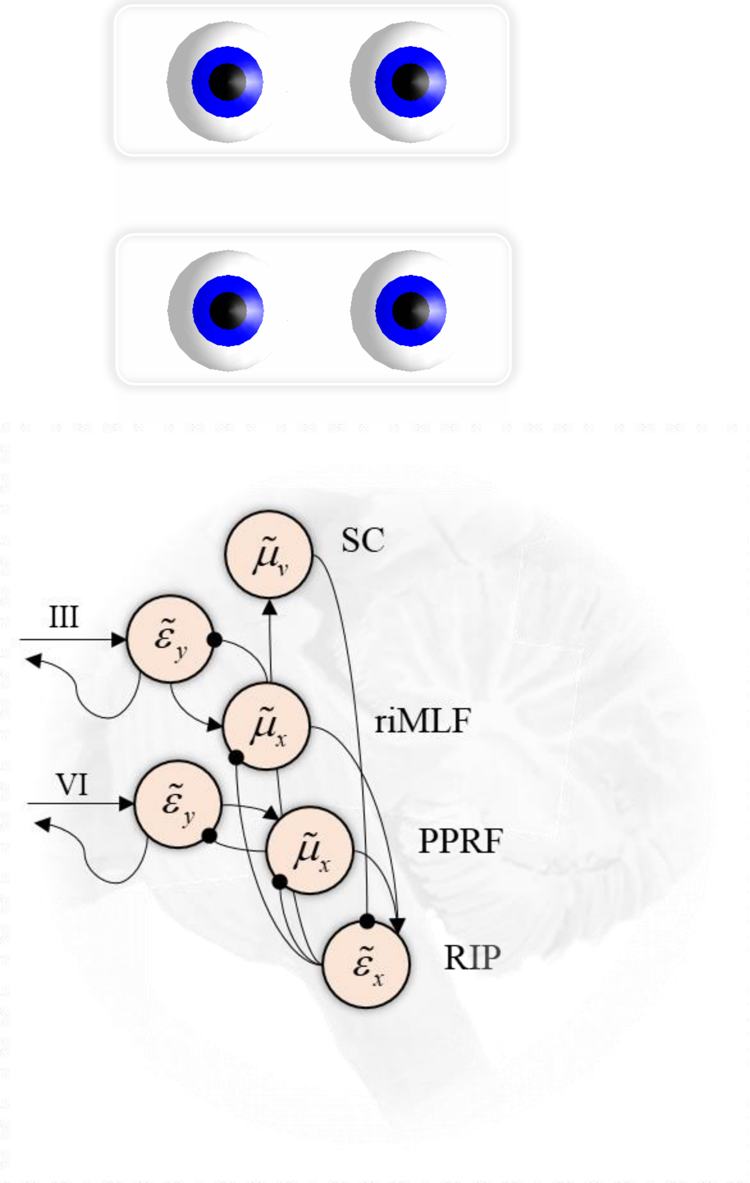
$$P(\pi) = \sigma[-G(\pi)]$$

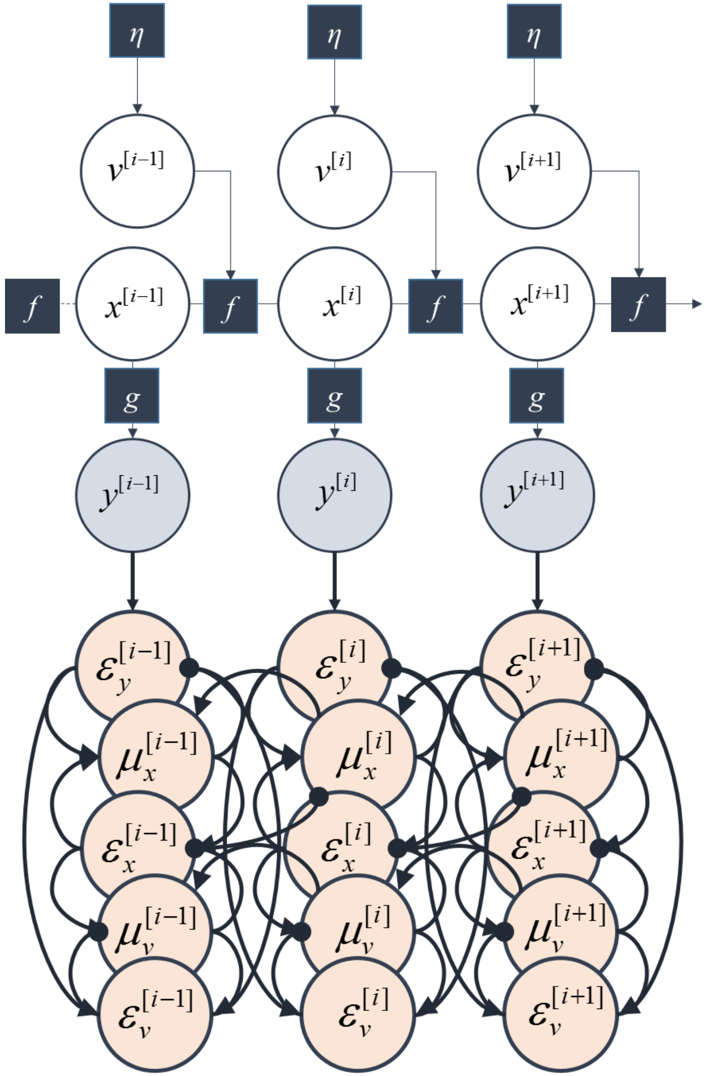
$$-G(\pi) = \mathrm{E}_{P(o|\pi)}\left[\ln P(o|C)\right] + H\left[P(o|\pi)\right] - \mathrm{E}_{P(s|\pi)}\left[H\left[P(o|s)\right]\right]$$

$$= \mathrm{E}_{P(o|\pi)}\left[\ln P(o|C)\right] + \mathrm{E}_{P(o,s|\pi)}\left[\ln P(s|\pi,o) - \ln P(s|\pi)\right]$$

$$-F(\pi) = \ln P(o) + \mathrm{E}_{Q(s|\pi)}\left[\ln P(s|\pi,o) - \ln Q(s|\pi)\right]$$

Active inference
Generative models
Exploitation
Exploration
Movement
Hierarchy





Generative model

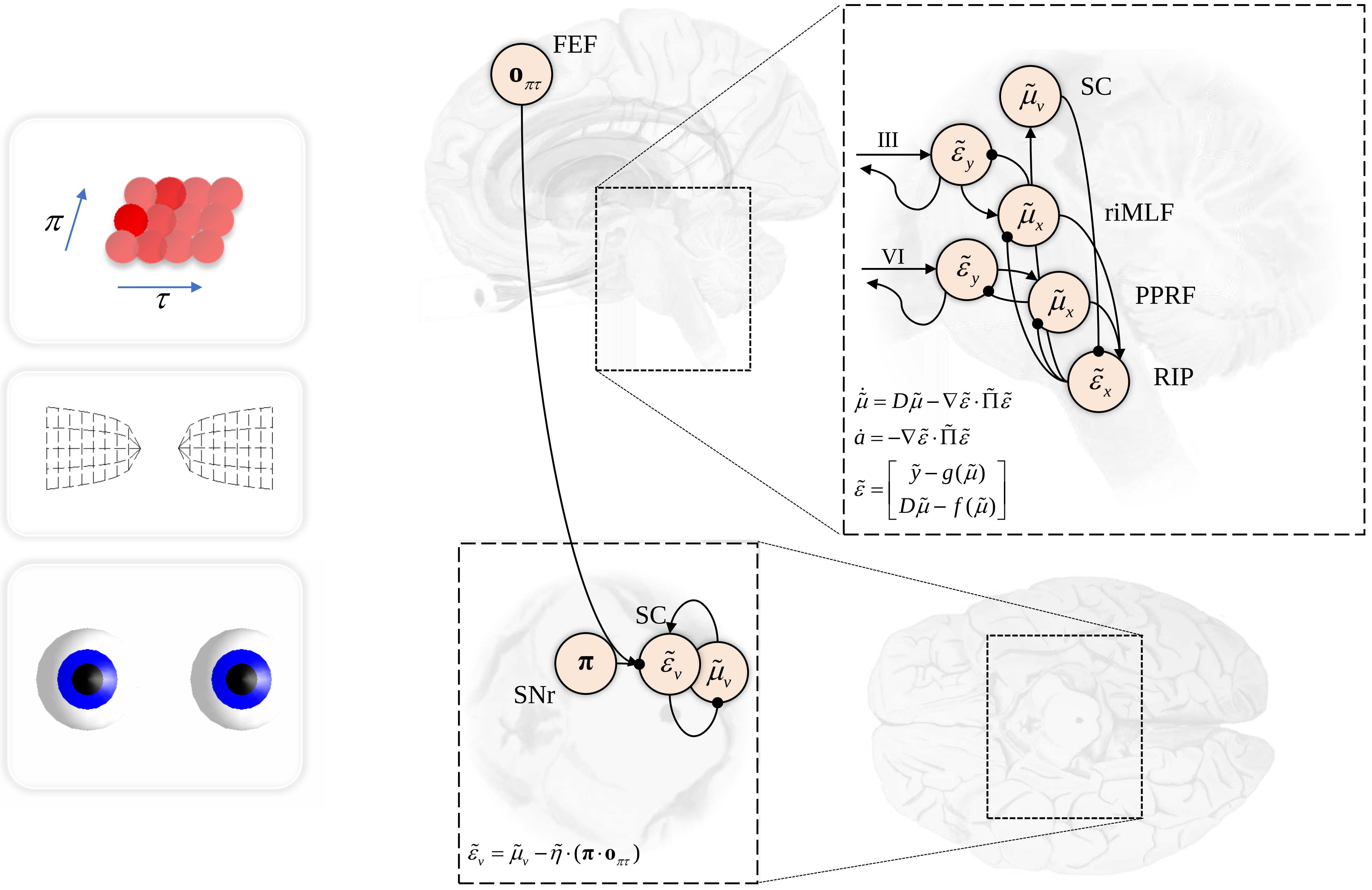
$$p(\tilde{y},\tilde{x},\tilde{v}) = \prod_i p(v^{[i]})\,p(x^{[i+1]} \mid x^{[i]},v^{[i]})\,p(y^{[i]} \mid x^{[i]},v^{[i]})$$

$$p(y^{[i]} \mid x^{[i]},v^{[i]}) = \mathcal{N}(g^{[i]}(x^{[i]},v^{[i]}),\Pi_y^{[i]})$$
$$p(x^{[i+1]} \mid x^{[i]},v^{[i]}) = \mathcal{N}(f^{[i]}(x^{[i]},v^{[i]}),\Pi_x^{[i]})$$
$$p(v^{[i]}) = \mathcal{N}(\eta^{[i]},\Pi_v^{[i]})$$

Bayesian message passing

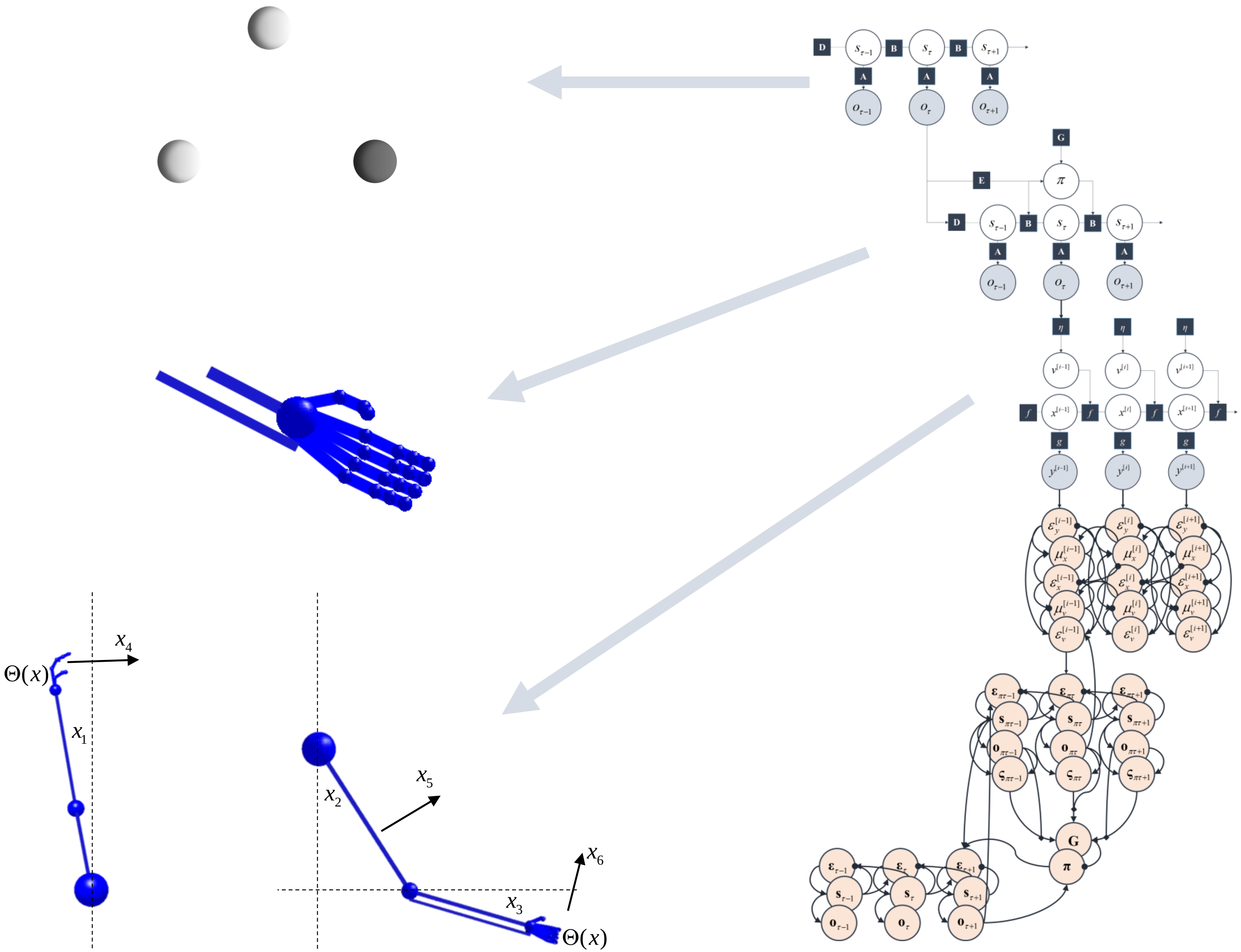
$$\varepsilon_y^{[i]} = y^{[i]} - g^{[i]}(\mu_x^{[i]},\mu_v^{[i]})$$
$$\varepsilon_x^{[i]} = \mu_x^{[i+1]} - f^{[i]}(\mu_x^{[i]},\mu_v^{[i]})$$
$$\varepsilon_v^{[i]} = \mu_v^{[i]} - \eta^{[i]}$$

$$\begin{aligned}\dot{\mu}_x^{[i]} &= \mu_x^{[i+1]} \\ &\quad + \partial_{\mu_x^{[i]}} g^{[i]} \cdot \Pi_y^{[i]} \varepsilon_y^{[i]} - \Pi_x^{[i-1]} \varepsilon_x^{[i-1]} + \partial_{\mu_x^{[i]}} f^{[i]} \cdot \Pi_x^{[i]} \varepsilon_x^{[i]}\end{aligned}$$
$$\begin{aligned}\dot{\mu}_v^{[i]} &= \mu_v^{[i+1]} \\ &\quad + \partial_{\mu_v^{[i]}} g^{[i]} \cdot \Pi_y^{[i]} \varepsilon_y^{[i]} + \partial_{\mu_v^{[i]}} f^{[i]} \cdot \Pi_x^{[i]} \varepsilon_x^{[i]} - \Pi_v^{[i]} \varepsilon_v^{[i]}\end{aligned}$$

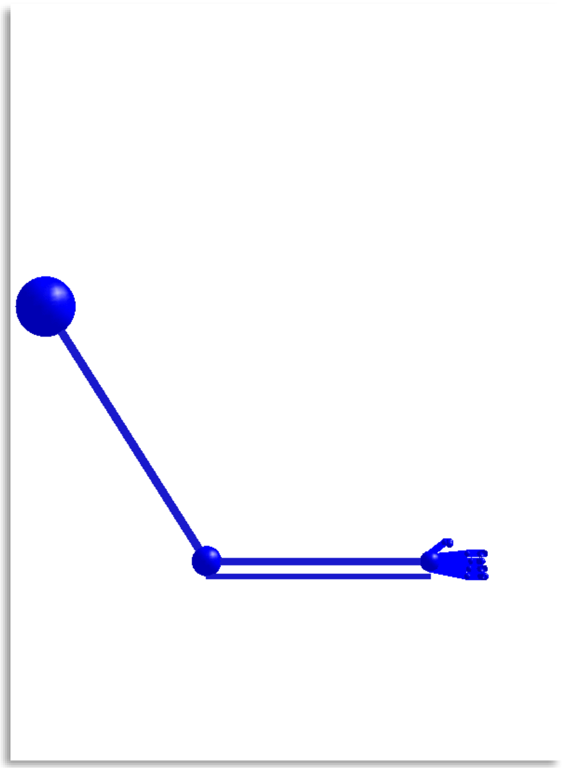


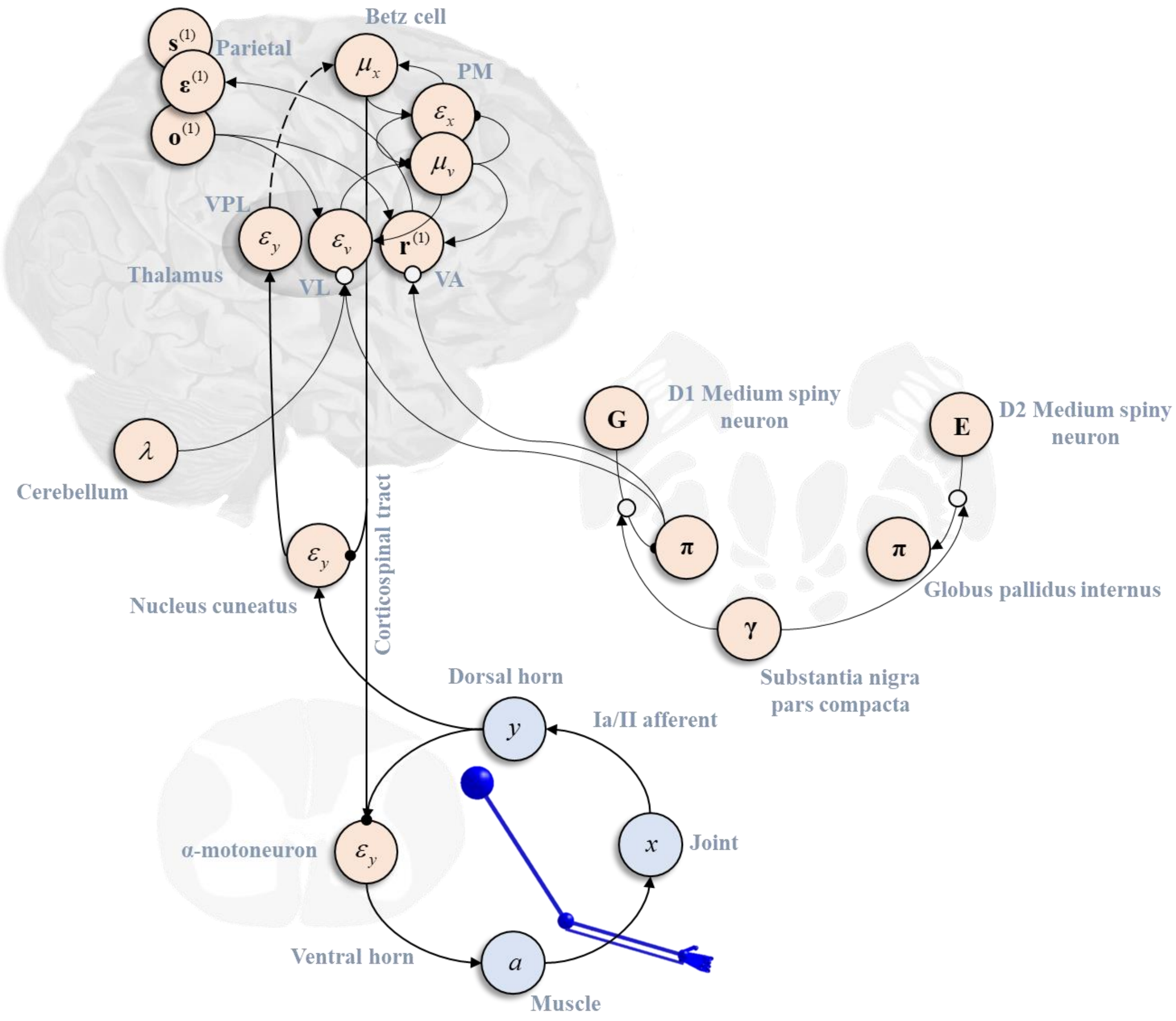
π
τ
FEF
$\mathbf{o}_{\pi\tau}$
SC
$\tilde{\mu}_v$
III
$\tilde{\varepsilon}_y$
$\tilde{\mu}_x$
riMLF
VI
$\tilde{\varepsilon}_y$
$\tilde{\mu}_x$
PPRF
$\tilde{\varepsilon}_x$
RIP
$\dot{\tilde{\mu}} = D\tilde{\mu} - \nabla\tilde{\varepsilon}\cdot\tilde{\Pi}\tilde{\varepsilon}$
$\dot{a} = -\nabla\tilde{\varepsilon}\cdot\tilde{\Pi}\tilde{\varepsilon}$
$\tilde{\varepsilon} = \begin{bmatrix} \tilde{y} - g(\tilde{\mu}) \\ D\tilde{\mu} - f(\tilde{\mu}) \end{bmatrix}$
SC
$\boldsymbol{\pi}$
$\tilde{\varepsilon}_v$
$\tilde{\mu}_v$
SNr
$\tilde{\varepsilon}_v = \tilde{\mu}_v - \tilde{\eta}\cdot(\boldsymbol{\pi}\cdot\mathbf{o}_{\pi\tau})$

Active inference
Generative models
Exploitation
Exploration
Movement
Hierarchy

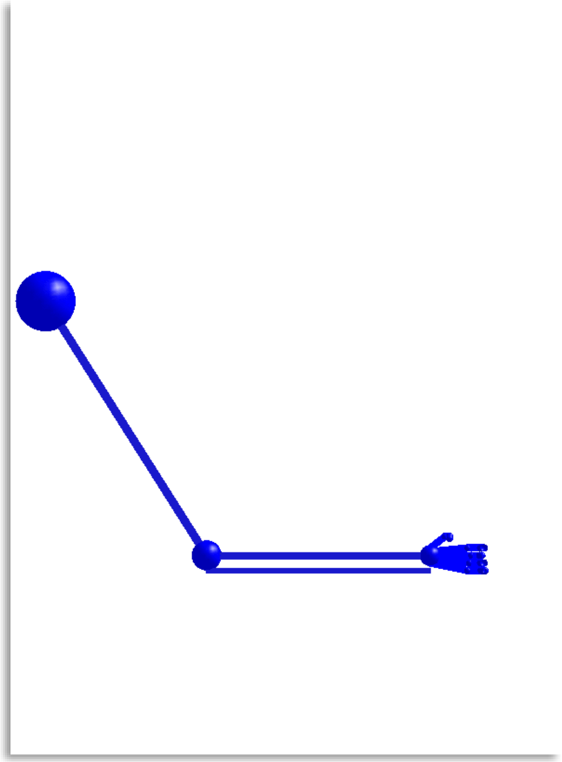


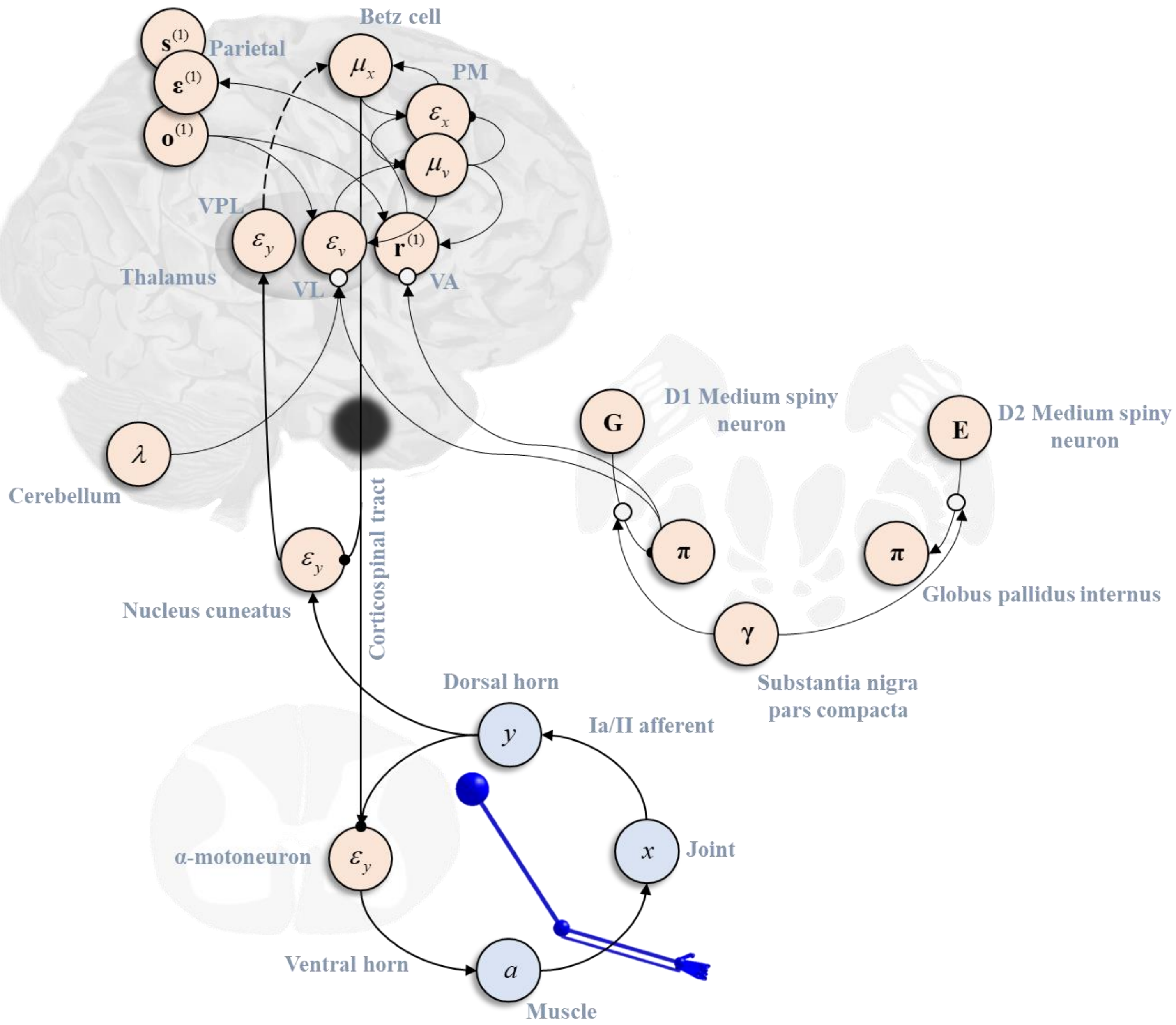
D
B
A
G
E
π
η
f
g
$\mathbf{G}$
$\boldsymbol{\pi}$
$\Theta(x)$
x_1
x_2
x_3
x_4
x_5
x_6



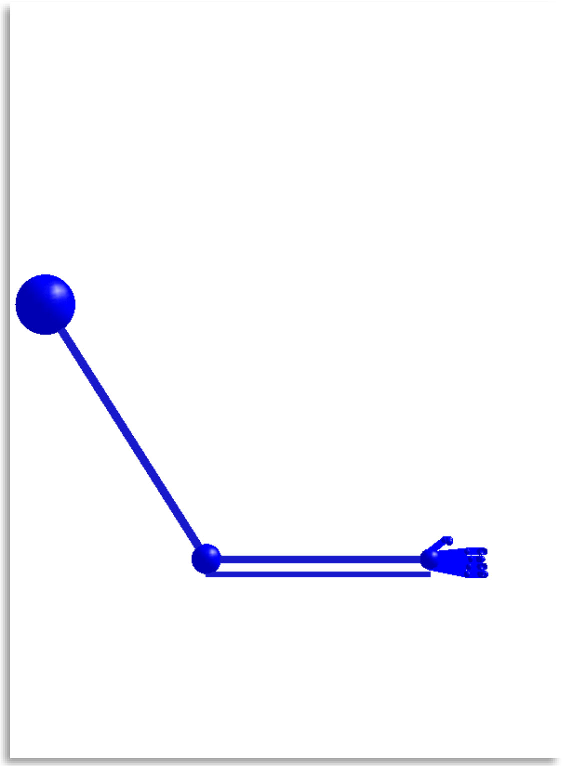


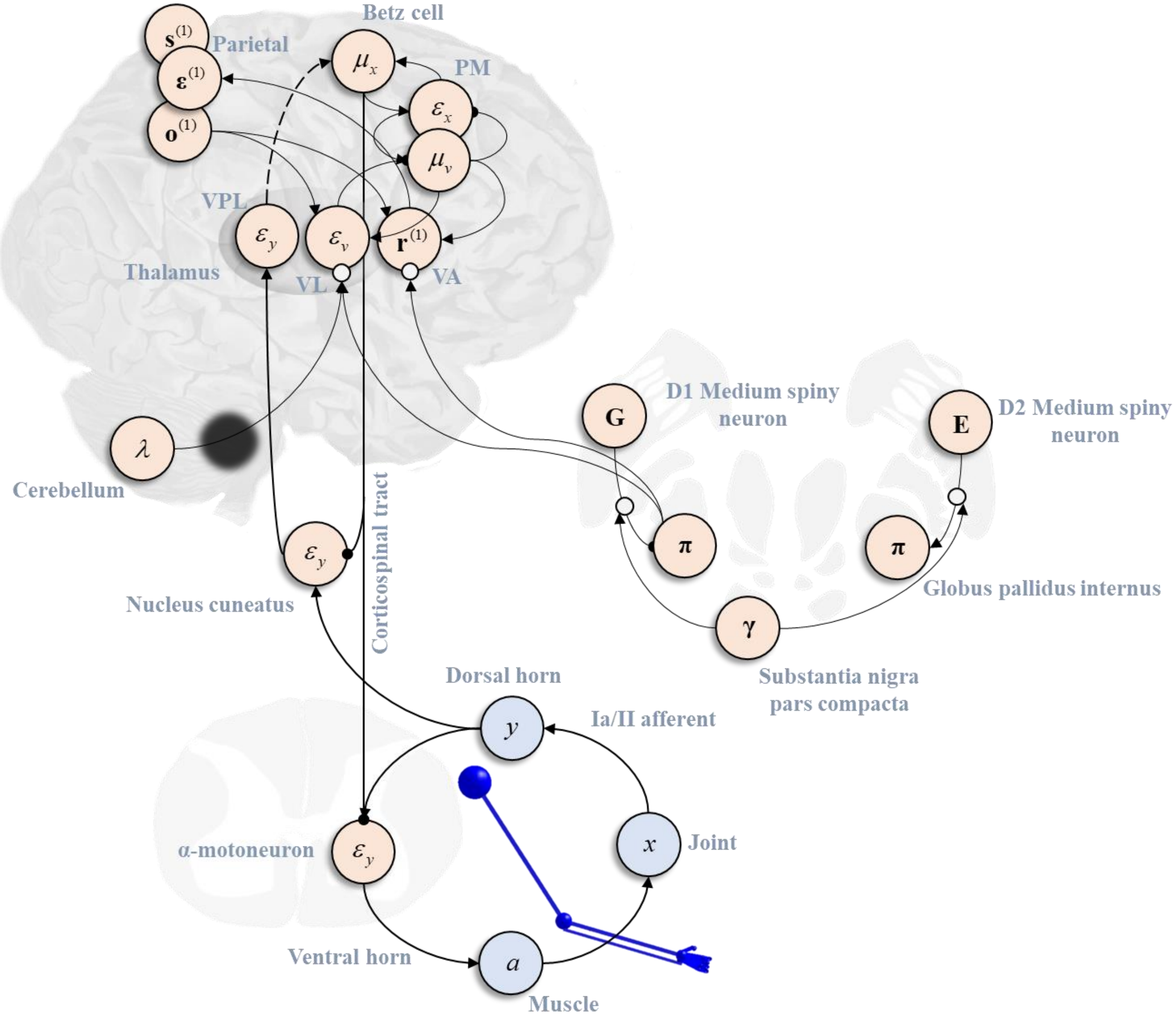
Betz cell
Parietal
PM
$\mathbf{s}^{(1)}$
$\boldsymbol{\varepsilon}^{(1)}$
$\mathbf{o}^{(1)}$
μ_x
ε_x
μ_v
VPL
ε_y
ε_v
$\mathbf{r}^{(1)}$
Thalamus
VL
VA
λ
Cerebellum
D1 Medium spiny neuron
D2 Medium spiny neuron
$\mathbf{G}$
$\mathbf{E}$
$\boldsymbol{\pi}$
$\boldsymbol{\pi}$
Globus pallidus internus
$\boldsymbol{\gamma}$
Substantia nigra pars compacta
ε_y
Nucleus cuneatus
Corticospinal tract
Dorsal horn
y
Ia/II afferent
α-motoneuron
ε_y
x
Joint
Ventral horn
a
Muscle



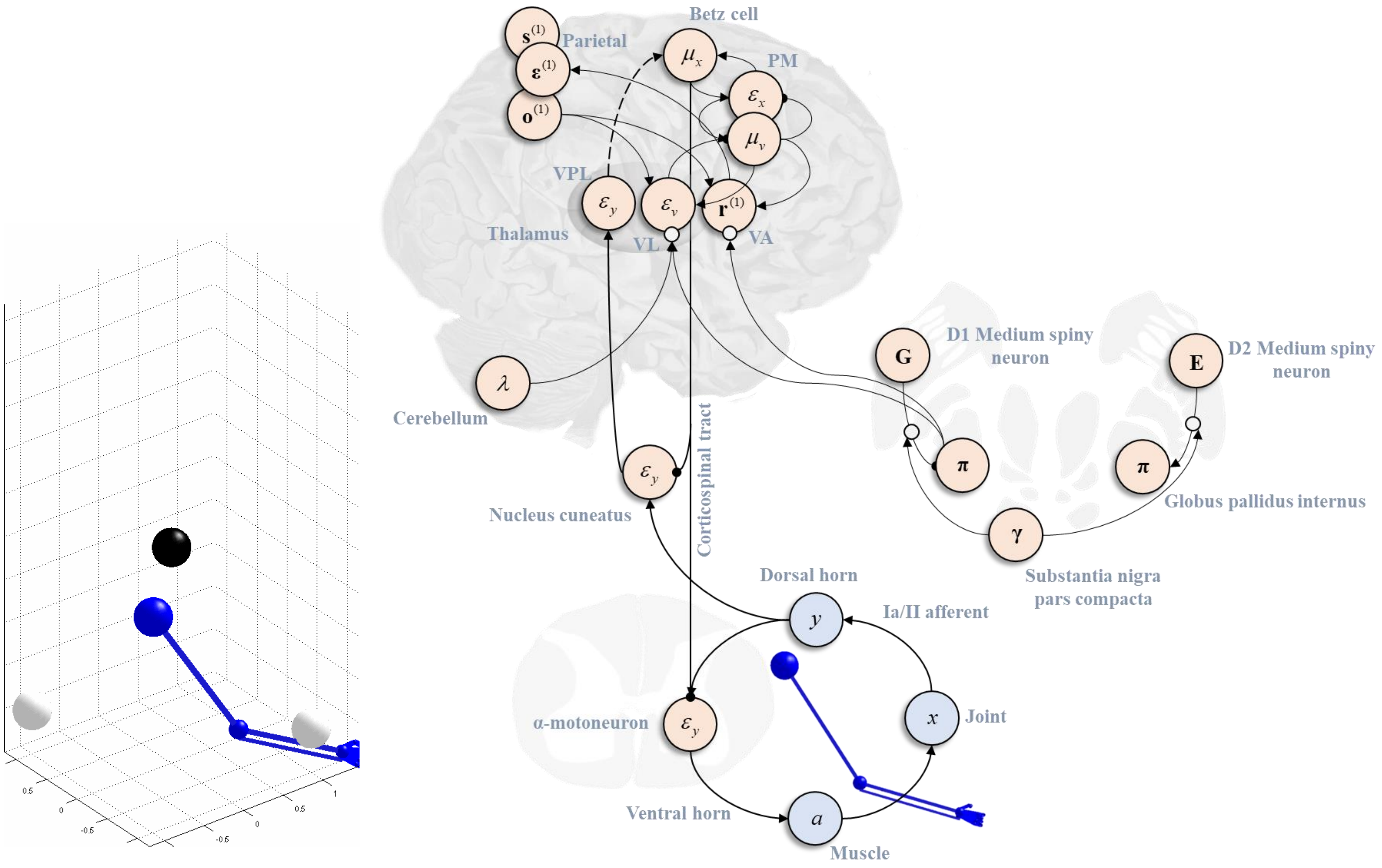


Betz cell
μ_x
PM
ε_x
μ_v
$\mathbf{s}^{(1)}$
$\boldsymbol{\varepsilon}^{(1)}$
$\mathbf{o}^{(1)}$
Parietal
VPL
ε_y
ε_v
$\mathbf{r}^{(1)}$
Thalamus
VL
VA
λ
Cerebellum
D1 Medium spiny neuron
G
D2 Medium spiny neuron
E
$\boldsymbol{\pi}$
$\boldsymbol{\pi}$
Globus pallidus internus
$\boldsymbol{\gamma}$
Substantia nigra pars compacta
ε_y
Nucleus cuneatus
Corticospinal tract
Dorsal horn
y
Ia/II afferent
x
Joint
α-motoneuron
ε_y
Ventral horn
a
Muscle

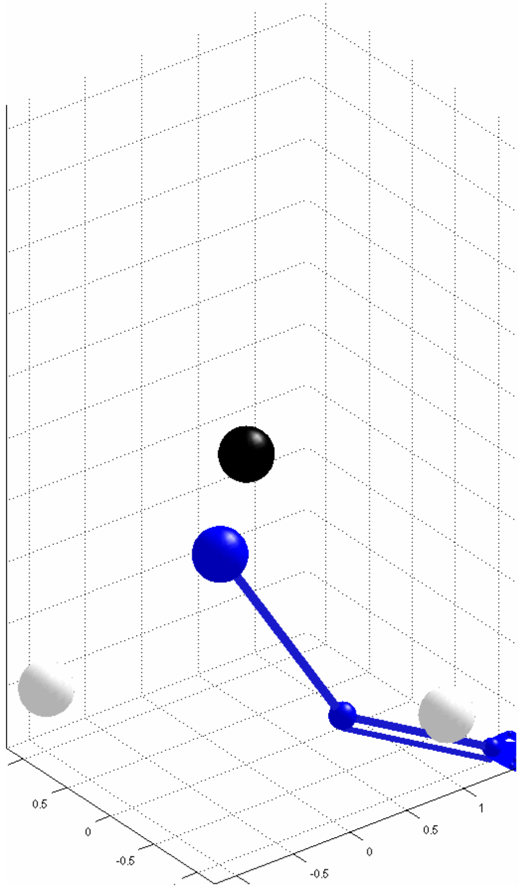


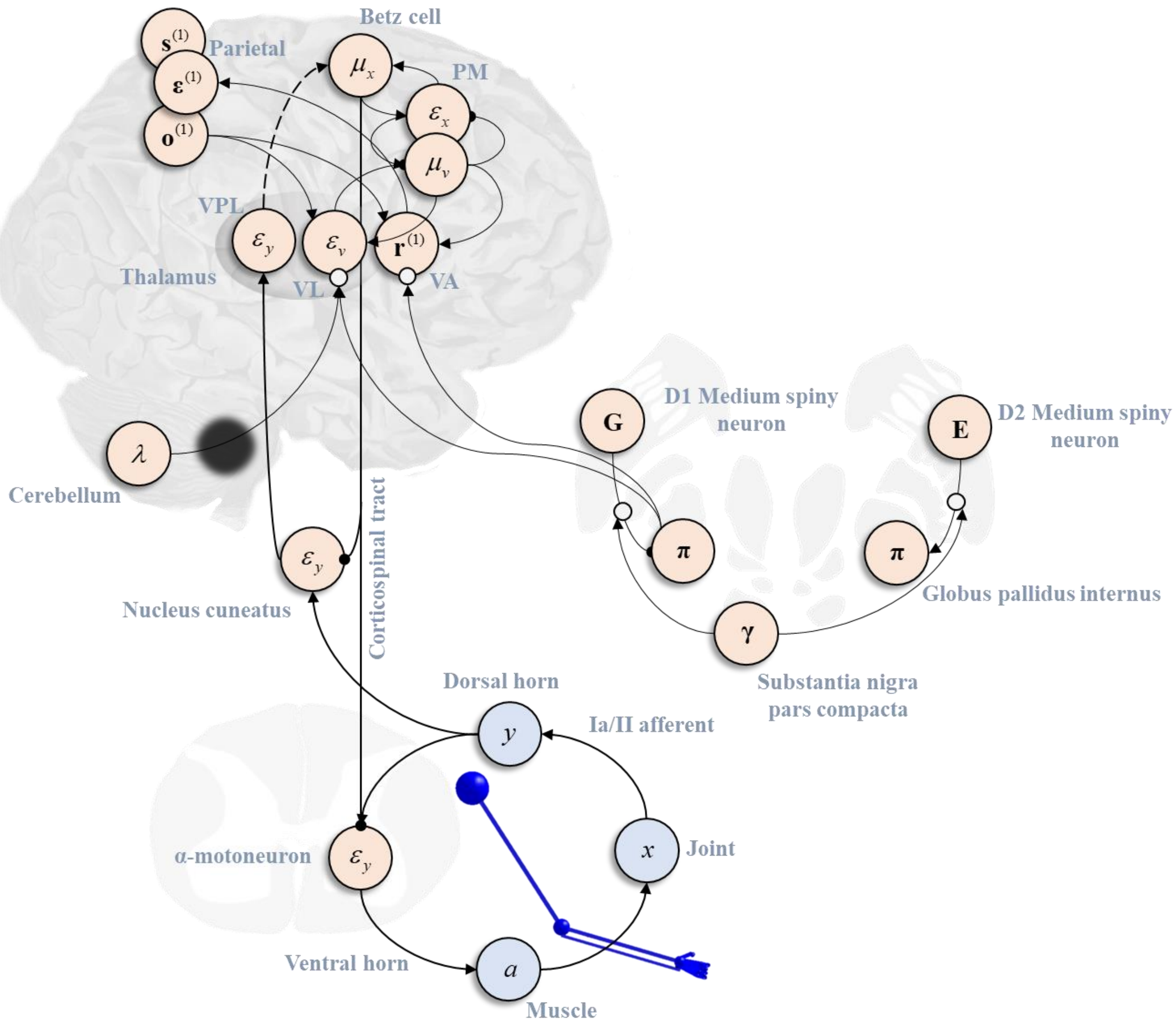


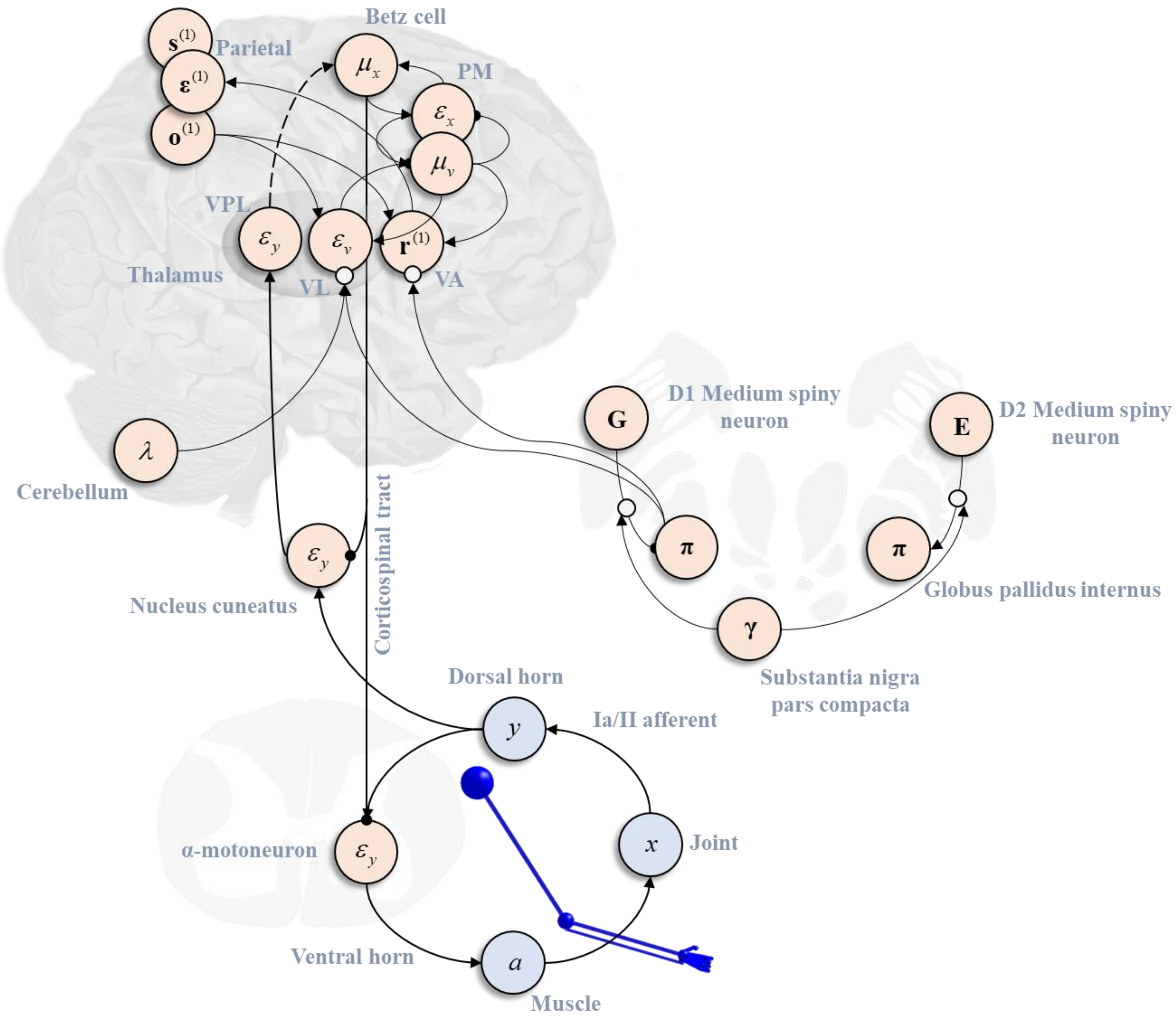
Betz cell
$\mathbf{s}^{(1)}$
Parietal
μ_x
PM
$\boldsymbol{\varepsilon}^{(1)}$
ε_x
$\mathbf{o}^{(1)}$
μ_v
VPL
ε_y
ε_v
$\mathbf{r}^{(1)}$
Thalamus
VL
VA
D1 Medium spiny neuron
D2 Medium spiny neuron
G
E
λ
Cerebellum
π
π
Corticospinal tract
ε_y
Nucleus cuneatus
Globus pallidus internus
γ
Dorsal horn
Substantia nigra pars compacta
Ia/II afferent
y
x
Joint
α-motoneuron
ε_y
Ventral horn
a
Muscle



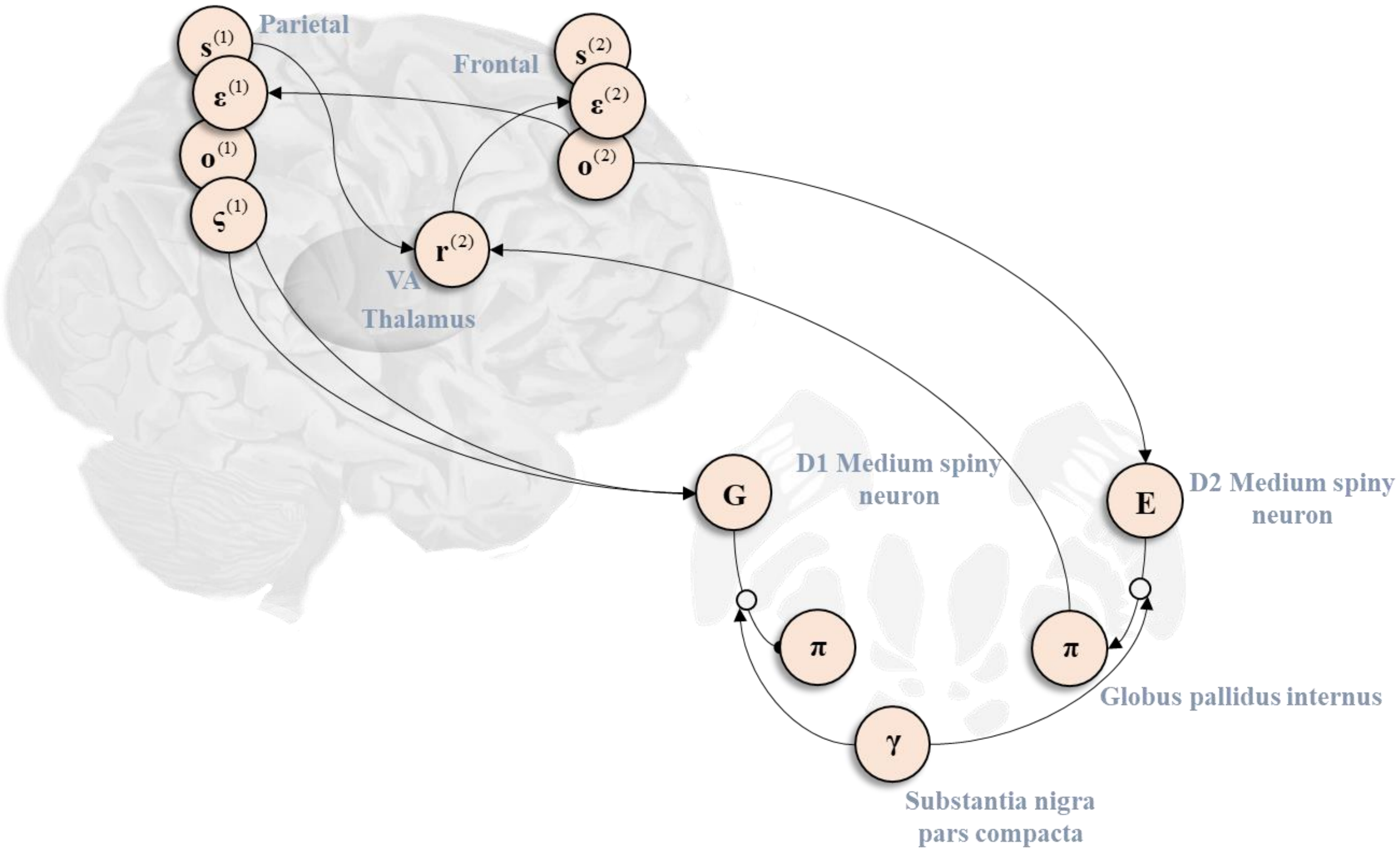
Betz cell
Parietal
PM
VPL
Thalamus
VL
VA
Cerebellum
D1 Medium spiny neuron
D2 Medium spiny neuron
Nucleus cuneatus
Corticospinal tract
Globus pallidus internus
Substantia nigra pars compacta
Dorsal horn
Ia/II afferent
Joint
α-motoneuron
Ventral horn
Muscle


0.5
0
-0.5
0.5
1
0
-0.5

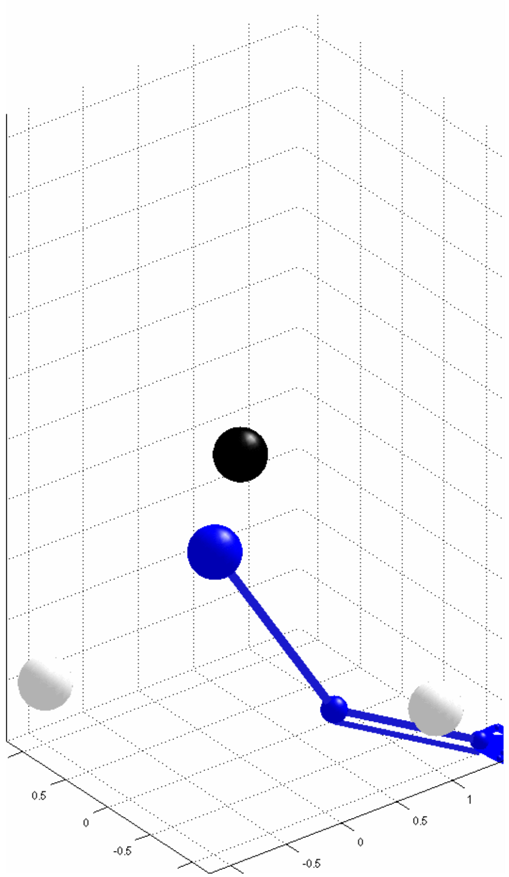

Betz cell
μ_x
$\mathbf{s}^{(1)}$
$\boldsymbol{\varepsilon}^{(1)}$
$\mathbf{o}^{(1)}$
Parietal
PM
ε_x
μ_v
VPL
ε_y
ε_v
$\mathbf{r}^{(1)}$
Thalamus
VL
VA
λ
Cerebellum
Corticospinal tract
ε_y
Nucleus cuneatus
G
D1 Medium spiny neuron
E
D2 Medium spiny neuron
$\boldsymbol{\pi}$
$\boldsymbol{\pi}$
Globus pallidus internus
$\boldsymbol{\gamma}$
Substantia nigra pars compacta
Dorsal horn
y
Ia/II afferent
α-motoneuron
ε_y
x
Joint
Ventral horn
a
Muscle



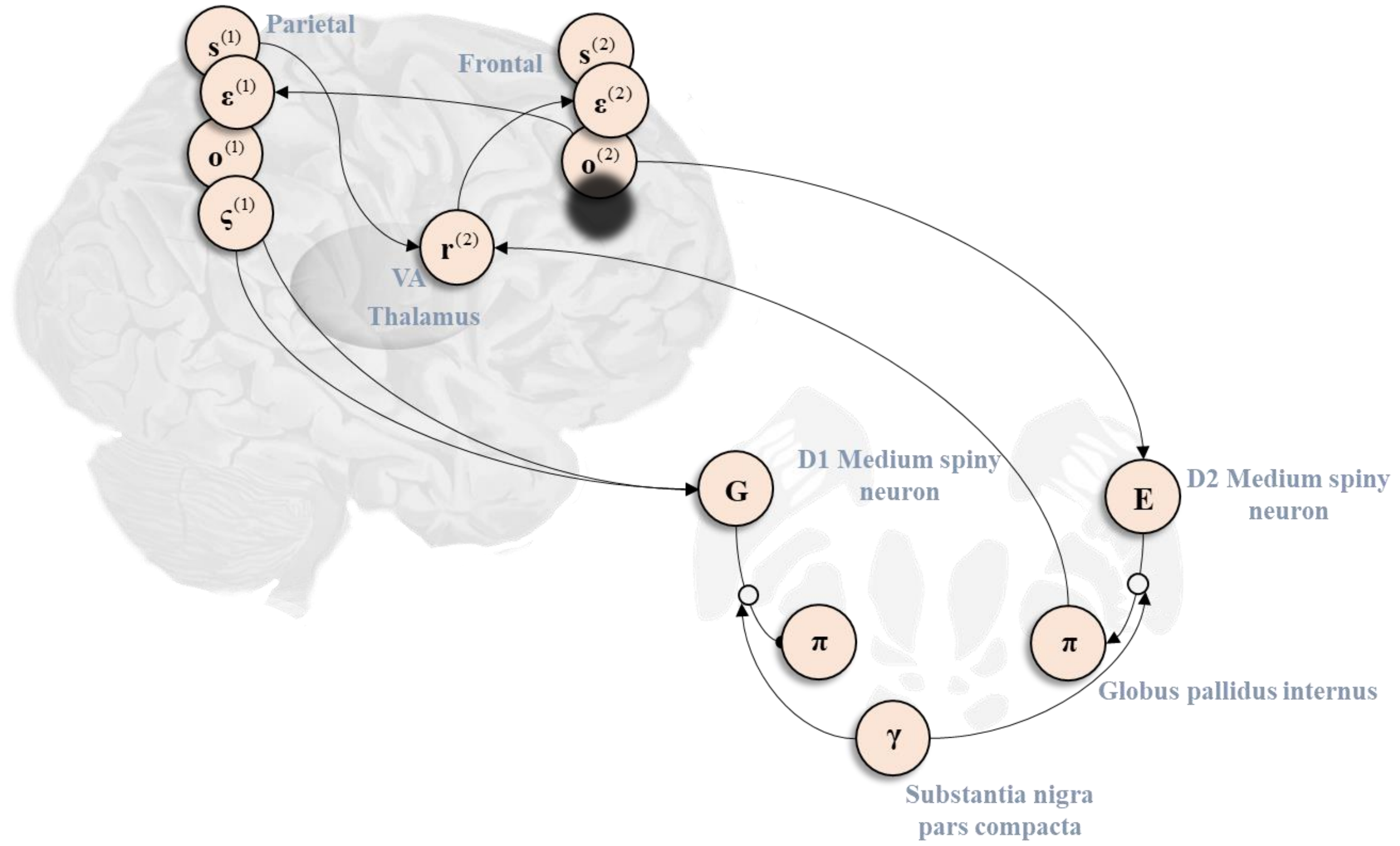
Betz cell
Parietal
PM
VPL
Thalamus
VL
VA
Cerebellum
D1 Medium spiny neuron
D2 Medium spiny neuron
Globus pallidus internus
Nucleus cuneatus
Corticospinal tract
Substantia nigra pars compacta
Dorsal horn
Ia/II afferent
Joint
α-motoneuron
Ventral horn
Muscle



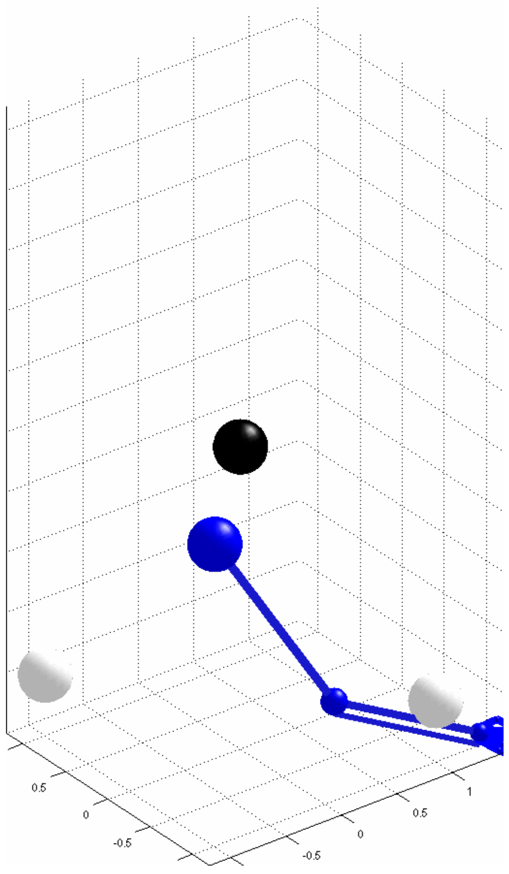
$s^{(1)}$
Parietal
$\varepsilon^{(1)}$
$o^{(1)}$
$\varsigma^{(1)}$
Frontal
$s^{(2)}$
$\varepsilon^{(2)}$
$o^{(2)}$
$r^{(2)}$
VA
Thalamus
G
D1 Medium spiny
neuron
E
D2 Medium spiny
neuron
π
π
Globus pallidus internus
γ
Substantia nigra
pars compacta

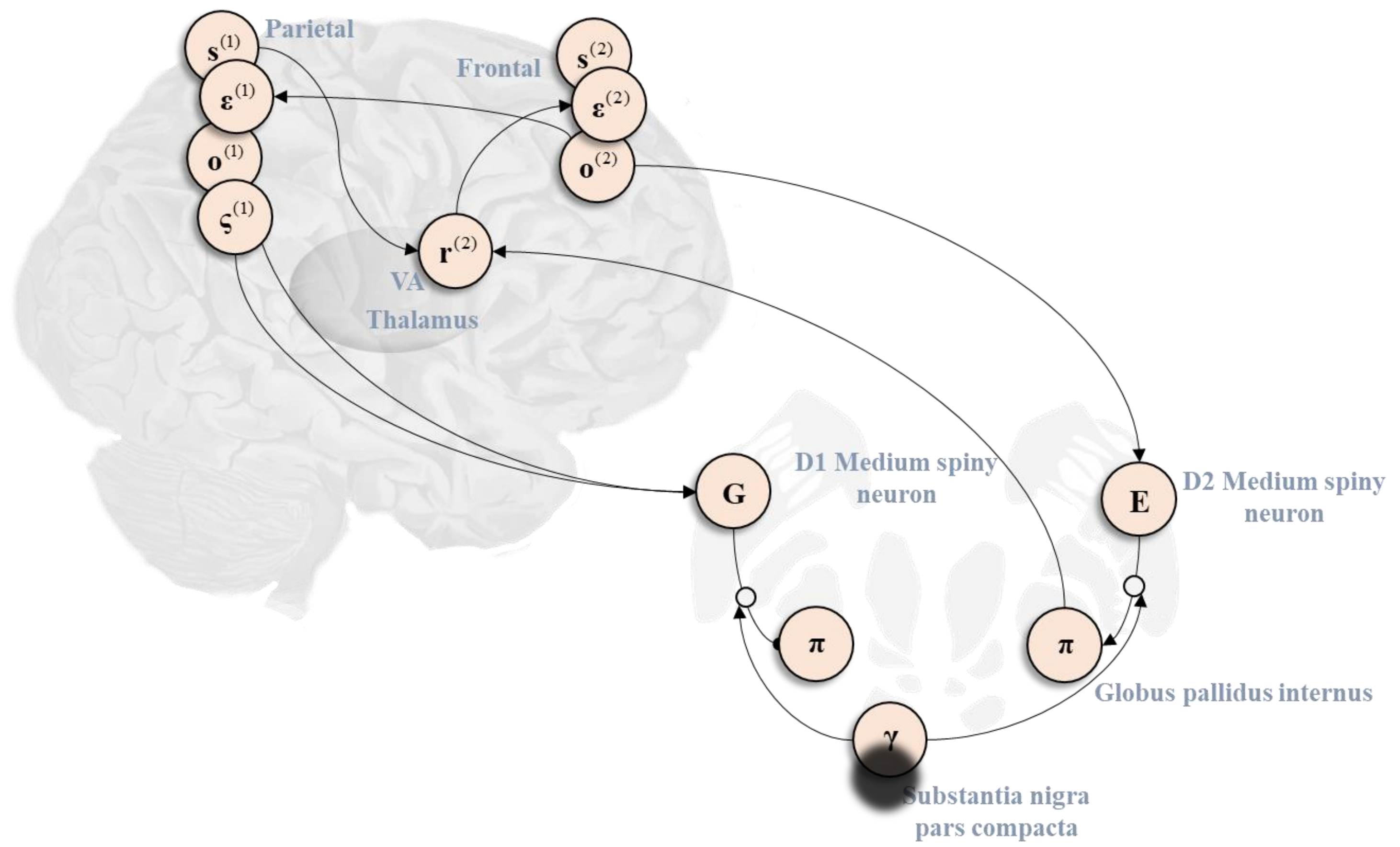


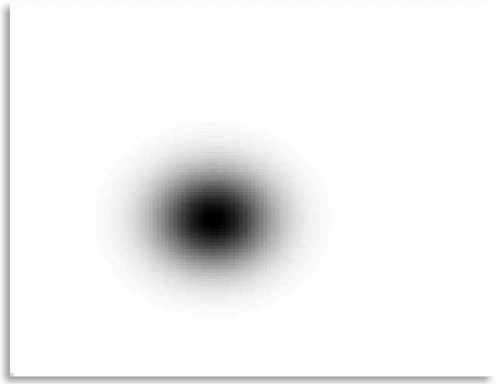
0.5
0
-0.5
-0.5
0
0.5
1

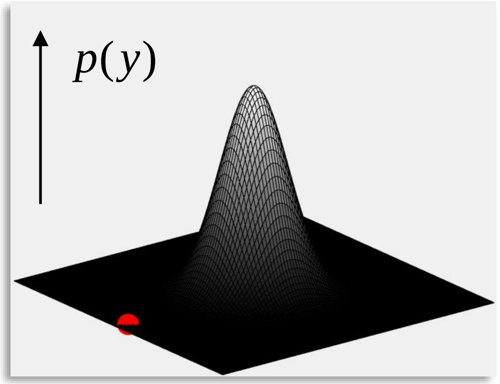


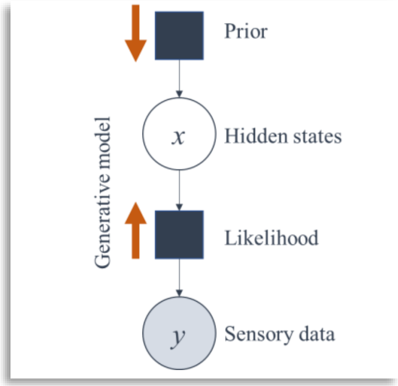
Parietal
Frontal
VA
Thalamus
D1 Medium spiny neuron
D2 Medium spiny neuron
Globus pallidus internus
Substantia nigra pars compacta
$s^{(1)}$
$\varepsilon^{(1)}$
$o^{(1)}$
$\varsigma^{(1)}$
$s^{(2)}$
$\varepsilon^{(2)}$
$o^{(2)}$
$r^{(2)}$
G
E
π
π
γ

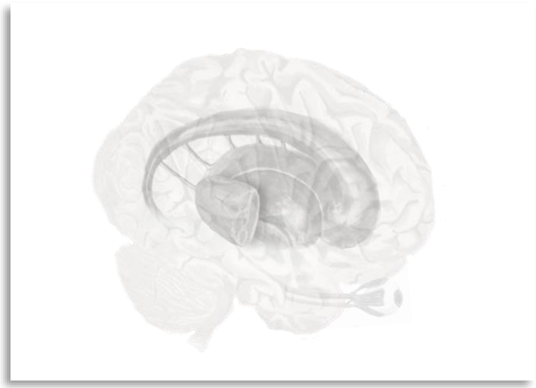

0.5
0
-0.5
-0.5
0
0.5
1

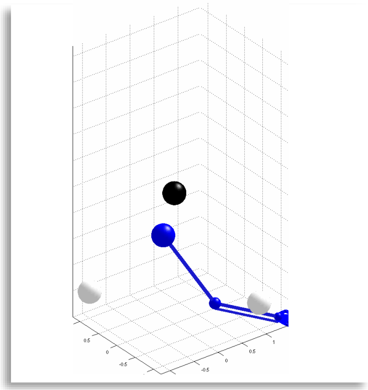

$s^{(1)}$
Parietal
$\varepsilon^{(1)}$
$o^{(1)}$
$\varsigma^{(1)}$
$s^{(2)}$
Frontal
$\varepsilon^{(2)}$
$o^{(2)}$
$r^{(2)}$
VA
Thalamus
G
D1 Medium spiny
neuron
E
D2 Medium spiny
neuron
π
π
Globus pallidus internus
γ
Substantia nigra
pars compacta




p(y)


Prior
x
Hidden states
Likelihood
y
Sensory data
Generative model





Thanks

Andrew Corcoran
Berk Mirza
David Benrimoh
Dimitrije Markovic
Ensor Palacios
Geraint Rees
Hayriye Cagnan
Jakub Limanowski
Jakob Hohwy
Jelle Bruineberg
Karl Friston
Lance Da Costa
Michael Kirchoff
Noor Sajid
Peter Vincent
Rick Adams
Stefan Kiebel
Tim Sandhu
Takuya Isomura

Rosetrees Trust
Supporting the best in medical research

UCL

wellcome centre
human neuroimaging