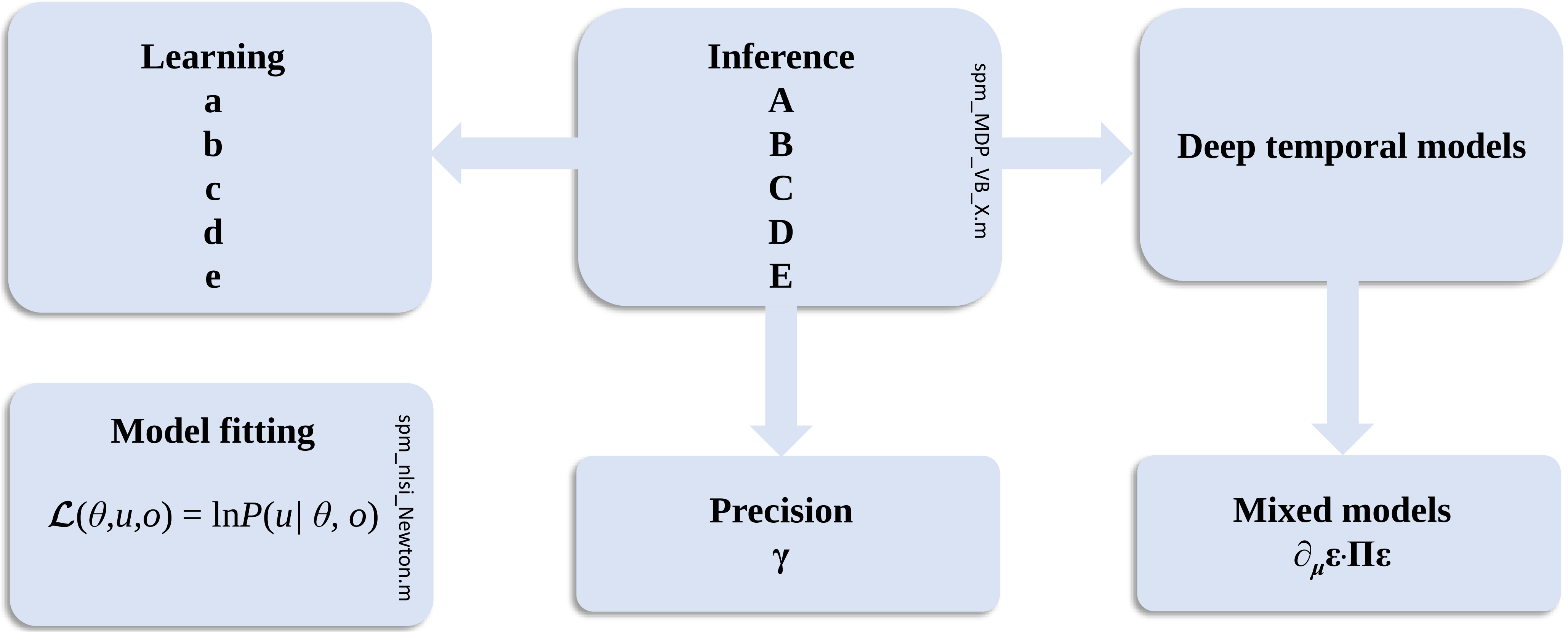
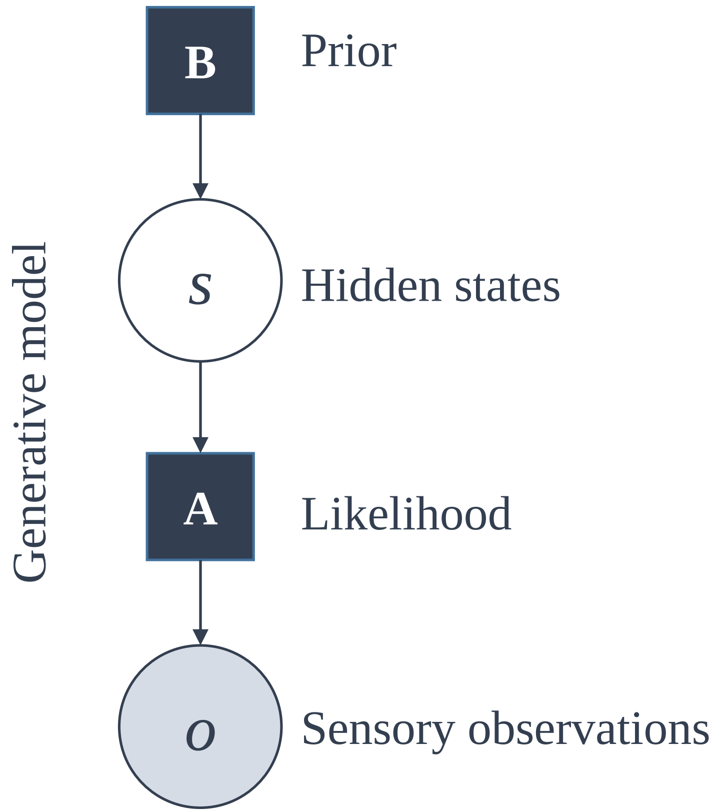
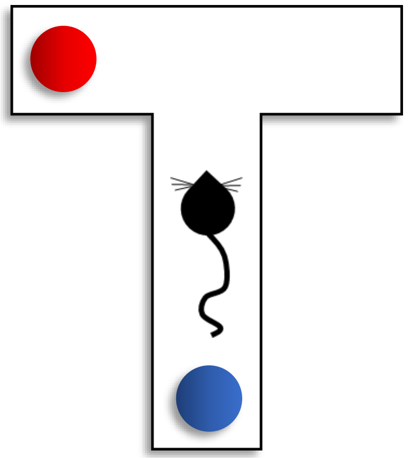
Active inference tutorial

Computational psychiatry course


Learning
a
b
c
d
e
Inference
A
B
C
D
E
spm_MDP_VB_X.m
Deep temporal models
Model fitting
$\mathcal{L}(\theta,u,o) = \ln P(u|\ \theta, o)$
spm_nlsi_Newton.m
Precision
γ
Mixed models
$\partial_{\mu}\varepsilon\cdot\Pi\varepsilon$

$$P(s \mid o) \propto P(o \mid s)P(s)$$

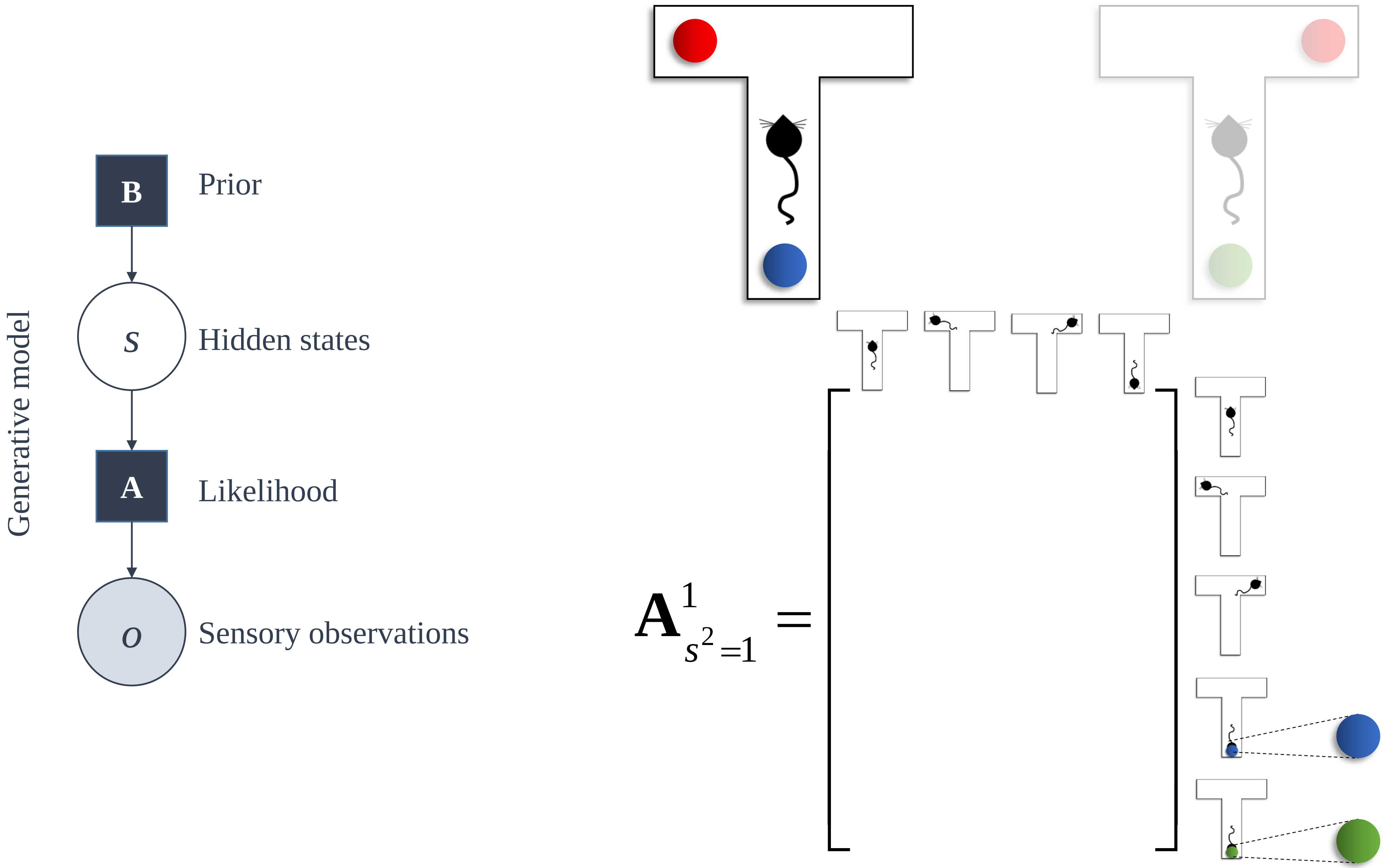


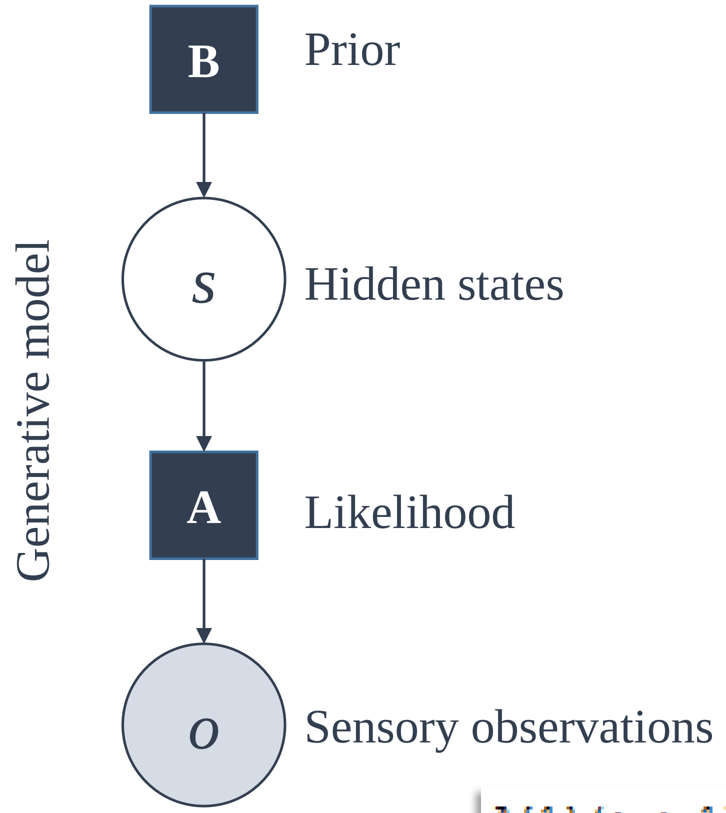


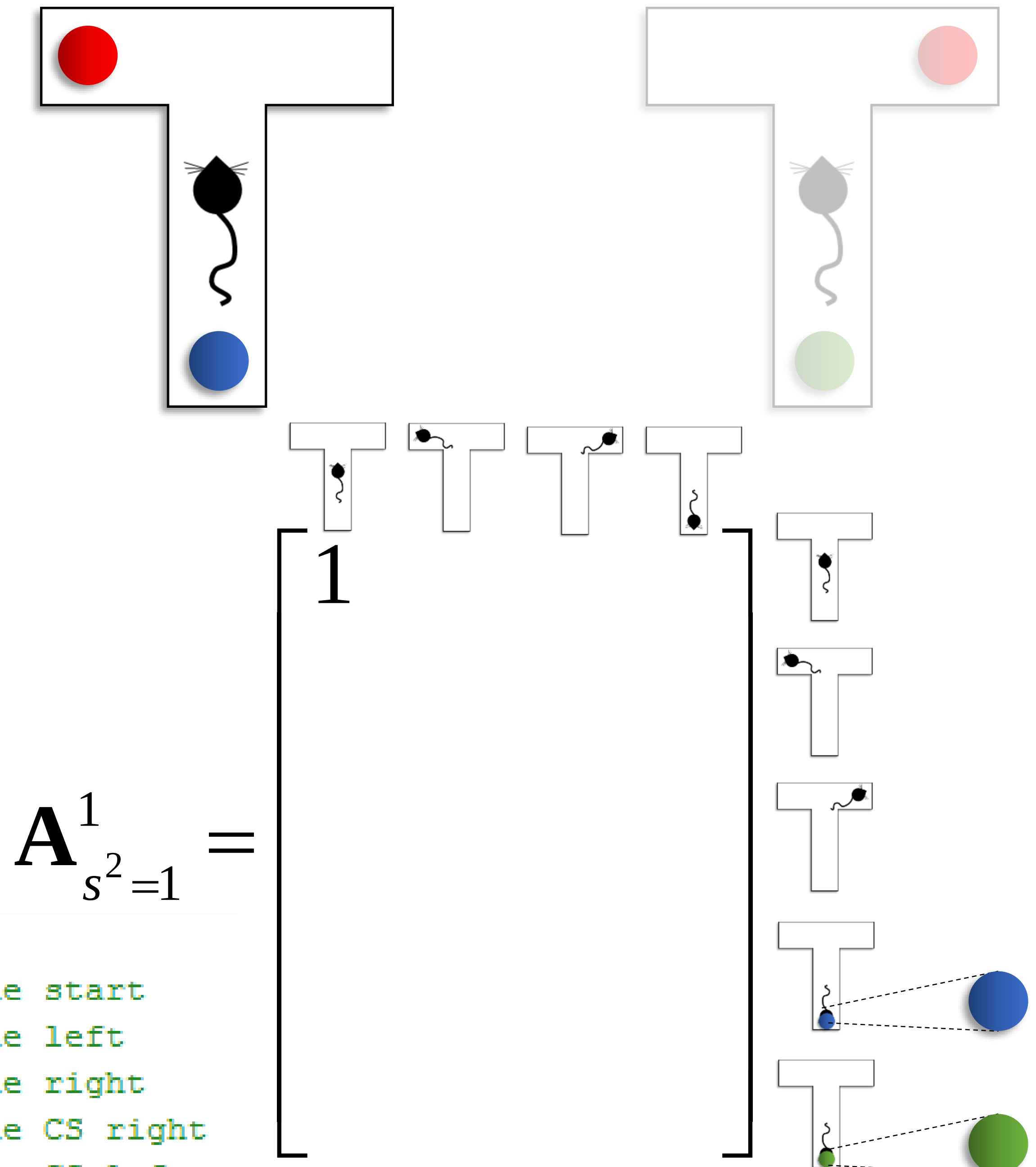
Navigating a T-maze

A, B, C, D, E

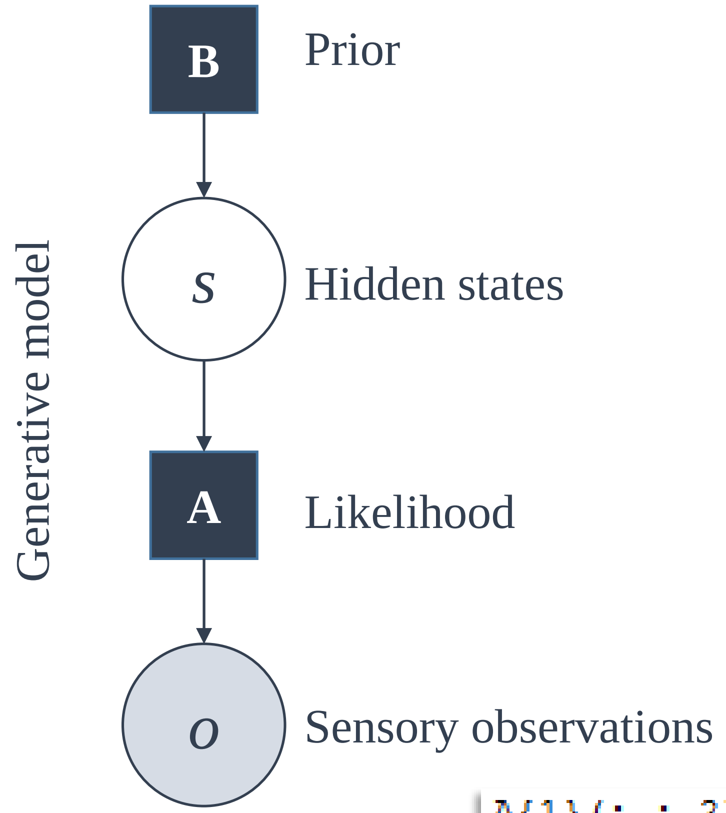
A, **B**, **C**, **D**, **E**

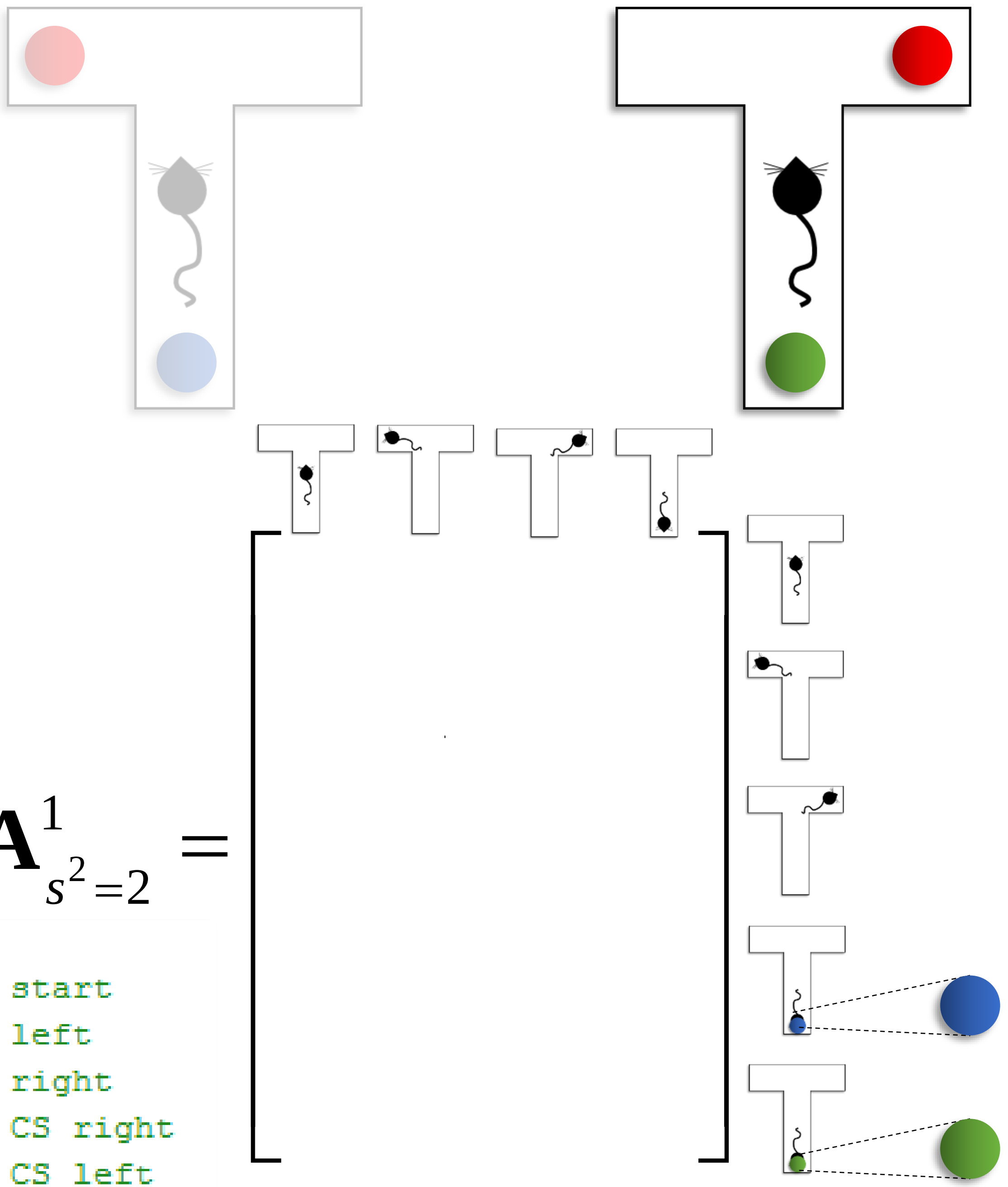

Generative model
B
Prior
s
Hidden states
A
Likelihood
o
Sensory observations
$\mathbf{A}^{1}_{s^{2}=1} =$





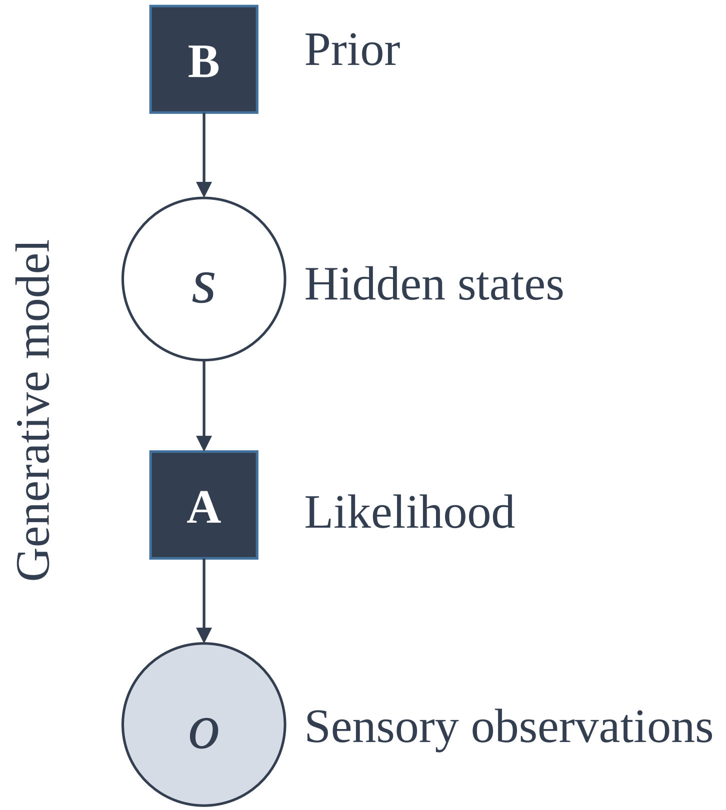

```
A{1}(:,:,1) = [...
     1 0 0 0;     % cue start
     0 1 0 0;     % cue left
     0 0 1 0;     % cue right
     0 0 0 1      % cue CS right
     0 0 0 0];    % cue CS left
```

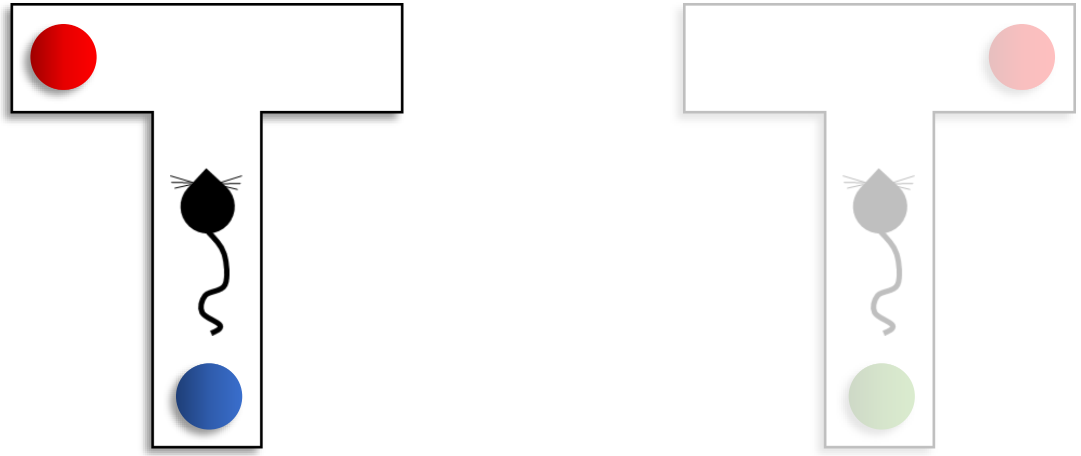




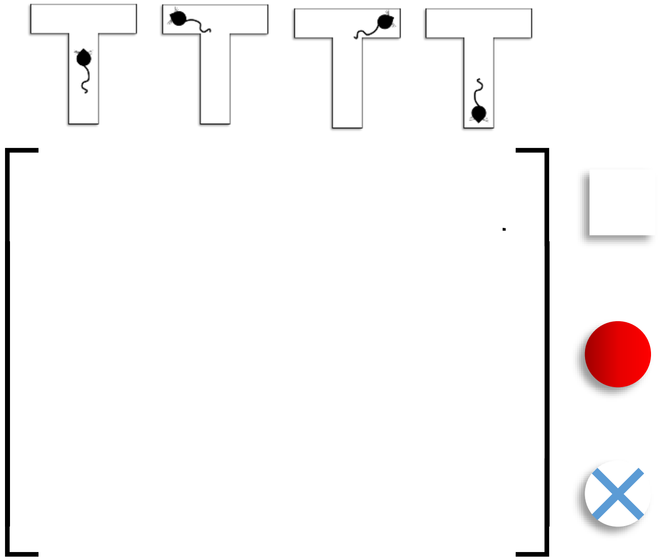
$$\mathbf{A}^{1}_{s^2=2} =$$

```
A{1}(:,:,2) = [...
     1 0 0 0;     % cue start
     0 1 0 0;     % cue left
     0 0 1 0;     % cue right
     0 0 0 0      % cue CS right
     0 0 0 1];    % cue CS left
```



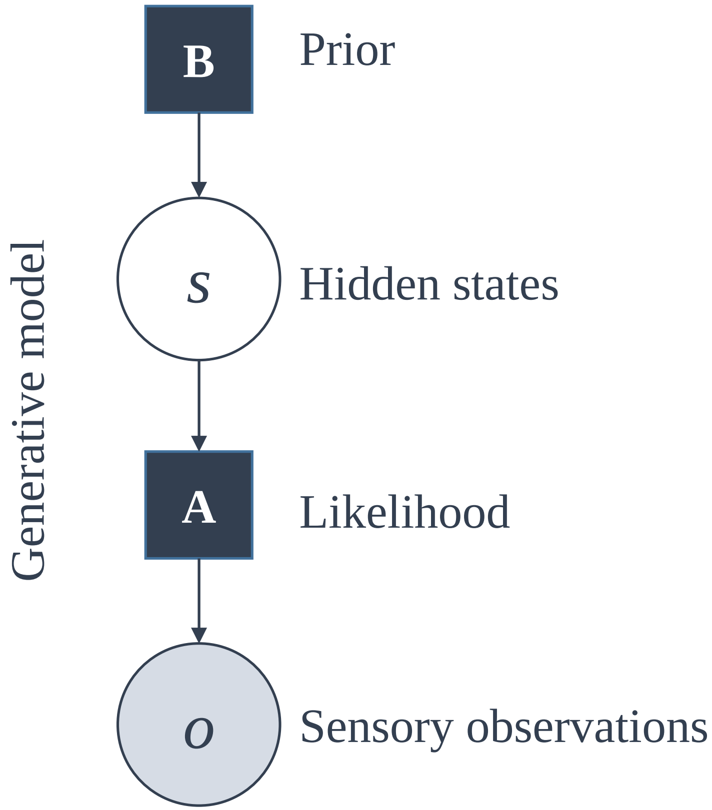


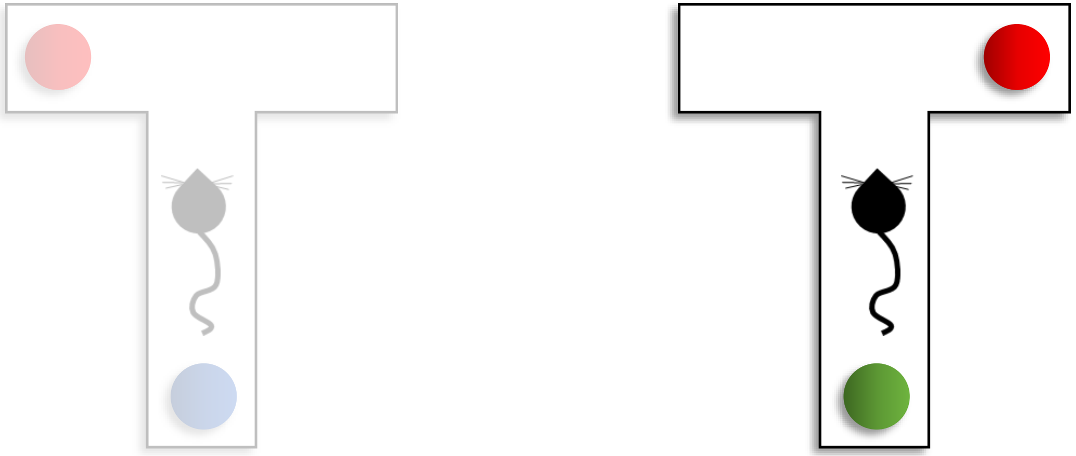
$$\mathbf{A}^{2}_{s^{2}=1} =$$



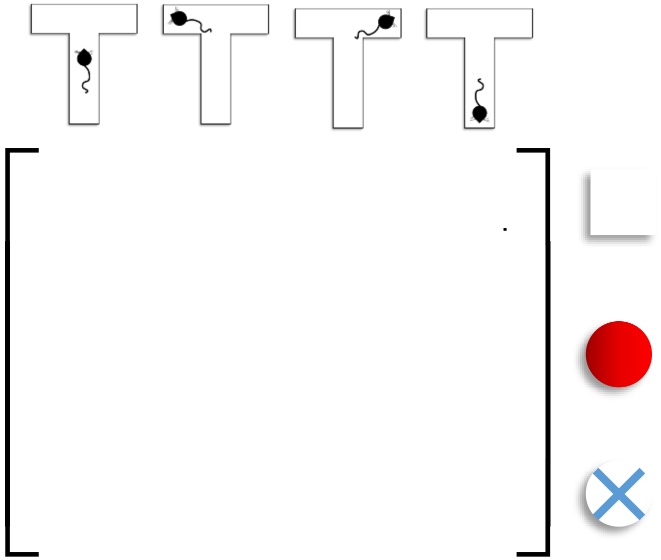
```
a          = .98;
b          = 1 - a;
```

```
A{2}(:,:,1) = [...
    1 0 0 1;     % reward neutral
    0 a b 0;     % reward positive
    0 b a 0];    % reward negative
```



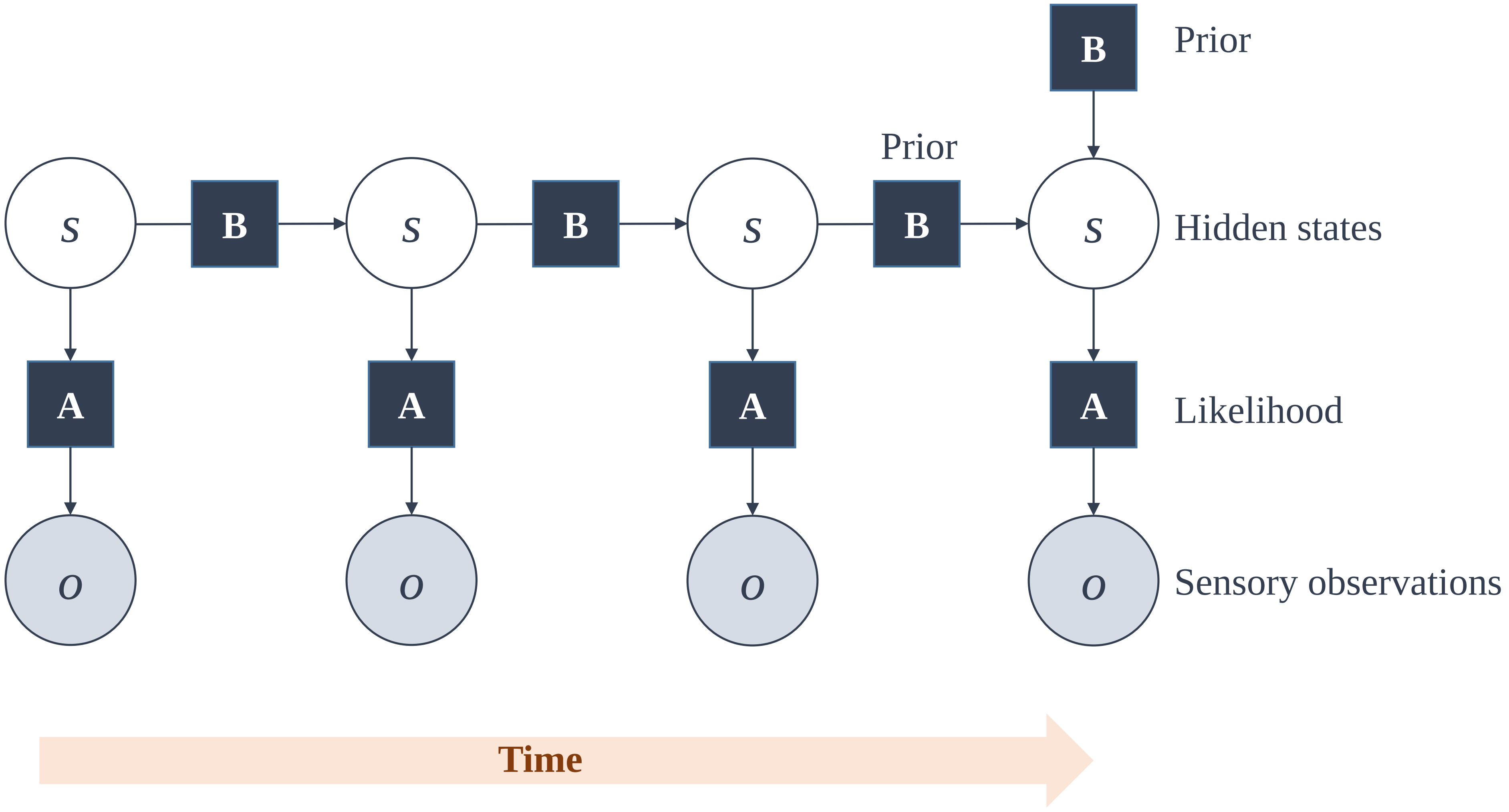


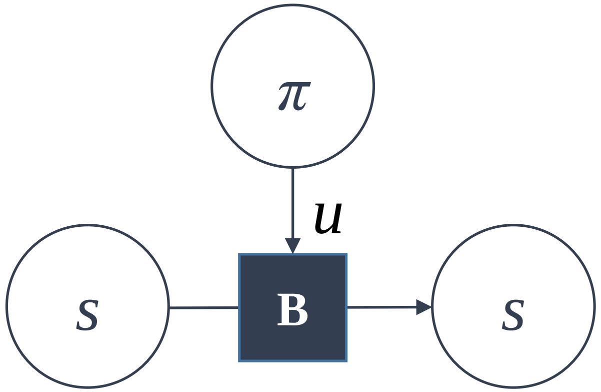
$$\mathbf{A}^{2}_{s^2=2} =$$



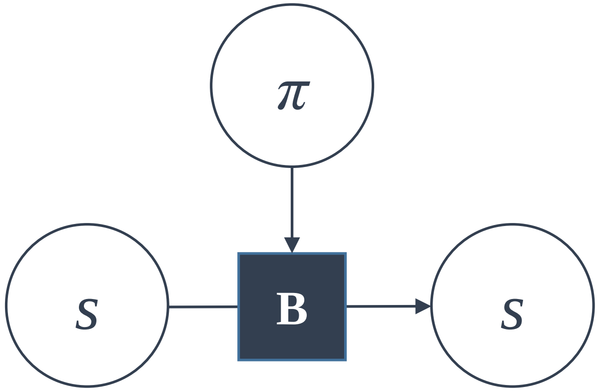
```
A{2}(:,:,2) = [...
    1 0 0 1;    % reward neutral
    0 b a 0;    % reward positive
    0 a b 0];   % reward negative
```

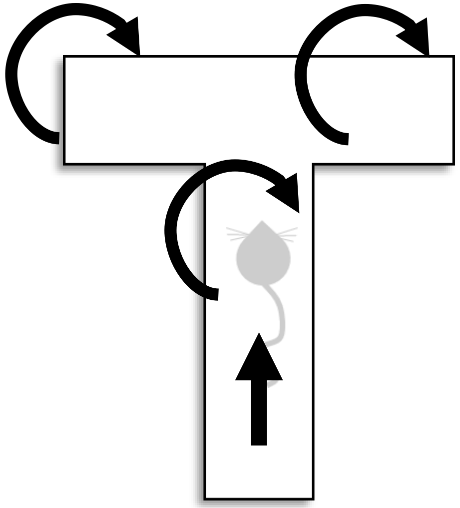
A, **B**, C, D, E


B
Prior
Prior
s
B
s
B
s
B
s
Hidden states
A
A
A
A
Likelihood
o
o
o
o
Sensory observations
Time



π
u
s
B
s

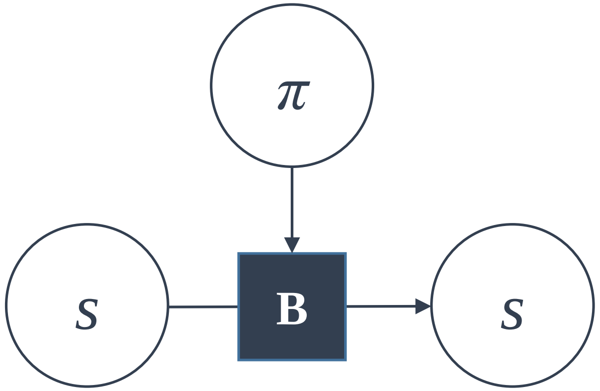




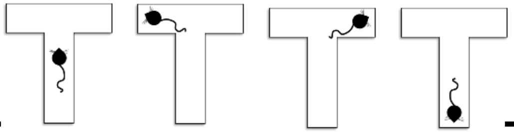
From

$$\mathbf{B}^1(u=1) = \begin{bmatrix} 1 & & & 1 \\ & 1 & & \\ & & 1 & \\ & & & \end{bmatrix}$$

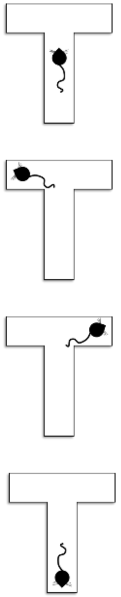
To



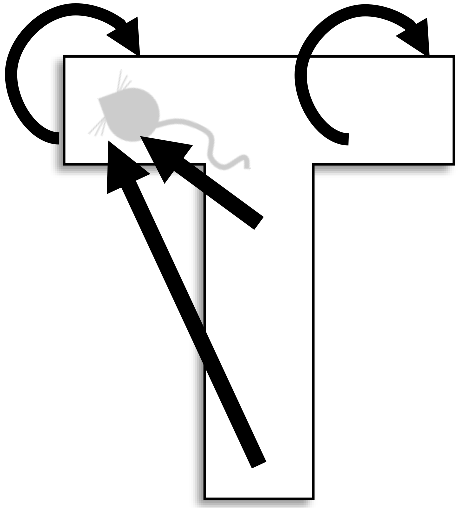
From

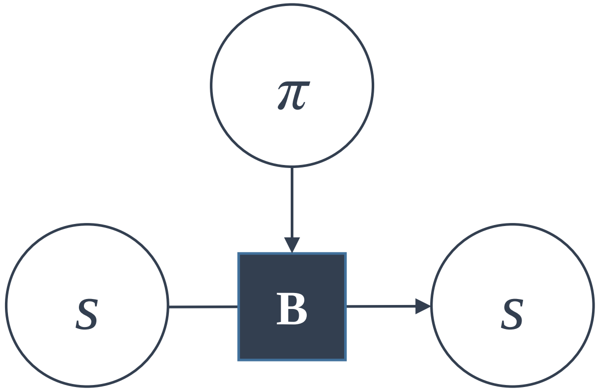


$$\mathbf{B}^1(u=2) = \begin{bmatrix} & & & \\ 1 & 1 & & 1 \\ & & 1 & \\ & & & \end{bmatrix}$$



To

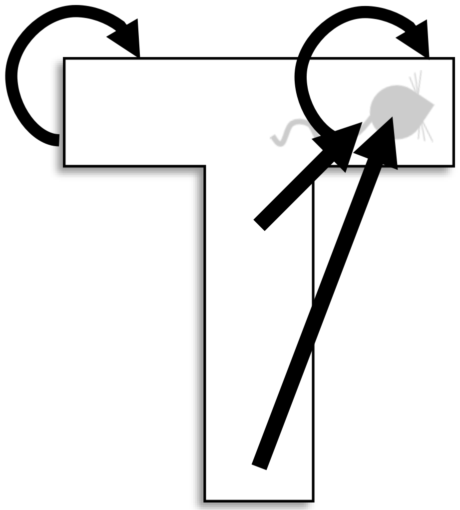


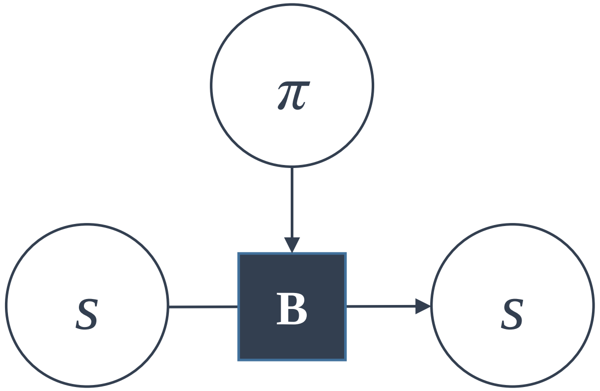


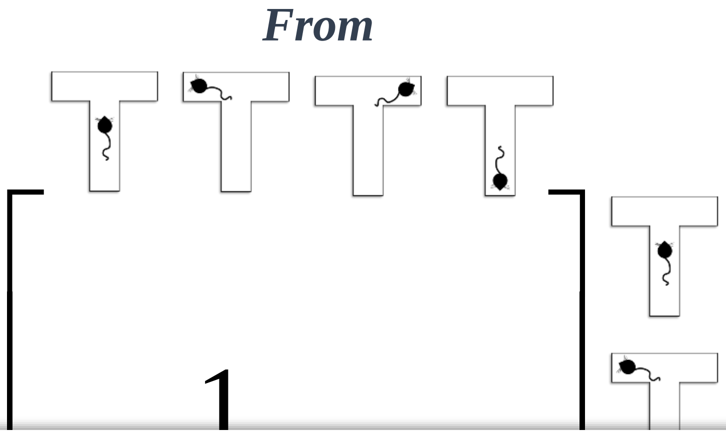
From

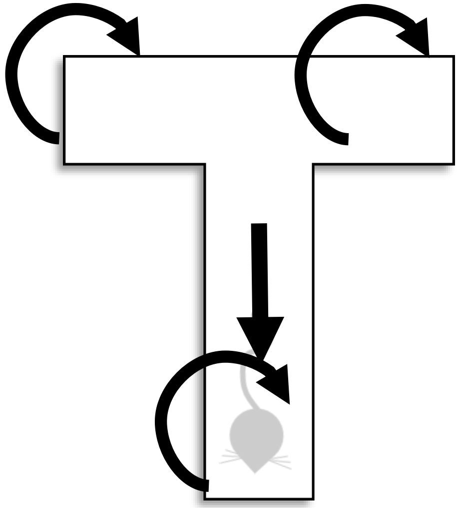
$$\mathbf{B}^1(u=3) = \begin{bmatrix} & & & \\ & 1 & & \\ 1 & & 1 & 1 \\ & & & \end{bmatrix}$$

To

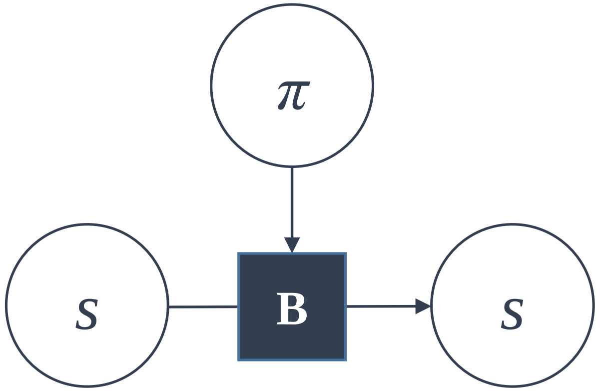








```
B{1}(:,:,1)  = [1 0 0 1; 0 1 0 0;0 0 1 0;0 0 0 0];
B{1}(:,:,2)  = [0 0 0 0; 1 1 0 1;0 0 1 0;0 0 0 0];
B{1}(:,:,3)  = [0 0 0 0; 0 1 0 0;1 0 1 1;0 0 0 0];
B{1}(:,:,4)  = [0 0 0 0; 0 1 0 0;0 0 1 0;1 0 0 1];
```

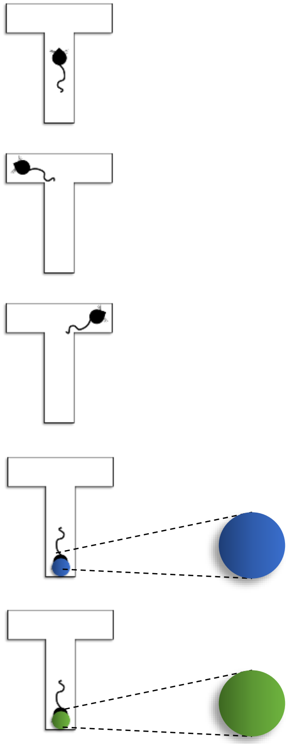


$$\begin{array}{cc} & \textit{From} \\ \mathbf{B}^2 = & \begin{bmatrix} 1 & \\ & 1 \end{bmatrix} \end{array} \quad \textit{To}$$

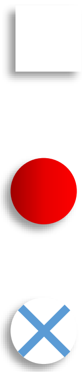
```
B{2}   = eye(2);
```

A, B, **C**, D, E

$$\mathbf{C}^1 = \begin{bmatrix} -1 & -1 & -1 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}$$

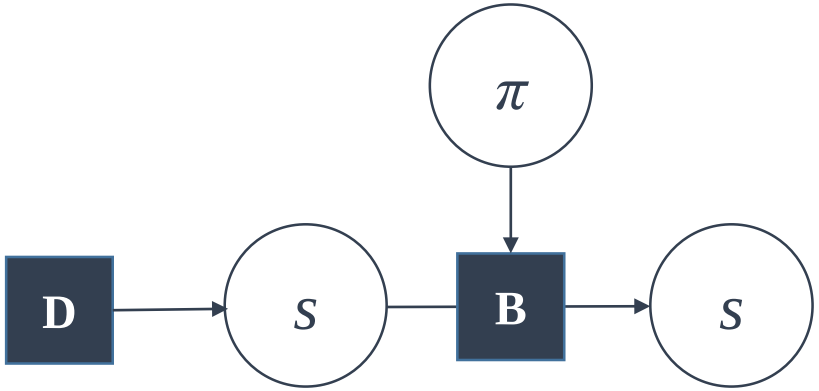


$$\mathbf{C}^2 = \begin{bmatrix} 0 & 0 & 0 \\ c & c & c \\ -c & -c & -c \end{bmatrix}$$



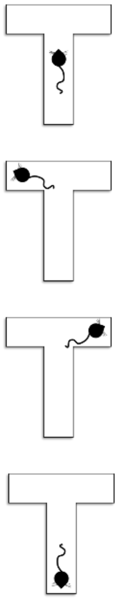
```
C{1}   = [-1 -1 -1;
           0  0  0;
           0  0  0;
           0  0  0;
           0  0  0];
c      = 6;
C{2}   = [ 0  0  0;
           c  c  c;
          -c -c -c];
```

A, B, C, D, E

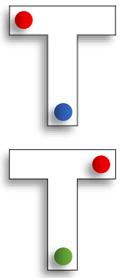



```
D{1} = [1 0 0 0]';
D{2} = [1 1]';
```

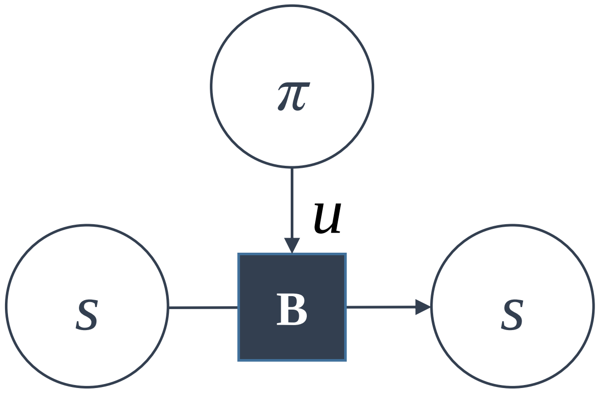
$$\mathbf{D}^1 = \begin{bmatrix} 1 \\ 0 \\ 0 \\ 0 \end{bmatrix}$$



$$\mathbf{D}^2 = \frac{1}{2}\begin{bmatrix} 1 \\ 1 \end{bmatrix}$$



A, B, C, D, **E**

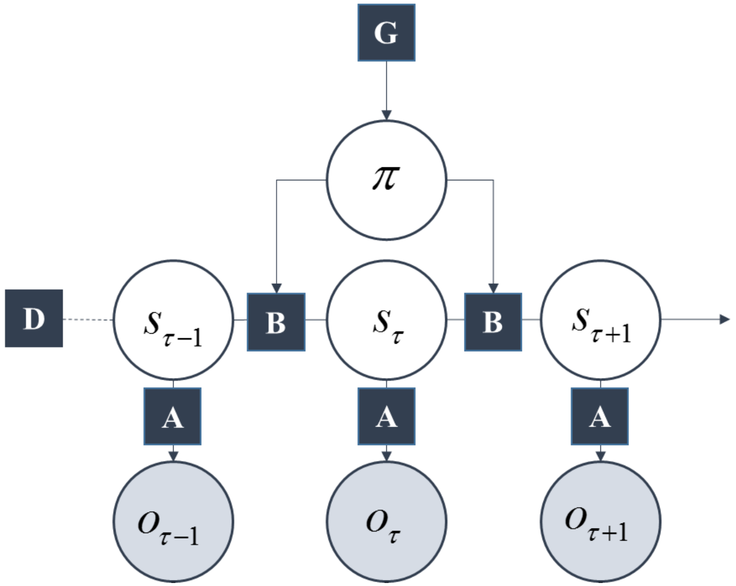


$$u = V_{\tau\pi}$$

```
V(:,:,1) = [1   1   1   1   2   3   4   4   4   4
            1   2   3   4   2   3   1   2   3   4];
V(:,:,2) = 1;
```

$$\mathbf{E} = \tfrac{1}{10}\begin{bmatrix}1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1\end{bmatrix}^T$$

```
E = ones(10,1)/10;
```



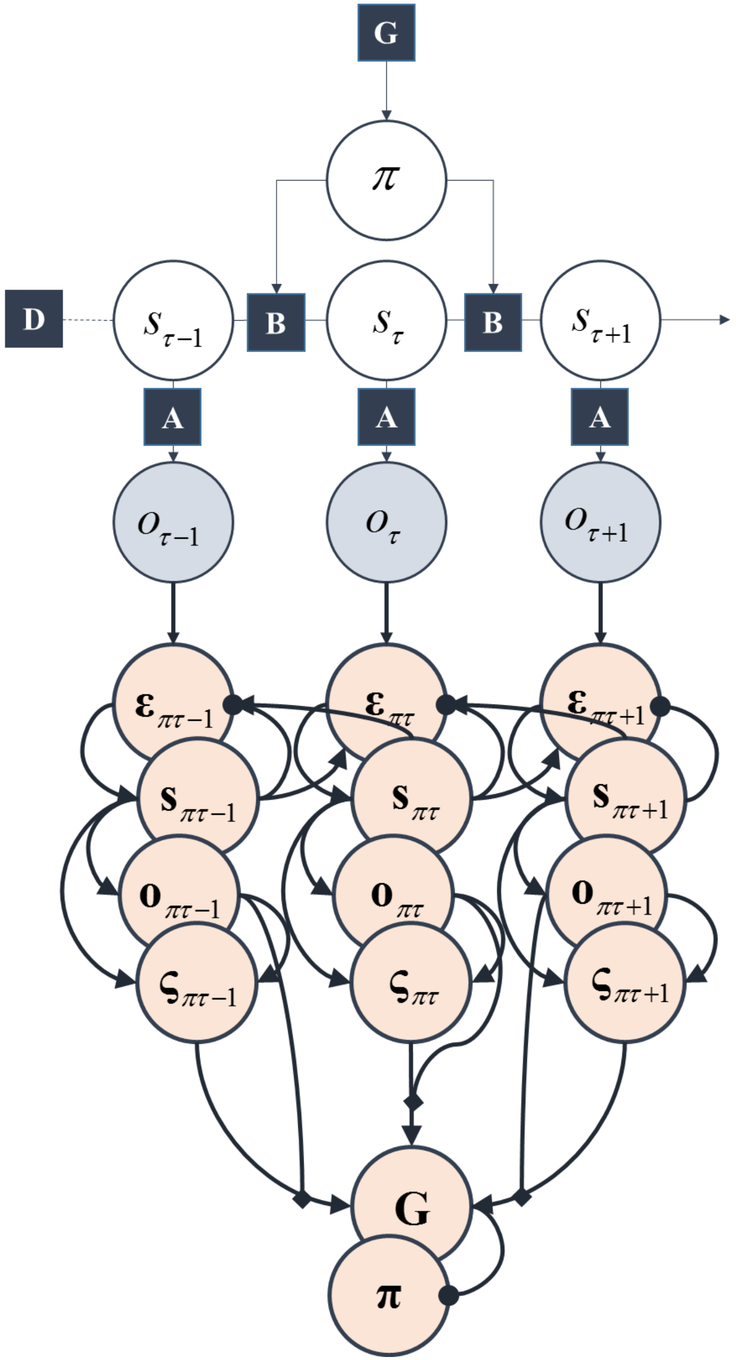
Generative model

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

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

Can omit and instead specify mdp.T

```
mdp.E = E;
mdp.V = V;                     % allowable policies
mdp.A = A;                     % observation model
mdp.B = B;                     % transition probabilities
mdp.C = C;                     % preferred outcomes
mdp.D = D;                     % prior over initial states
mdp.s = [1 1]';                % true initial state
```



Generative model

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

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

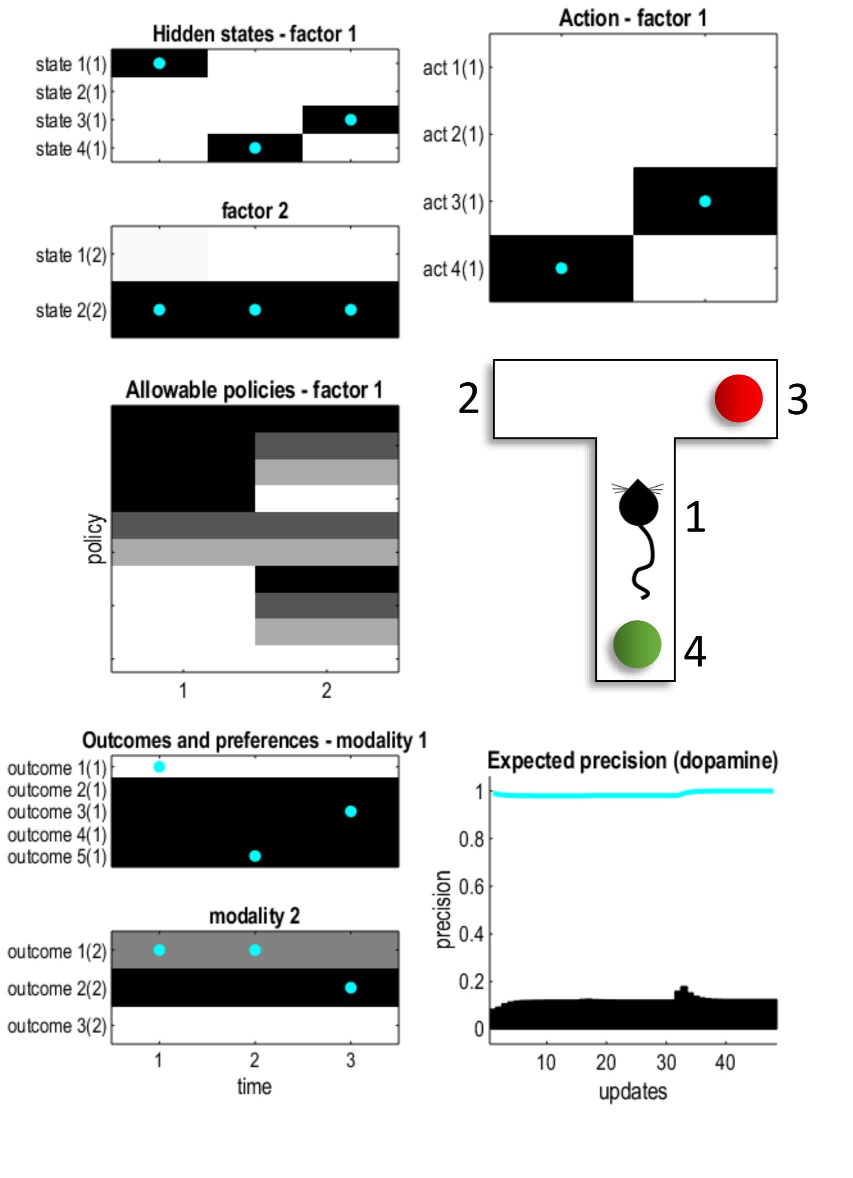
Bayesian message passing

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

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

```
MDP   = spm_MDP_VB_X(mdp);
```

```
spm_figure('GetWin','Figure 1'); clf
spm_MDP_VB_trial(MDP)
```



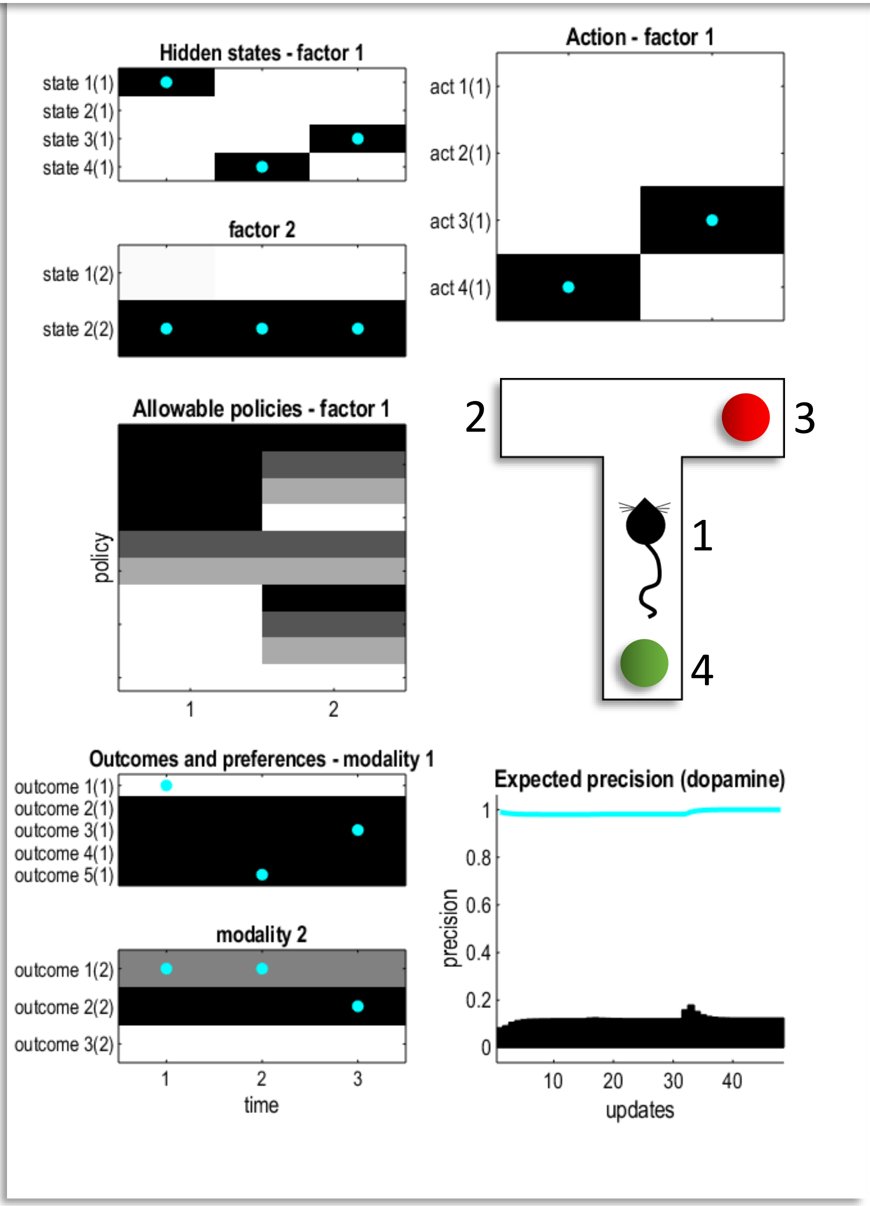
$$P(\pi \mid \gamma, \mathbf{E}) = \sigma(\qquad - \gamma \cdot \mathbf{G})$$

$$\mathbf{G}_\pi = -\underbrace{D_{KL}[P(o \mid s)Q(s \mid \pi) \,||\, Q(o \mid \pi)Q(s \mid \pi)]}_{\text{Information gain}}$$

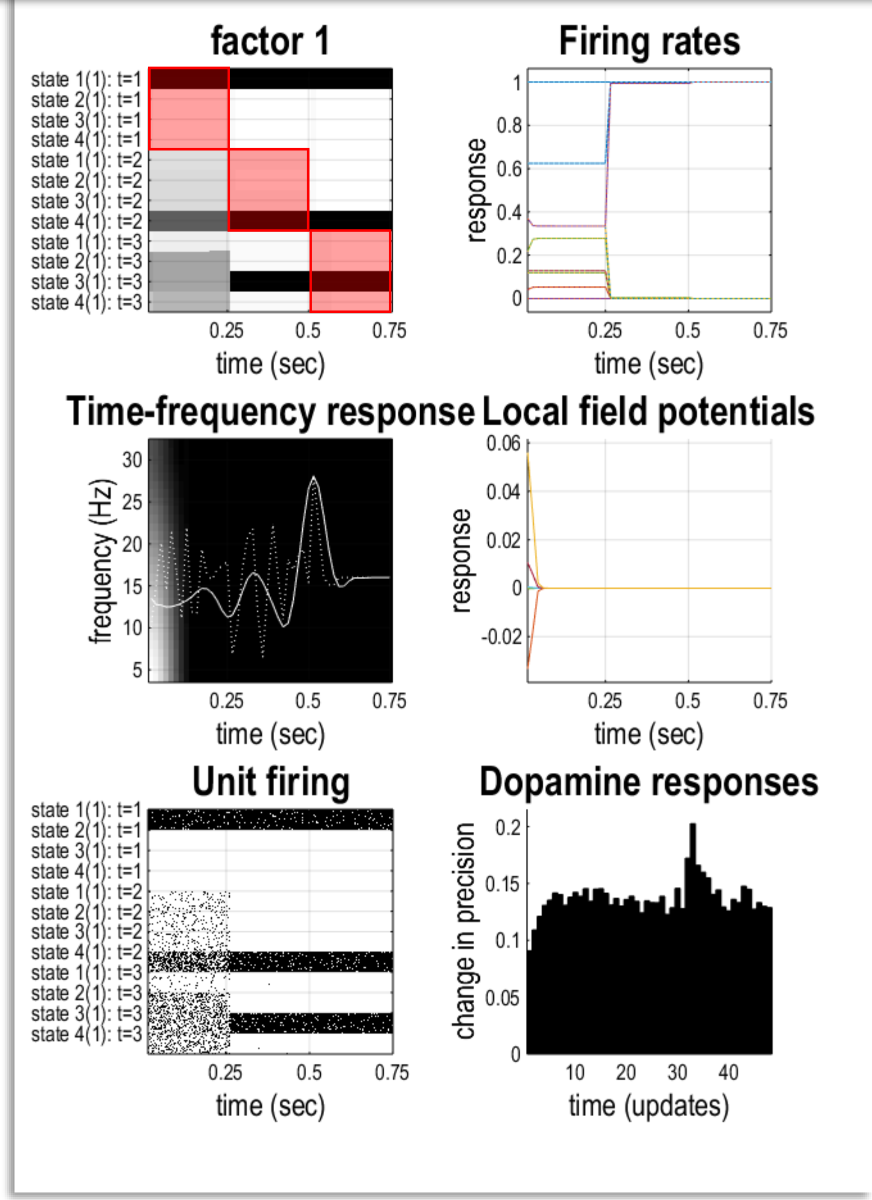
$$-\underbrace{E[\ln P(o)]}_{\text{Preferences}}$$

$$\sigma(\mathbf{x}) \triangleq \frac{e^{\mathbf{x}}}{\sum_i e^{\mathbf{x}_i}}$$

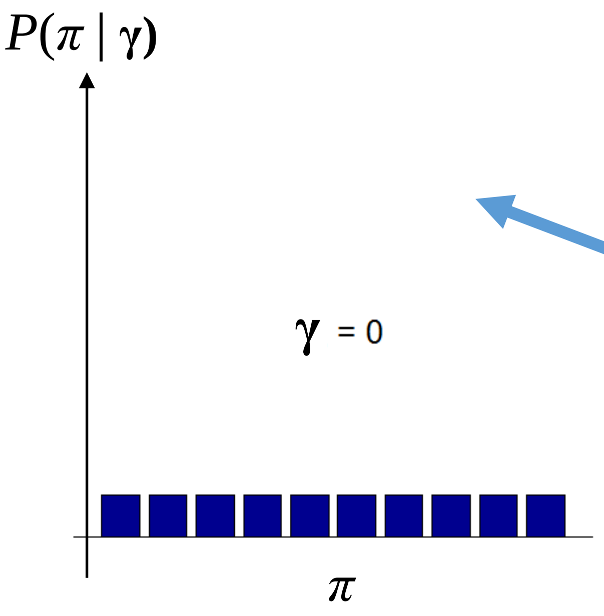
```
spm_figure('GetWin','Figure 1'); clf
spm_MDP_VB_trial(MDP)
```




```
spm_figure('GetWin','Figure 2'); clf
spm_MDP_VB_LFP(MDP)
```

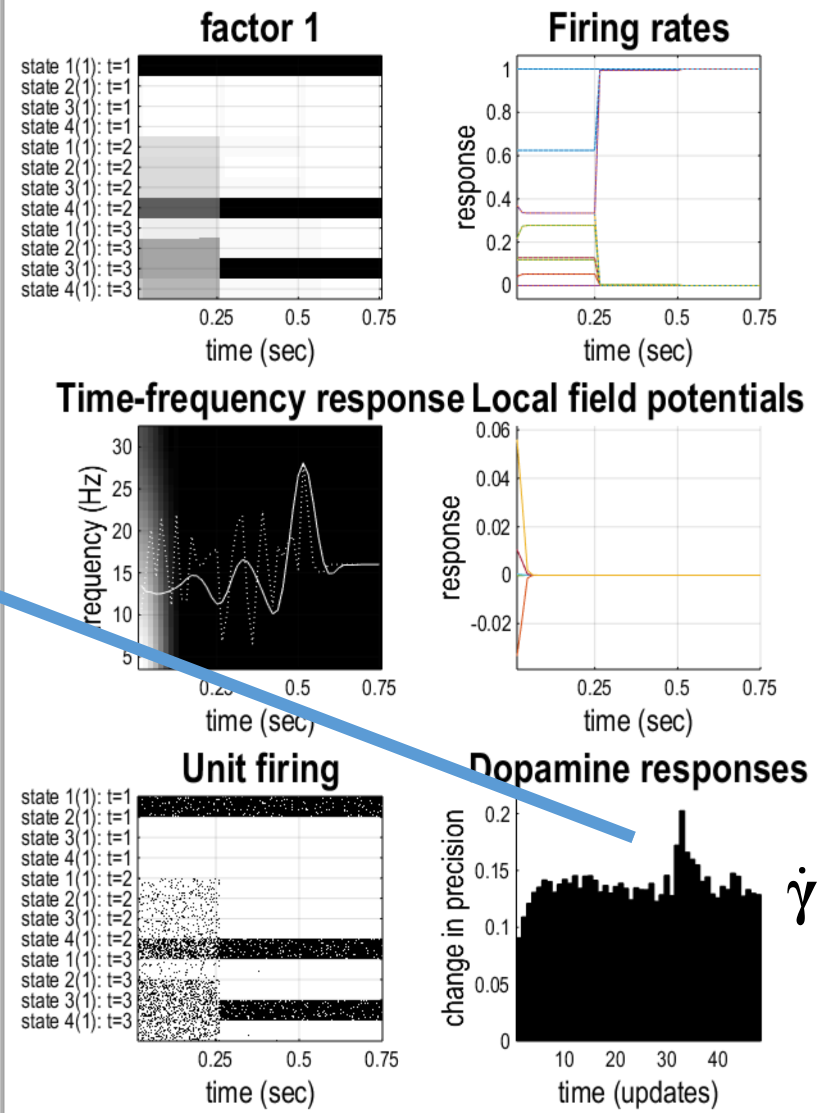


Precision



$P(\gamma) = \Gamma(1,\beta)$

```
mdp.beta
```

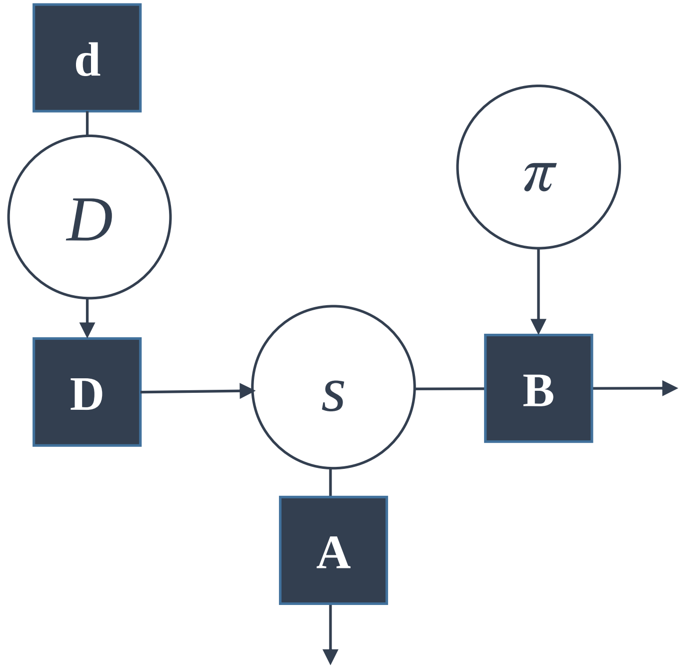


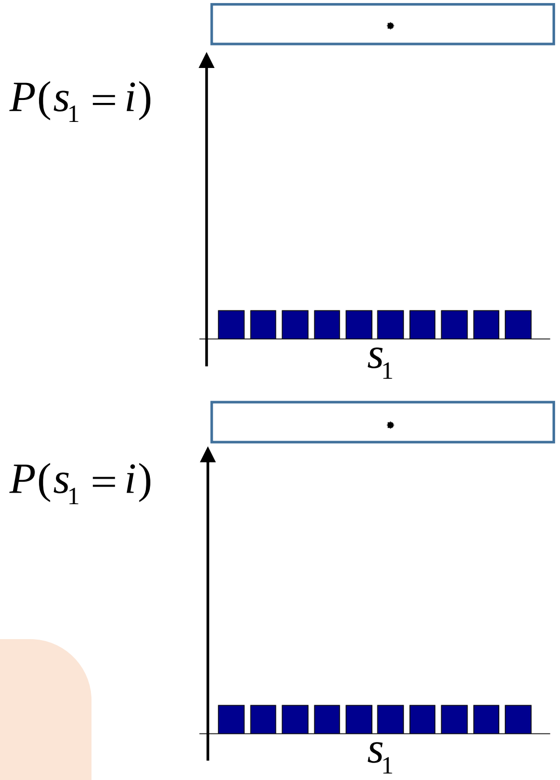
$\dot{\gamma}$

Neurotransmitter	Precision	Evidence
Acetylcholine	Likelihood	• Presence of presynaptic receptors on thalamocortical afferents (Sahin, Bowen et al. 1992, Lavine, Reuben et al. 1997) • Modulation of gain of visually evoked responses (Gil, Connors et al. 1997, Disney, Aoki et al. 2007) • Changes in effective connectivity with pharmacological manipulations (Moran, Campo et al. 2013) • Modelling of behavioral responses under pharmacological manipulation (Vossel, Bauer et al. 2014, Marshall, Mathys et al. 2016)
Noradrenaline	Transitions	• Maintenance of persistent prefrontal (delay-period) activity (requiring precise transition probabilities) depends upon noradrenaline (Arnsten and Li 2005, Zhang, Cordeiro Matos et al. 2013) • Pupillary responses to surprising (i.e. imprecise) sequences (Lavín, San Martín et al. 2013, Liao, Yoneya et al. 2016, Vincent et al, 2019) • Modelling of behavioral responses under pharmacological manipulation (Marshall, Mathys et al. 2016)
Dopamine	Policies	• Expressed post-synaptically on striatal medium spiny neurons (Freund, Powell et al. 1984, Yager, Garcia et al. 2015) • Computational fMRI reveals midbrain activity with changes in precision (Schwartenbeck, FitzGerald et al. 2015) • Modelling of behavioral responses under pharmacological manipulation (Marshall, Mathys et al. 2016)
Serotonin	Preferences or interoceptive likelihood	• Receptors expressed on layer V pyramidal cells (Aghajanian and Marek 1999, Lambe, Goldman-Rakic et al. 2000, Elliott, Tanaka et al. 2018) in medial prefrontal cortex • Medial prefrontal cortical regions heavily implicated in interoceptive processing and autonomic regulation (Marek, Strobel et al. 2013, Mukherjee, Sabharwal et al. 2016)

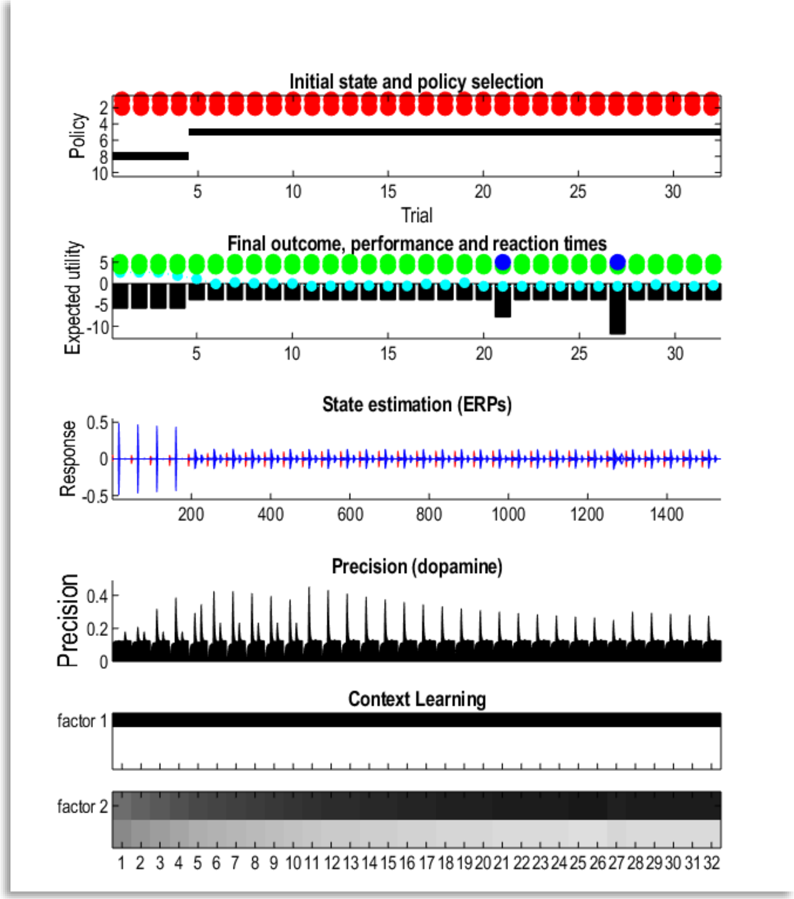
Parr and Friston 2019

a, b, c, **d**, e





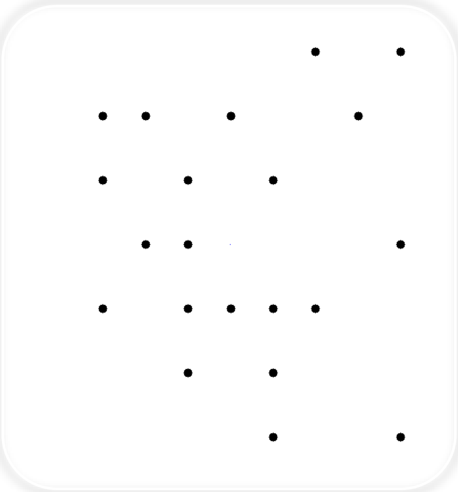

```
mdp.d{1} = D{1}*128;
mdp.d{2} = D{2}*4;
clear MDP
[MDP(1:32)] = deal(mdp);
MDP = spm_MDP_VB_X(MDP);
spm_figure('GetWin','Figure 3'); clf
spm_MDP_VB_game(MDP)
```

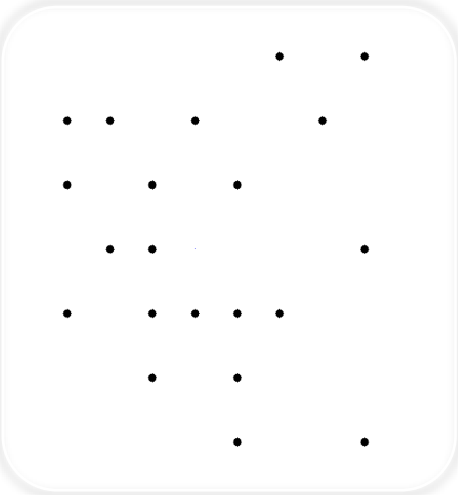


Learning

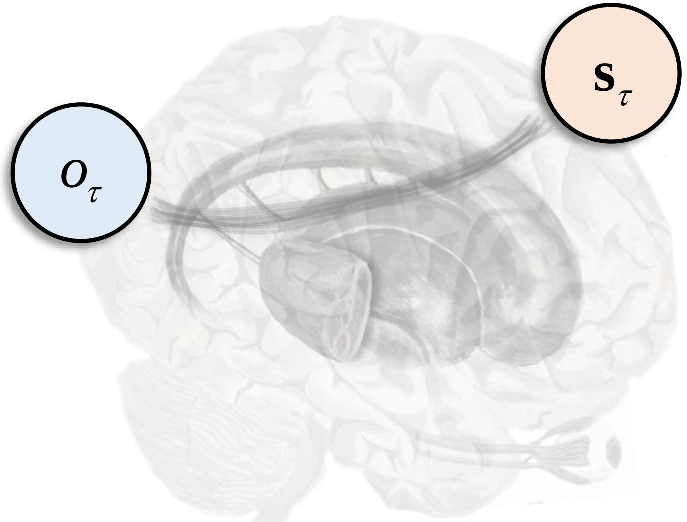
$$\nabla_{E[\ln D]} F = 0 \Leftrightarrow \mathbf{d} = d + \mathbf{s}_1$$

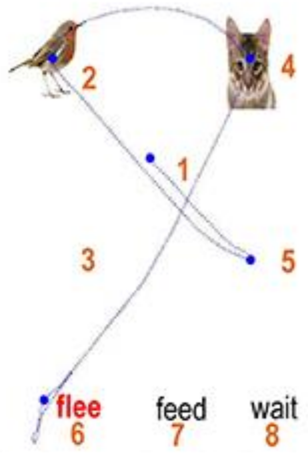
$$E[D_i] = \frac{\mathbf{d}_i}{\sum_k \mathbf{d}_k}$$





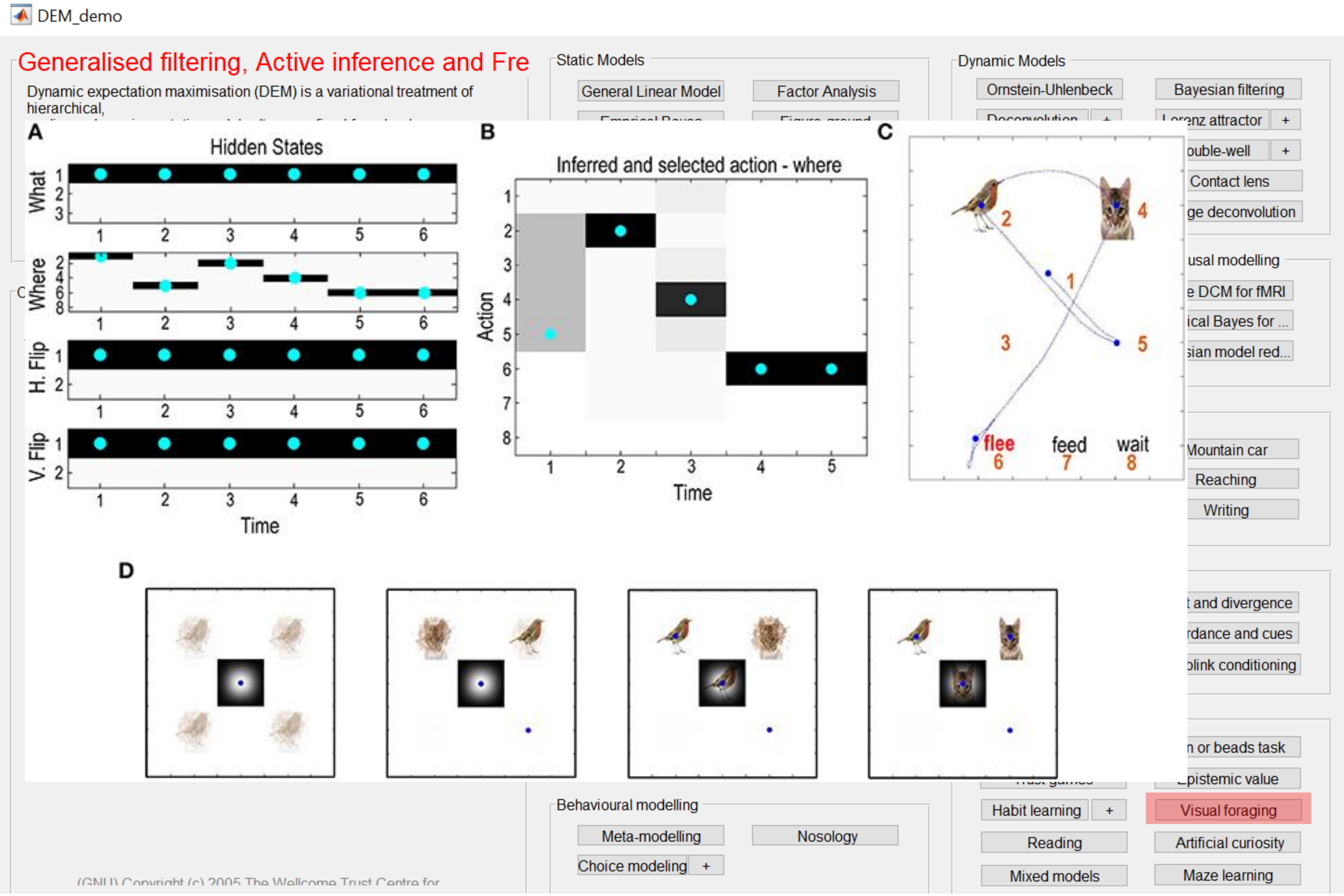
$$
\begin{aligned}
P(\pi) &= \sigma(-\mathbf{G}) \\
&= \sigma\Big(E_{\tilde{Q}}[\ln P(\tilde{o}) + D_{KL}[Q(A \mid \tilde{o}) \,\|\, Q(A)]]\Big)
\end{aligned}
$$



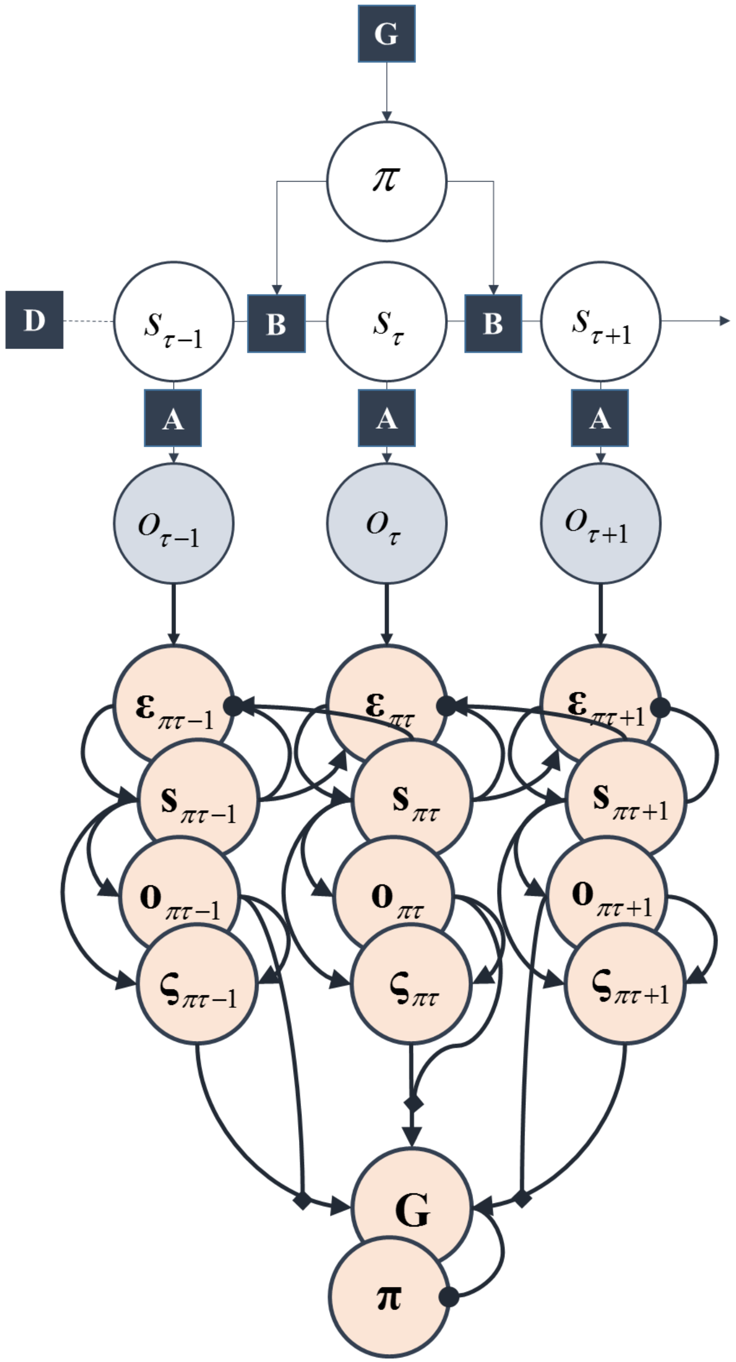


Visual foraging and hierarchical inference

>> DEM



Mirza et al., 2016



G
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o_{τ}
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$\boldsymbol{\varepsilon}_{\pi\tau-1}$
$\boldsymbol{\varepsilon}_{\pi\tau}$
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$\mathbf{o}_{\pi\tau}$
$\mathbf{o}_{\pi\tau+1}$
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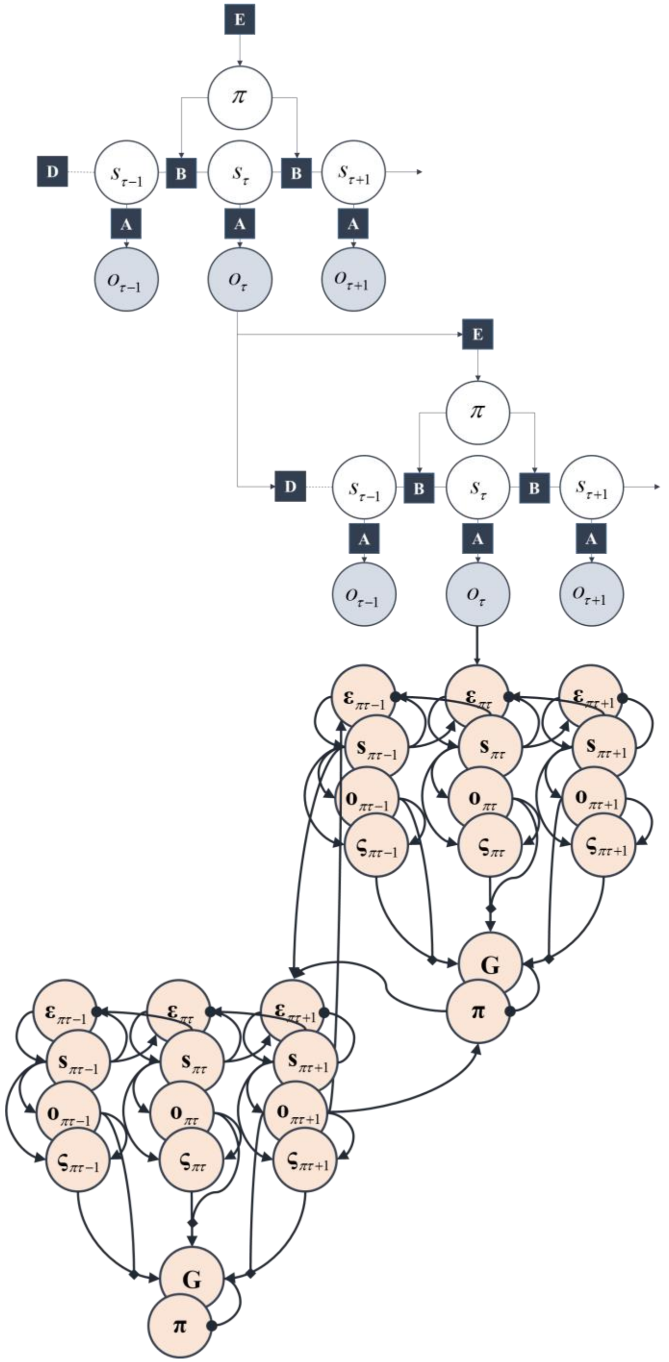
$\boldsymbol{\pi}$



E
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D
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B
$s_{\tau-1}$
s_{τ}
$s_{\tau+1}$
A
A
A
$o_{\tau-1}$
o_{τ}
$o_{\tau+1}$
E
π
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$s_{\tau-1}$
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$s_{\tau+1}$
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A
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$\mathbf{s}_{\pi\tau}$
$\mathbf{s}_{\pi\tau+1}$
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$\mathbf{o}_{\pi\tau}$
$\mathbf{o}_{\pi\tau+1}$
$\varsigma_{\pi\tau-1}$
$\varsigma_{\pi\tau}$
$\varsigma_{\pi\tau+1}$
G
$\boldsymbol{\pi}$
$\boldsymbol{\varepsilon}_{\pi\tau-1}$
$\boldsymbol{\varepsilon}_{\pi\tau}$
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$\mathbf{s}_{\pi\tau-1}$
$\mathbf{s}_{\pi\tau}$
$\mathbf{s}_{\pi\tau+1}$
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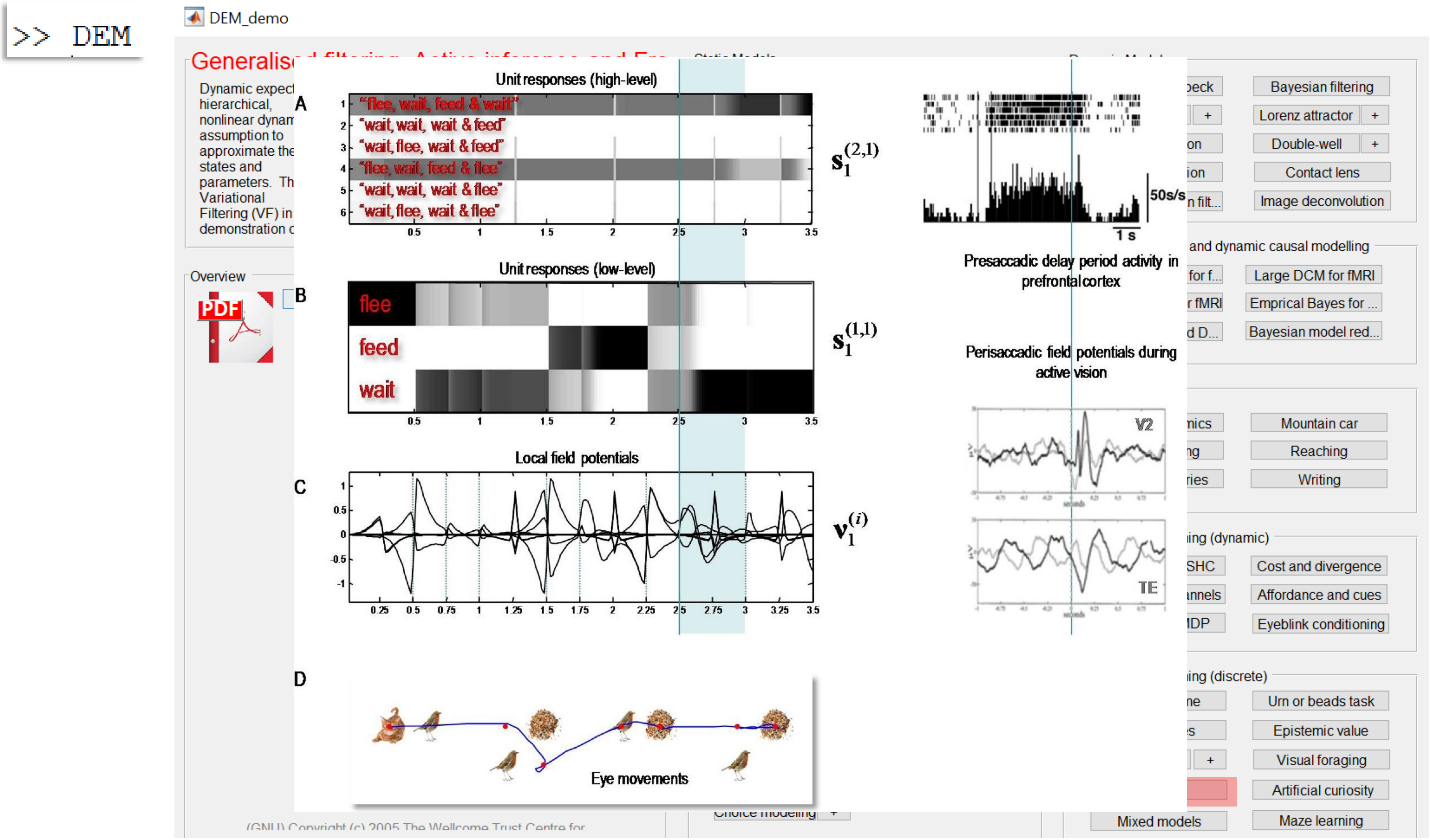
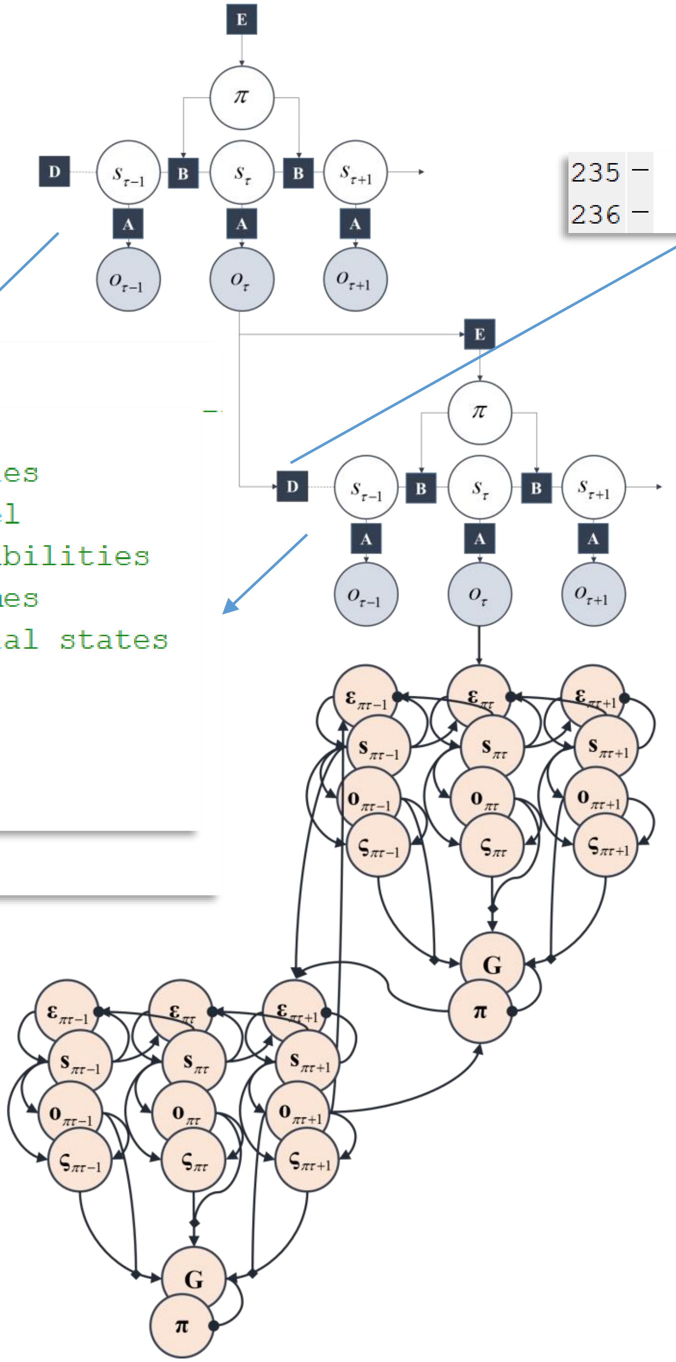
$\mathbf{o}_{\pi\tau}$
$\mathbf{o}_{\pi\tau+1}$
$\varsigma_{\pi\tau-1}$
$\varsigma_{\pi\tau}$
$\varsigma_{\pi\tau+1}$
G
$\boldsymbol{\pi}$



Friston et al., 2018

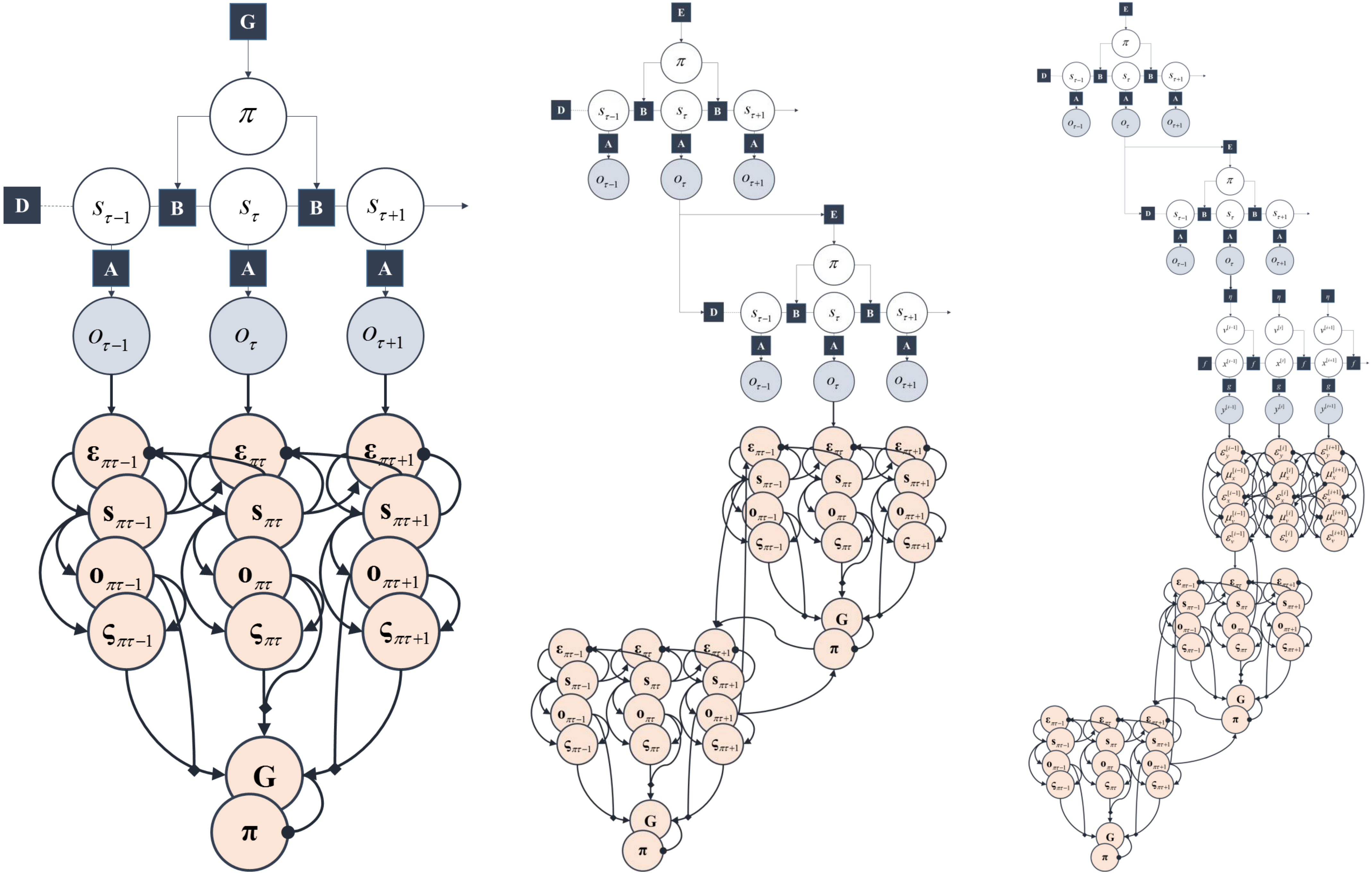
```
mdp.MDP   = MDP;
mdp.link  = sparse(1,1,1,numel(MDP.D),Ng);
```

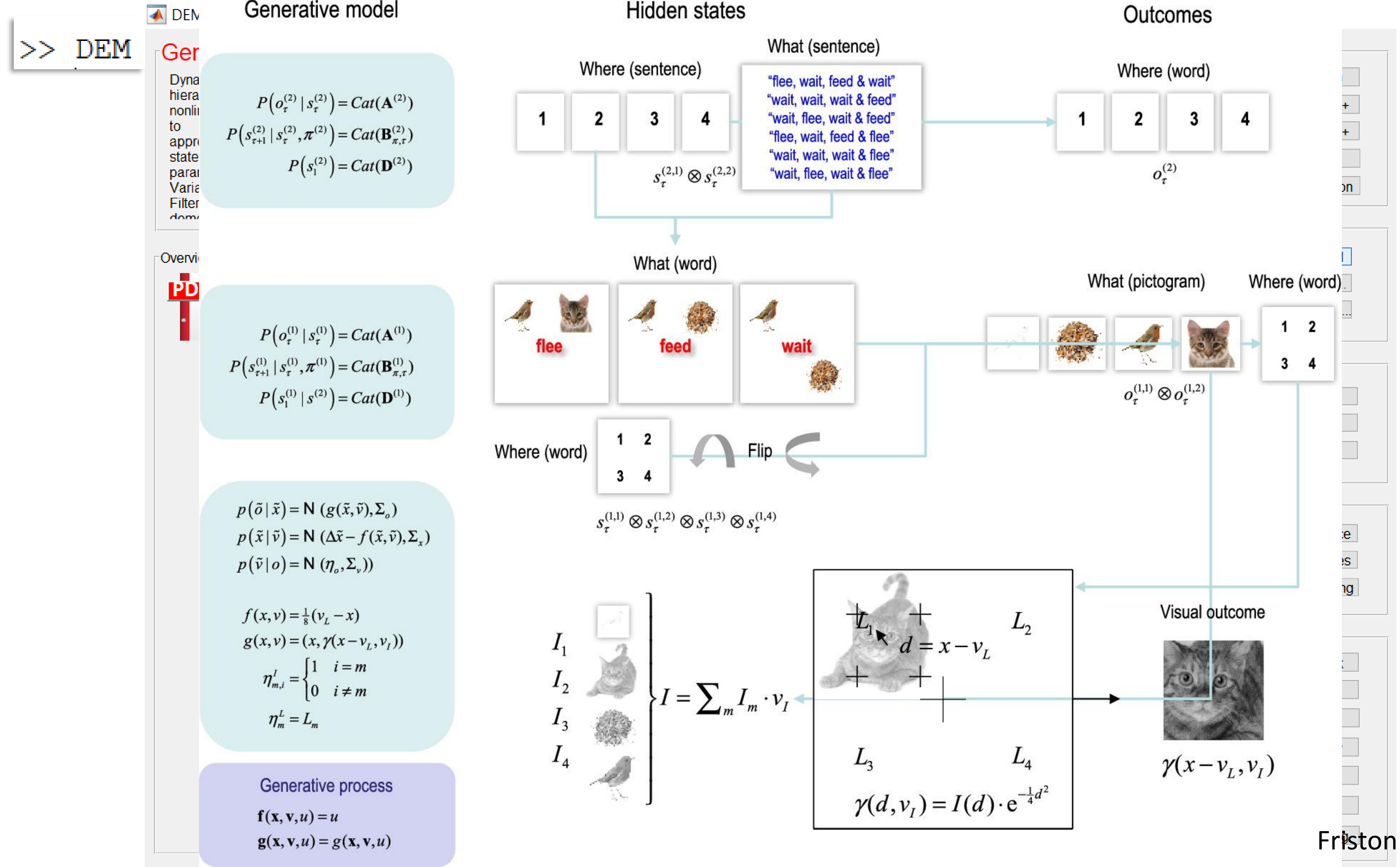


```
% MDP Structure
```

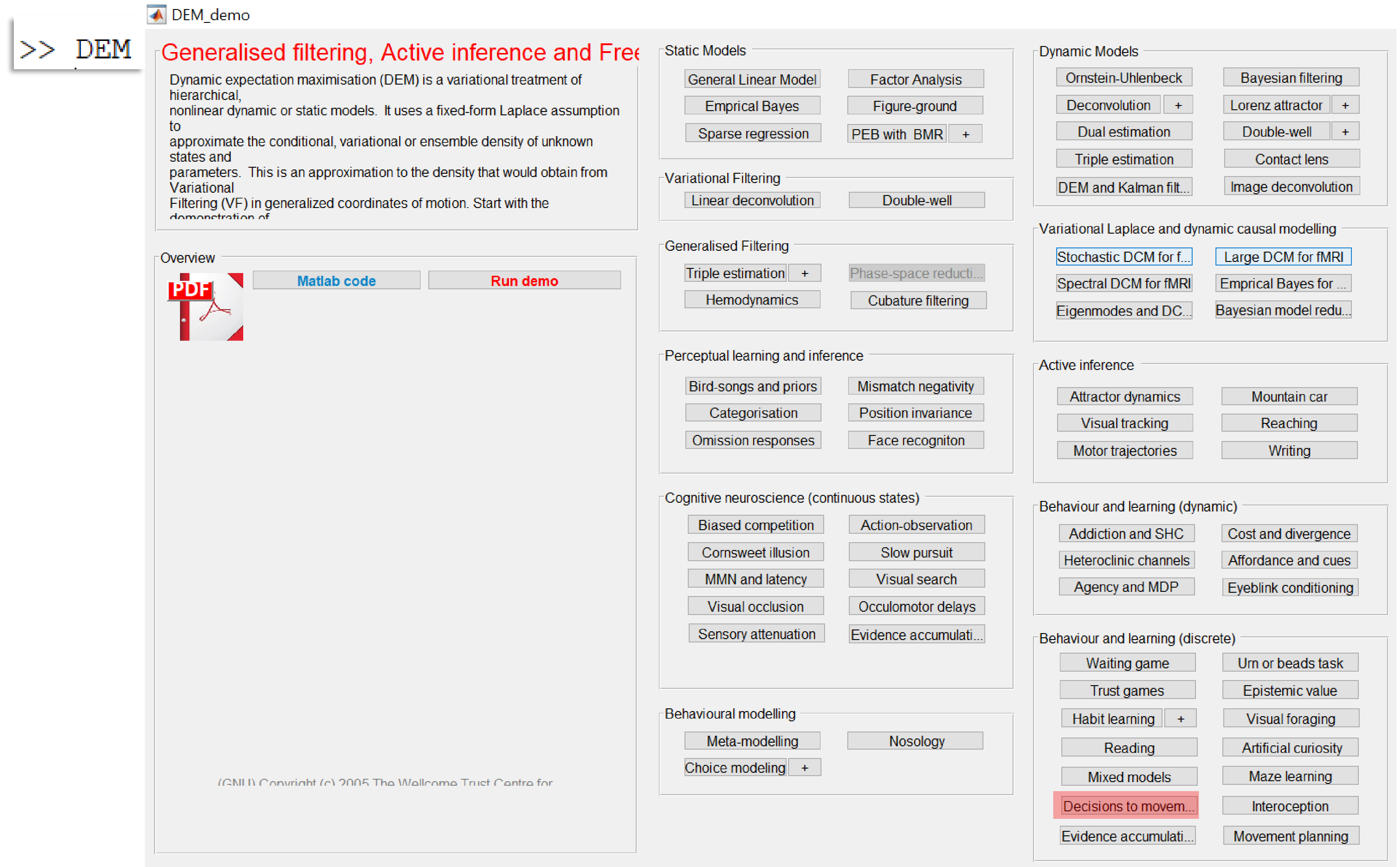
```
mdp.T = 5;                      % number of moves
mdp.U = U;                      % allowable policies
mdp.A = A;                      % observation model
mdp.B = B;                      % transition probabilities
mdp.C = C;                      % preferred outcomes
mdp.D = D;                      % prior over initial states
mdp.s = [1 1 1]';               % initial state

mdp.Aname   = {'picture','where','feedback'};
mdp.Bname   = {'story','where','decision'};
```

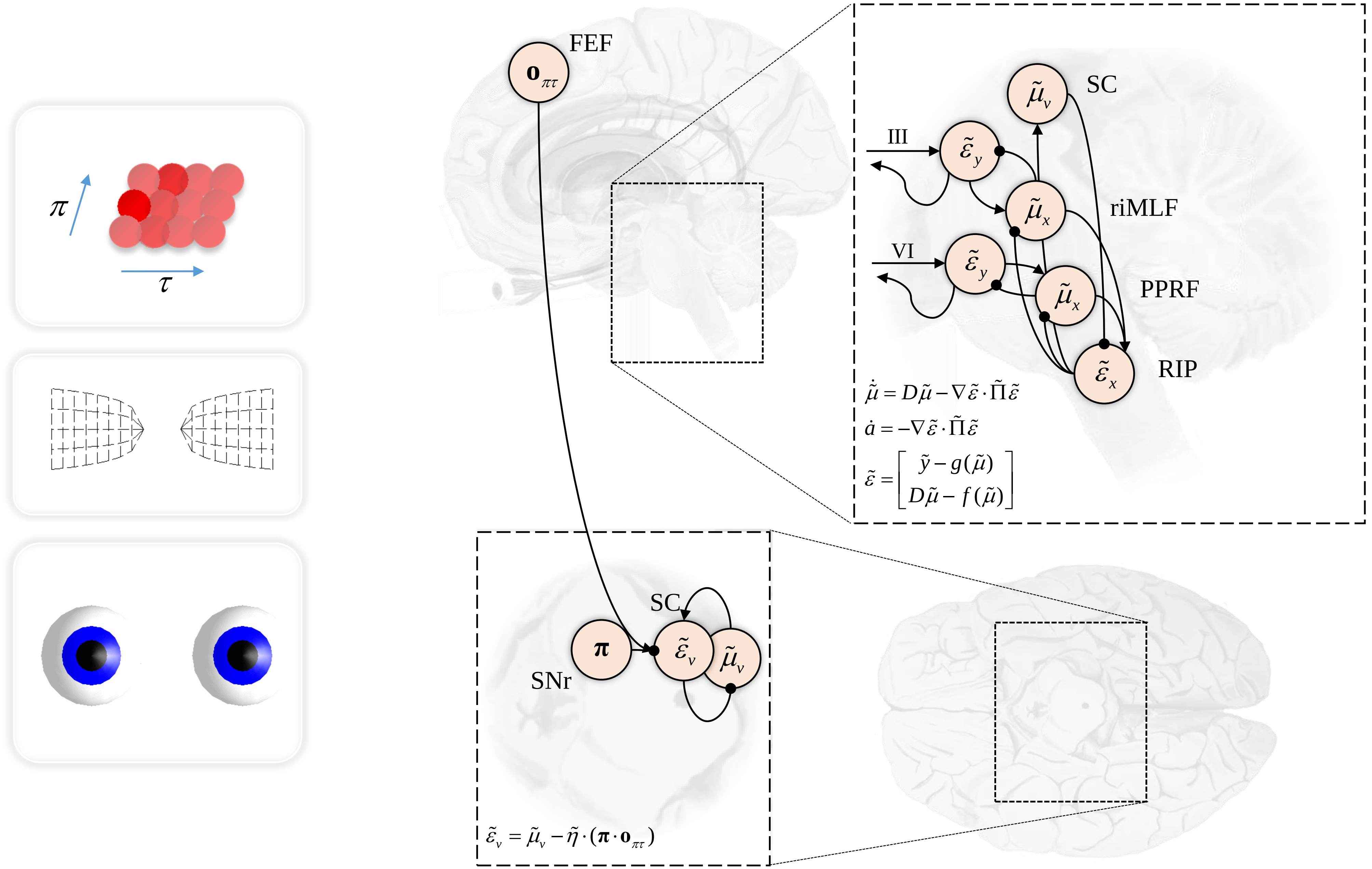
```
clear A B D
```



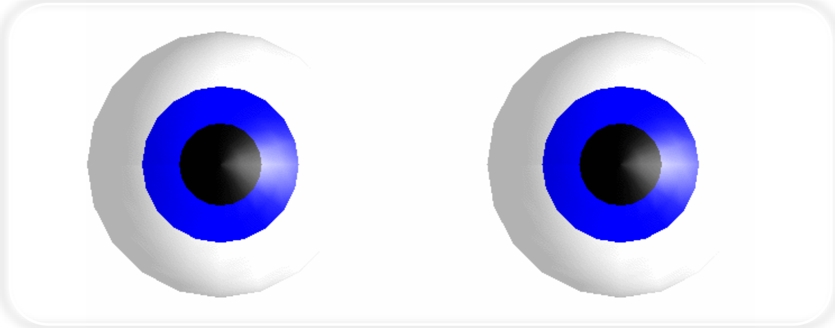


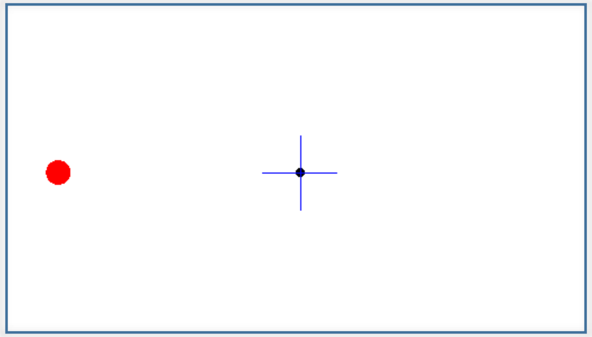
Friston et al., 2018

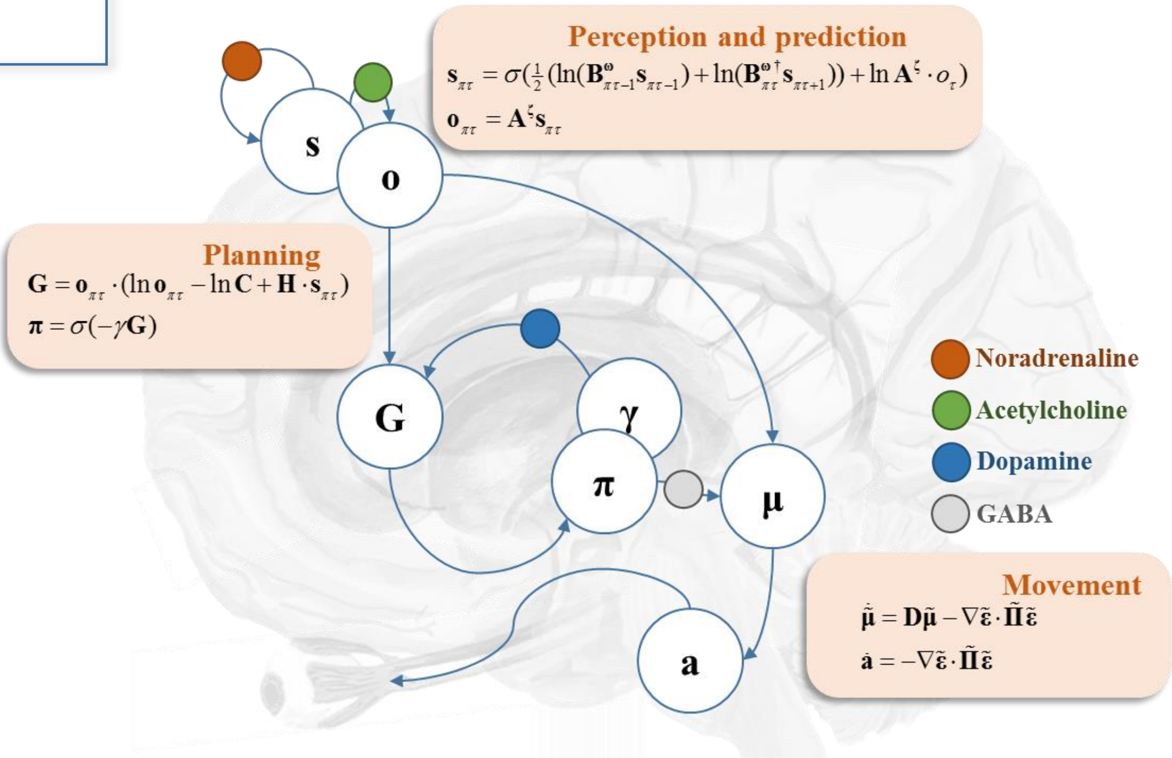

>> DEM
DEM_demo
Generalised filtering, Active inference and Free
Dynamic expectation maximisation (DEM) is a variational treatment of hierarchical,
nonlinear dynamic or static models. It uses a fixed-form Laplace assumption to
approximate the conditional, variational or ensemble density of unknown states and
parameters. This is an approximation to the density that would obtain from Variational
Filtering (VF) in generalized coordinates of motion. Start with the
Overview
PDF
Matlab code
Run demo
(GNU) Copyright (c) 2005 The Wellcome Trust Centre for
Static Models
General Linear Model
Factor Analysis
Emprical Bayes
Figure-ground
Sparse regression
PEB with BMR
+
Variational Filtering
Linear deconvolution
Double-well
Generalised Filtering
Triple estimation
+
Phase-space reducti...
Hemodynamics
Cubature filtering
Perceptual learning and inference
Bird-songs and priors
Mismatch negativity
Categorisation
Position invariance
Omission responses
Face recogniton
Cognitive neuroscience (continuous states)
Biased competition
Action-observation
Cornsweet illusion
Slow pursuit
MMN and latency
Visual search
Visual occlusion
Occulomotor delays
Sensory attenuation
Evidence accumulati...
Behavioural modelling
Meta-modelling
Nosology
Choice modeling
+
Dynamic Models
Ornstein-Uhlenbeck
Bayesian filtering
Deconvolution
+
Lorenz attractor
+
Dual estimation
Double-well
+
Triple estimation
Contact lens
DEM and Kalman filt...
Image deconvolution
Variational Laplace and dynamic causal modelling
Stochastic DCM for f...
Large DCM for fMRI
Spectral DCM for fMRI
Emprical Bayes for ...
Eigenmodes and DC...
Bayesian model redu...
Active inference
Attractor dynamics
Mountain car
Visual tracking
Reaching
Motor trajectories
Writing
Behaviour and learning (dynamic)
Addiction and SHC
Cost and divergence
Heteroclinic channels
Affordance and cues
Agency and MDP
Eyeblink conditioning
Behaviour and learning (discrete)
Waiting game
Urn or beads task
Trust games
Epistemic value
Habit learning
+
Visual foraging
Reading
Artificial curiosity
Mixed models
Maze learning
Decisions to movem...
Interoception
Evidence accumulati...
Movement planning



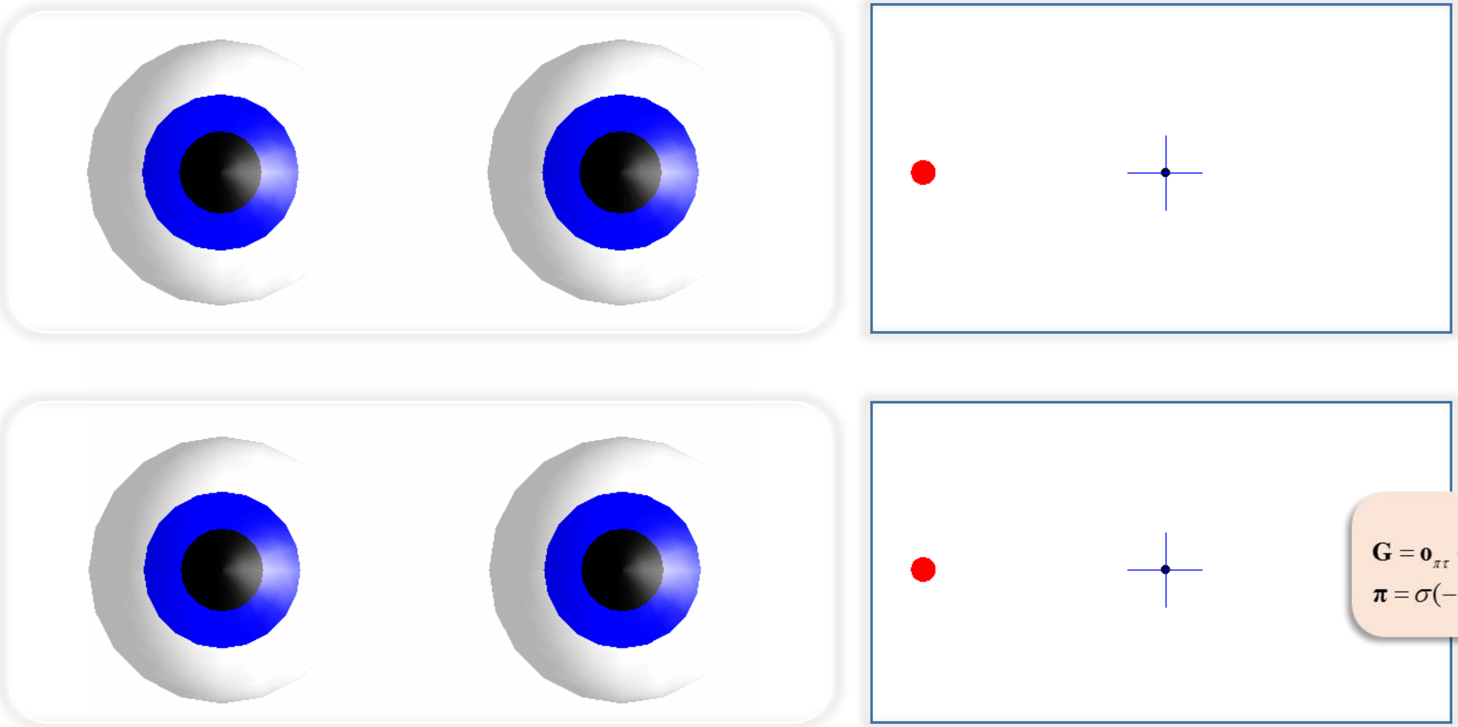
Parr and Friston 2018, Friston and Parr 2019

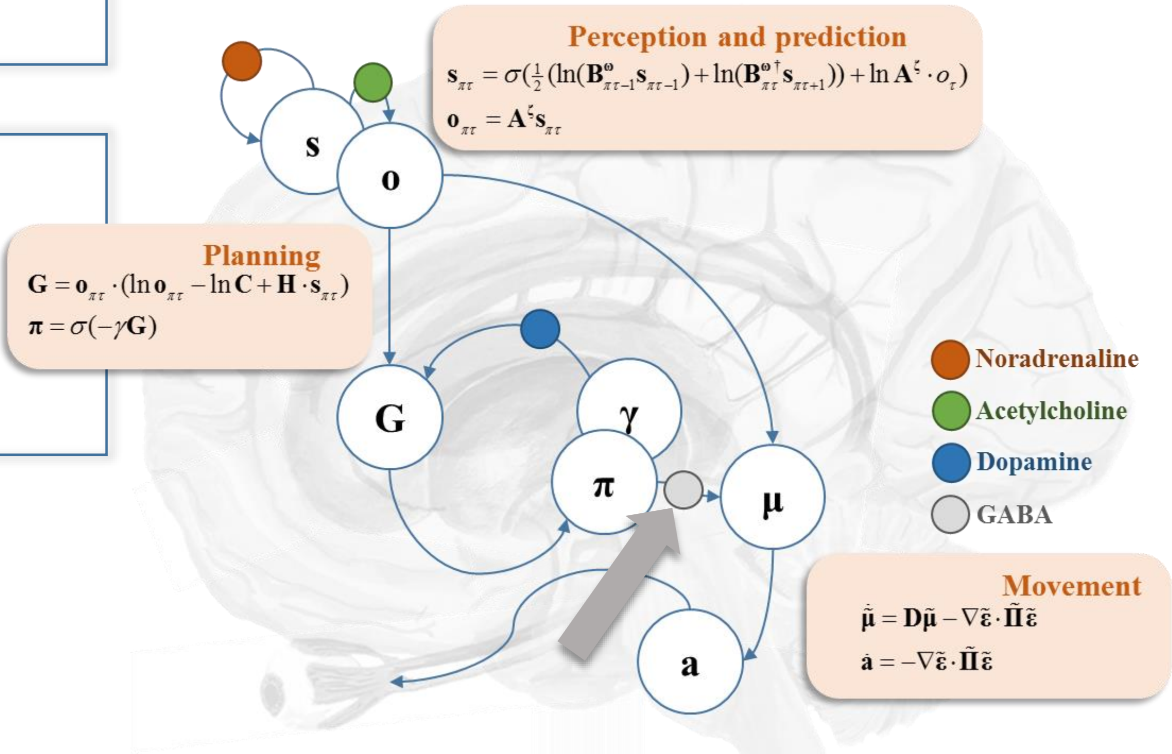




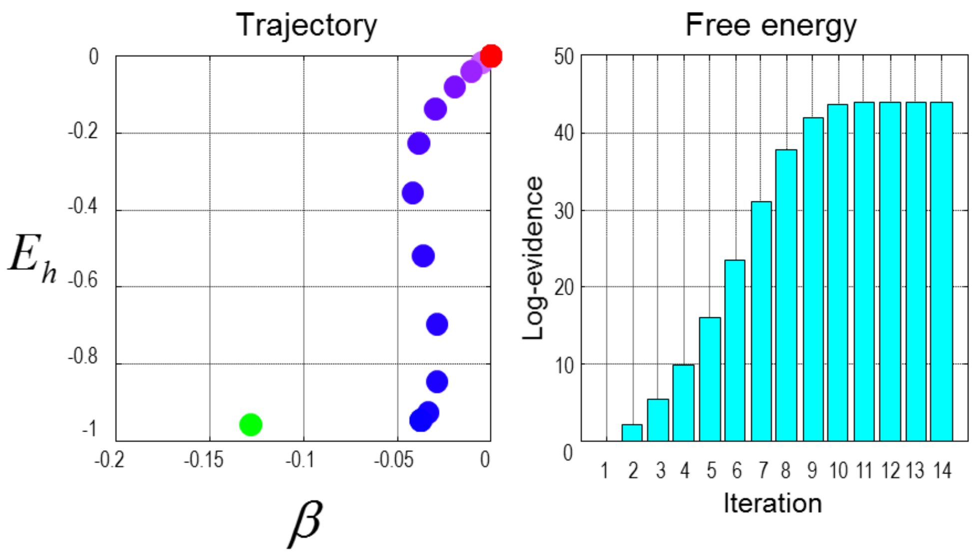


Parr and Friston 2019



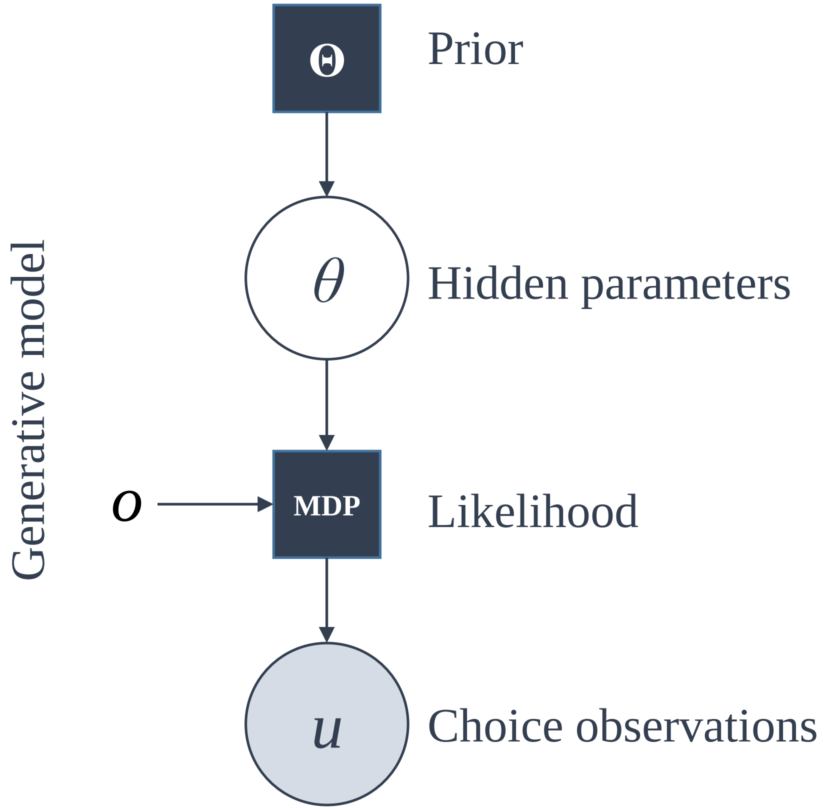


Parr and Friston 2019



Model fitting

$$P(\theta \mid o, u) \propto P(u \mid \theta, o) P(\theta)$$



>> DEM

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Overview

Matlab code | Run demo

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- Figure-ground
- Sparse regression
- PEB with BMR +

Variational Filtering

- Linear deconvolution
- Double-well

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- Phase-space reducti...
- Hemodynamics
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- Evidence accumulati...

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- Nosology
- Choice modeling +

Dynamic Models

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- Bayesian filtering
- Deconvolution +
- Lorenz attractor +
- Dual estimation
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- DEM and Kalman filt...
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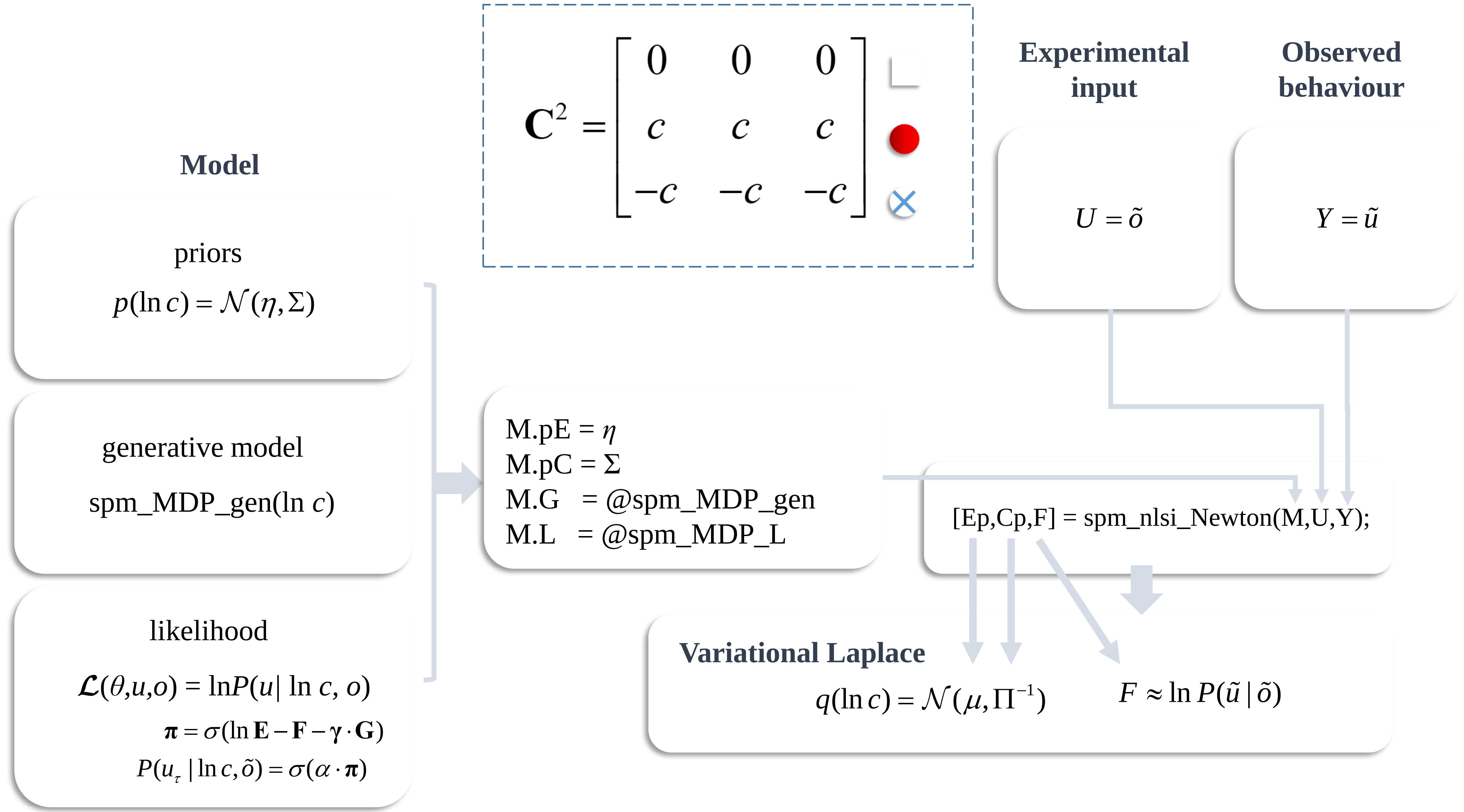


$$\mathbf{C}^2 = \begin{bmatrix} 0 & 0 & 0 \\ c & c & c \\ -c & -c & -c \end{bmatrix}$$
Experimental input
Observed behaviour
Model
$U = \tilde{o}$
$Y = \tilde{u}$
priors
$p(\ln c) = \mathcal{N}(\eta, \Sigma)$
generative model
spm_MDP_gen(ln c)
likelihood
$\mathcal{L}(\theta,u,o) = \ln P(u|\ln c, o)$
$\boldsymbol{\pi} = \sigma(\ln \mathbf{E} - \mathbf{F} - \boldsymbol{\gamma} \cdot \mathbf{G})$
$P(u_\tau | \ln c, \tilde{o}) = \sigma(\alpha \cdot \boldsymbol{\pi})$
M.pE = η
M.pC = Σ
M.G = @spm_MDP_gen
M.L = @spm_MDP_L
[Ep,Cp,F] = spm_nlsi_Newton(M,U,Y);
Variational Laplace
$q(\ln c) = \mathcal{N}(\mu, \Pi^{-1})$
$F \approx \ln P(\tilde{u} | \tilde{o})$

eNeuro

Methods/New Tools

Novel Tools and Methods

Computational Phenotyping in Psychiatry: A Worked Example

Philipp Schwartenbeck,[1,2,3,4] and Karl Friston[1]

DOI:http://dx.doi.org/10.1523/ENEURO.0049-16.2016

[1]The Wellcome Trust Centre for Neuroimaging, UCL, London WC1N 3BG, UK, [2]Centre for Cognitive Neuroscience, University of Salzburg, 5020 Salzburg, Austria, [3]Neuroscience Institute, Christian-Doppler-Klinik, Paracelsus Medical University Salzburg, A-5020 Salzburg, Austria, and [4]Max Planck UCL Centre for Computational Psychiatry and Ageing Research, London WC1B 5EH, UK

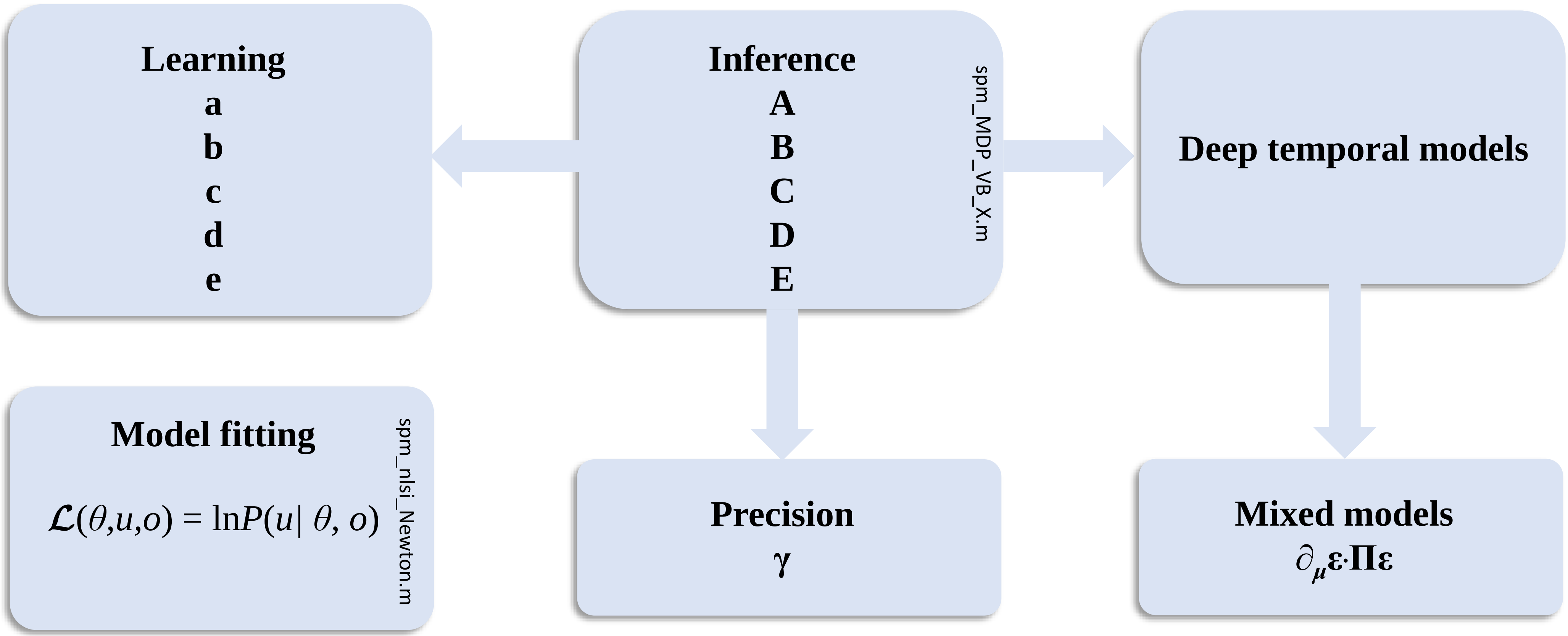
PLOS | ONE

RESEARCH ARTICLE

Human visual exploration reduces uncertainty about the sensed world

M. Berk Mirza[1]*, Rick A. Adams[2,3], Christoph Mathys[1,4,5,6], Karl J. Friston[1]

1 Wellcome Trust Centre for Neuroimaging, Institute of Neurology, University College London, London, United Kingdom, **2** Institute of Cognitive Neuroscience, University College London, London, United Kingdom, **3** Division of Psychiatry, University College London, London, United Kingdom, **4** Scuola Internazionale Superiore di Studi Avanzati (SISSA), Trieste, Italy, **5** Translational Neuromodeling Unit (TNU), Institute for Biomedical Engineering, University of Zurich and ETH Zurich, Zurich, Switzerland, **6** Max Planck UCL Centre for Computational Psychiatry and Ageing Research, London, United Kingdom


Learning
a
b
c
d
e
Inference
A
B
C
D
E
spm_MDP_VB_X.m
Deep temporal models
Model fitting
$\mathcal{L}(\theta,u,o) = \ln P(u|\ \theta, o)$
spm_nlsi_Newton.m
Precision
γ
Mixed models
$\partial_{\mu}\boldsymbol{\varepsilon}\cdot\boldsymbol{\Pi}\boldsymbol{\varepsilon}$

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Geraint Rees

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David Benrimoh
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Ensor Palacios
Hayriye Cagnan
Jakub Limanowski
Jakob Hohwy
Jelle Bruineberg
Michael Kirchoff
Peter Vincent
Philipp Schwartenbeck
Rick Adams
Stefan Kiebel
Tim Sandhu
Takuya Isomura

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