ETH zürich

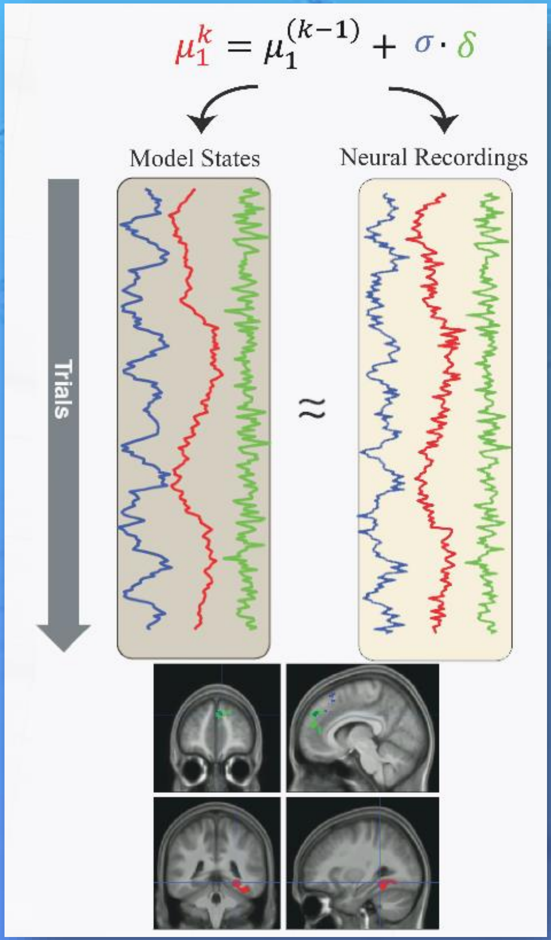
University of Zurich[UZH]

Translational Neuromodeling Unit

Computational Neuroimaging

Andreea Diaconescu

Methods & Models 2017



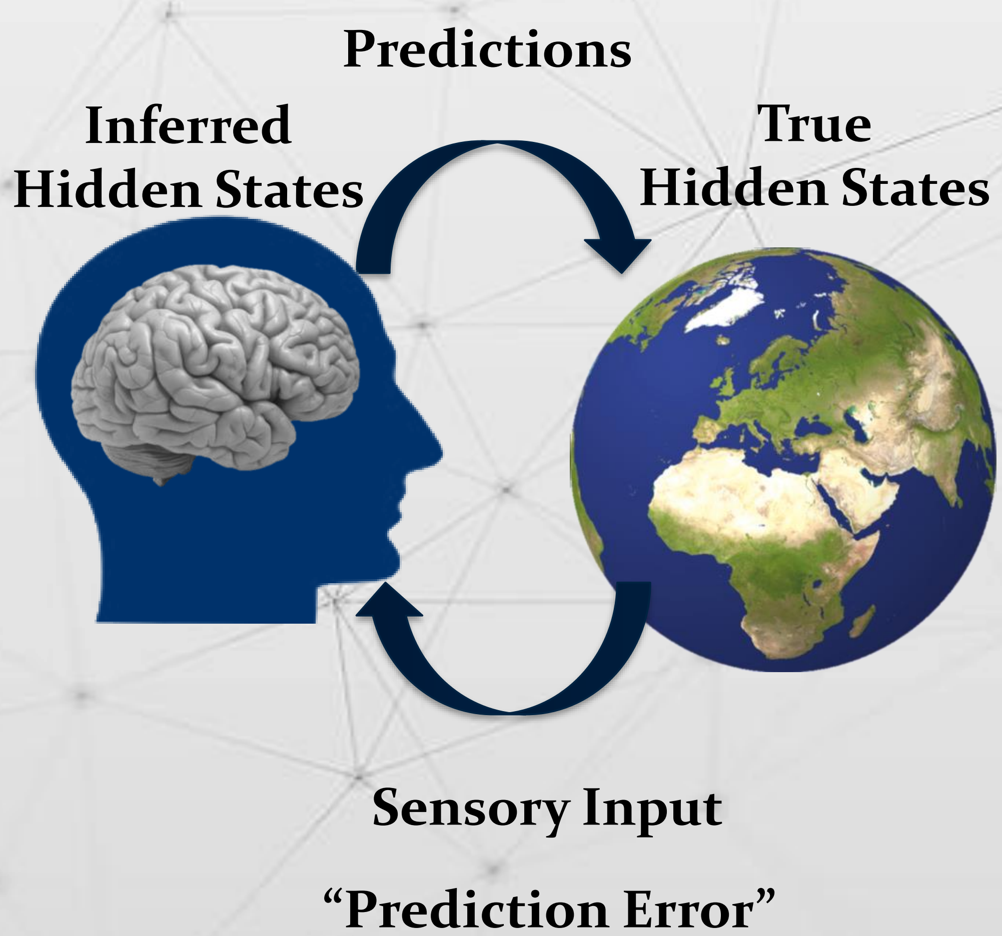
What is it all about?

Translational Neuromodeling Unit

- Why do we use functional magnetic resonance imaging?
  - To measure brain activity
- When does the brain become active?
  - When it learns
    i.e., when its predictions have to be adjusted
- Where do these predictions come from?
  - A model

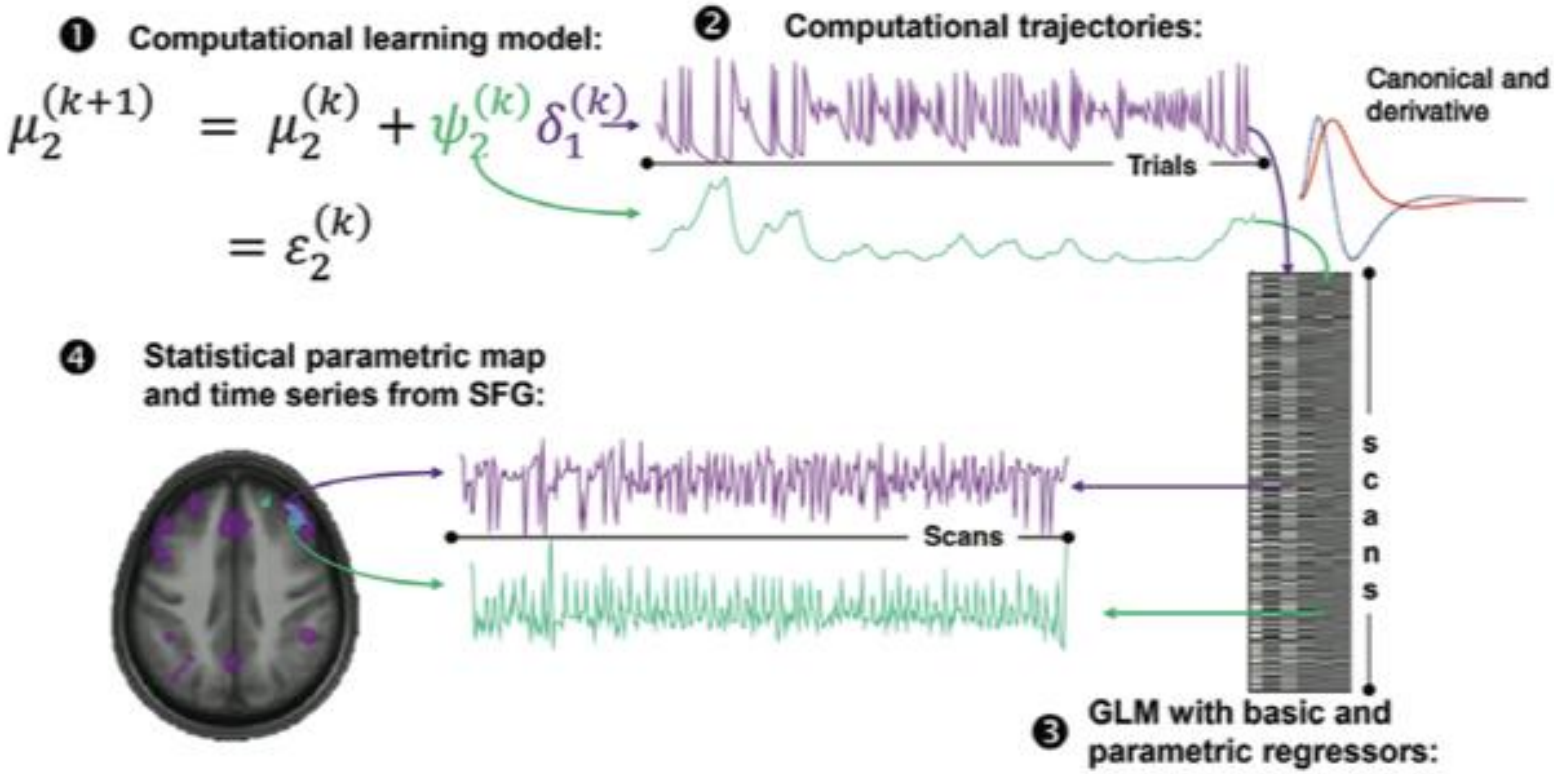
How to build a model

Translational Neuromodeling Unit



Computational Neuroimaging

Translational Neuromodeling Unit



Iglesias et al., 2016

Advantages of computational neuroimaging

Translational Neuromodeling Unit

- Computational neuroimaging permits us to:
  - **Infer** the computational mechanisms underlying brain function
  - **Localize** such mechanisms
  - **Compare** different models

Explanatory Gap

Translational Neuromodeling Unit

Biological

- Molecular
- Neurochemical

Cognitive

- Computational
- “cognitive/
- computational phenotyping”

Phenomenological

- Performance Accuracy
- Reaction Time
- Choices, preferences

Computational Models

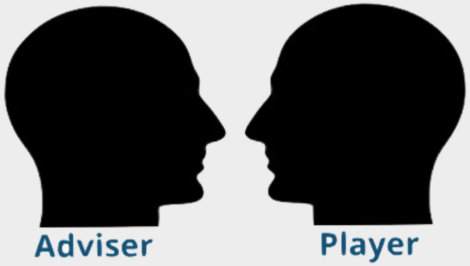
Three Levels of Inference

- *Computational Level*: predictions, prediction errors
- *Algorithmic Level*: reinforcement learning, hierarchical Bayesian inference, predictive coding
- *Implementational Level*: Brain activity, neuromodulation

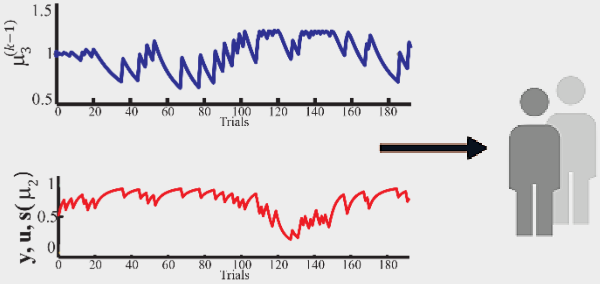
David Marr, 1982

- **3 ingredients**:

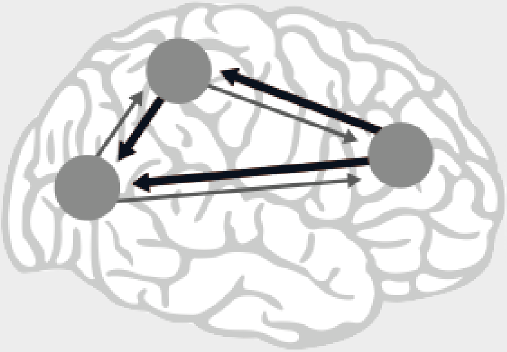
1. Experimental paradigm:



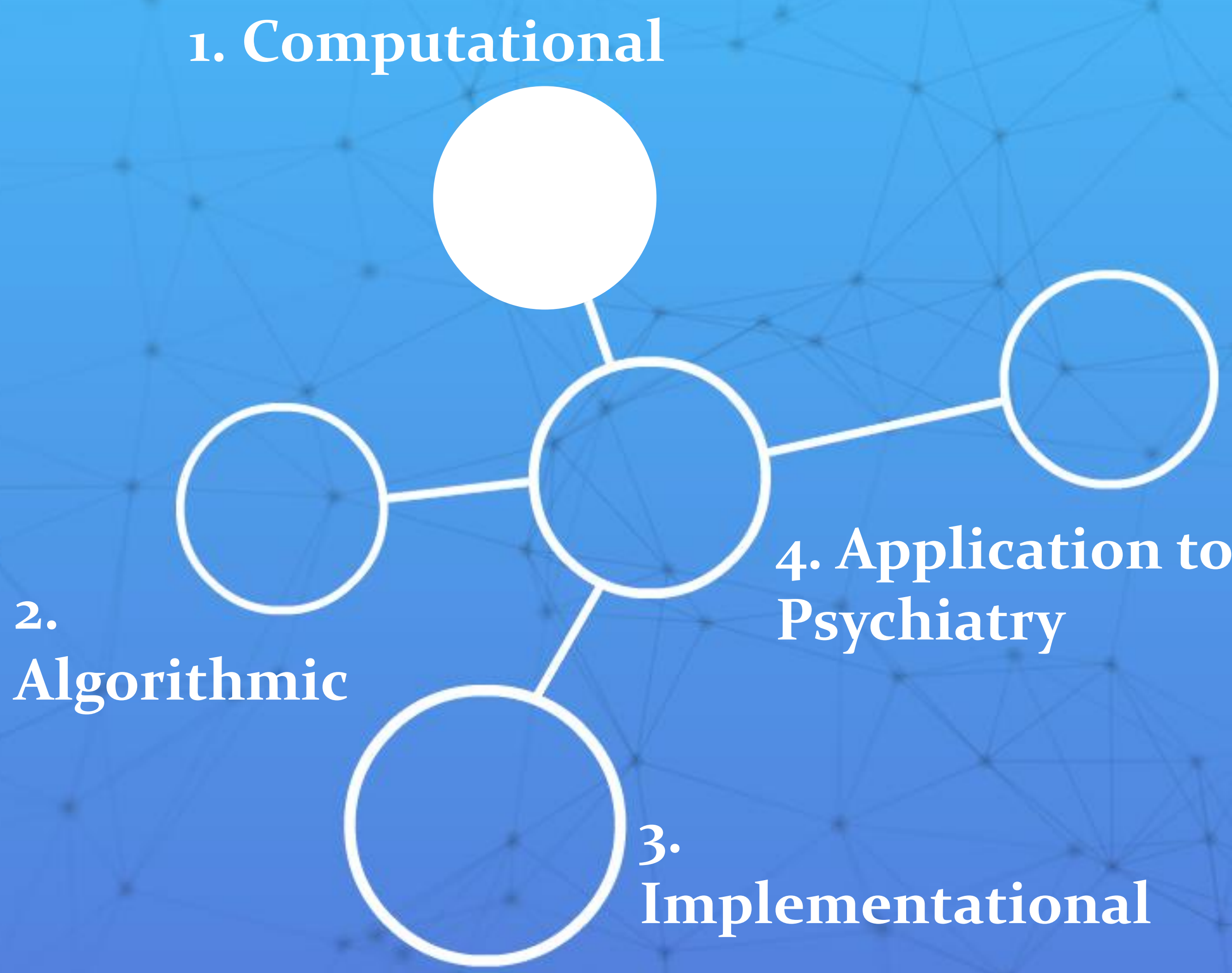
2. Computational model of learning:



3. Model-based fMRI analysis:



Outline


1. Computational
2. Algorithmic
3. Implementational
4. Application to Psychiatry

Example of a simple model

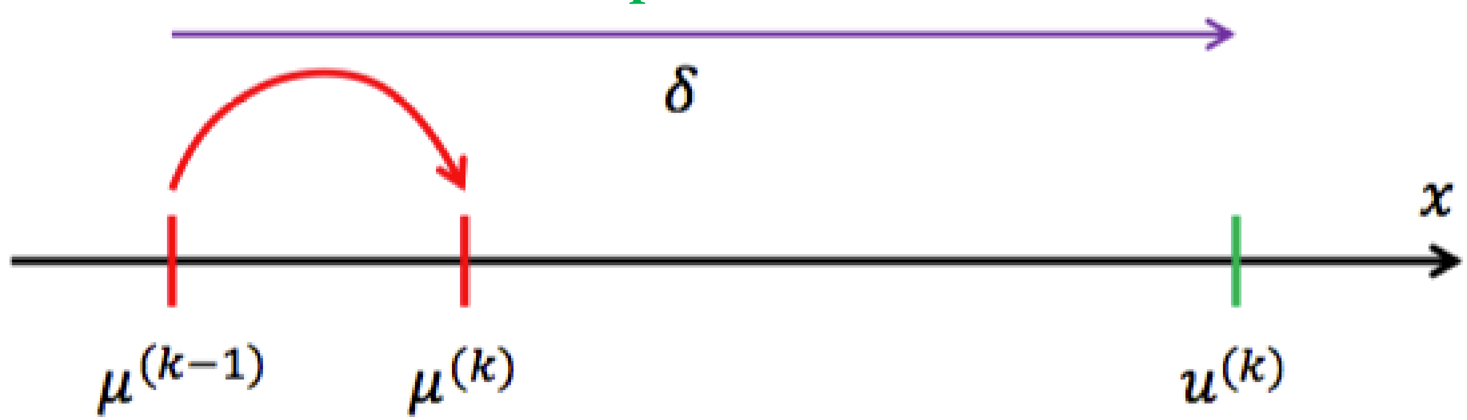
Rescorla-Wagner Learning:

Prediction Error

$$\mu^{(k)} = \mu^{(k-1)} + \alpha(u^{(k)} - \mu^{(k-1)})$$

Inferred States

New Input



Example of a simple model

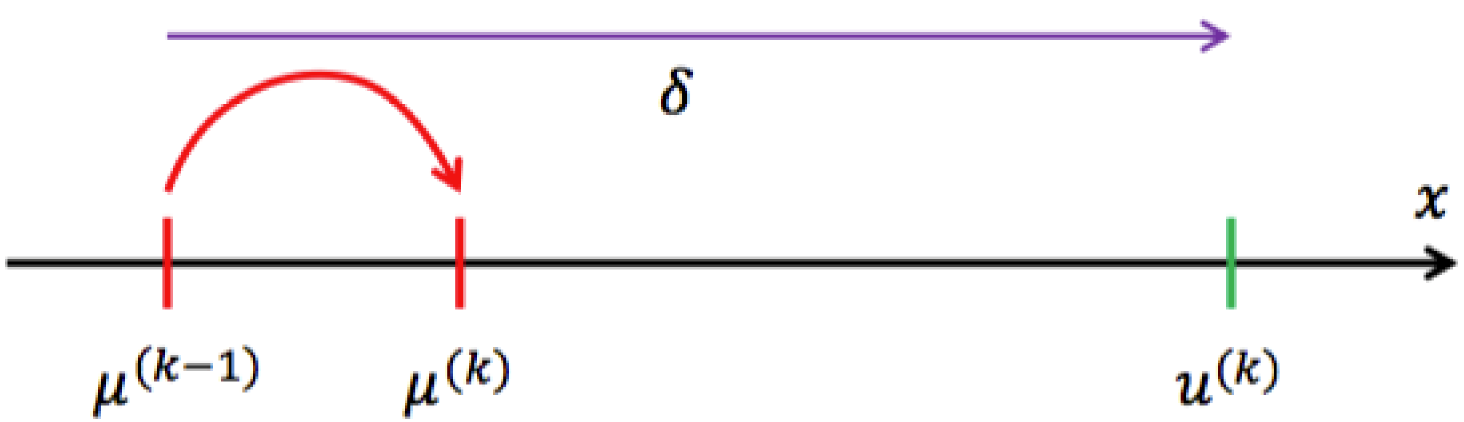
Translational Neuromodeling Unit

Rescorla-Wagner Learning:

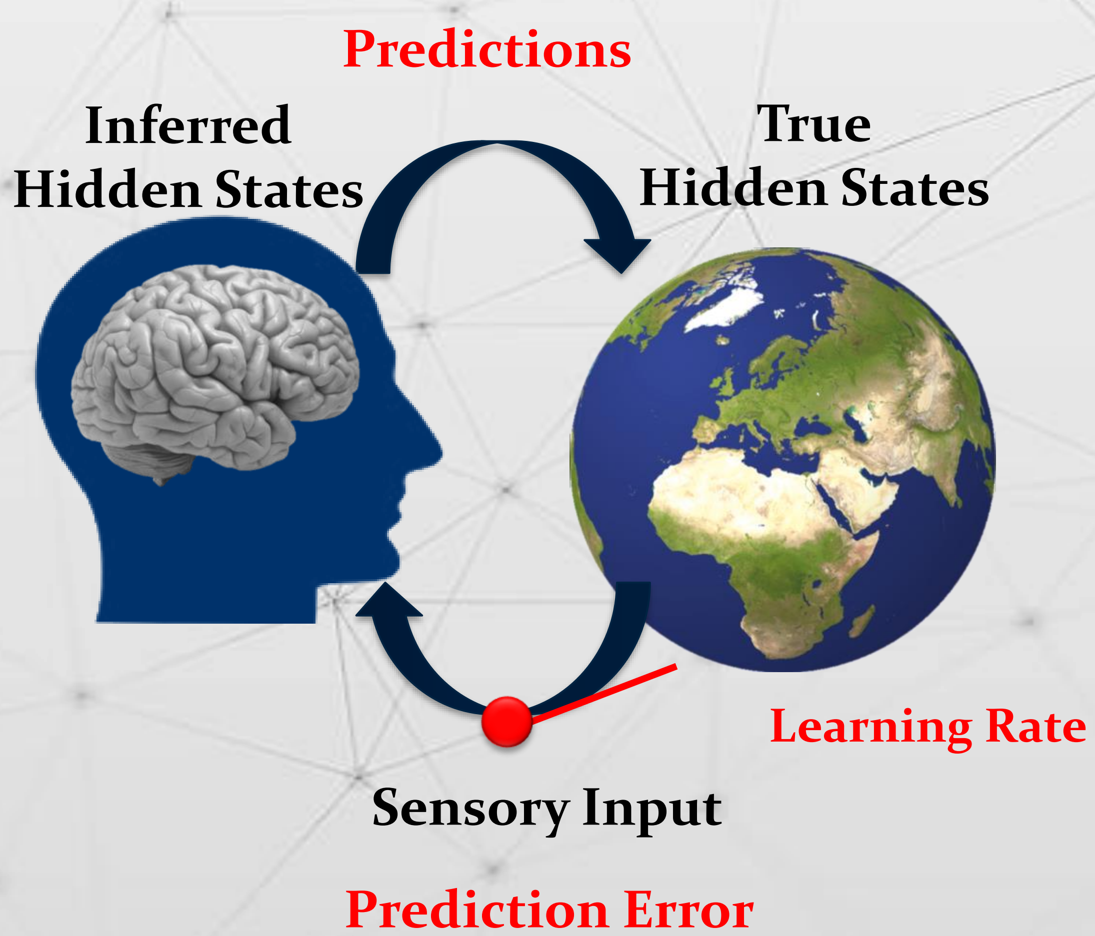
Learning Rate

Belief Update

$$\Delta\mu^{(k)} \propto \alpha\delta$$



Computational Variables



Example of a simple model

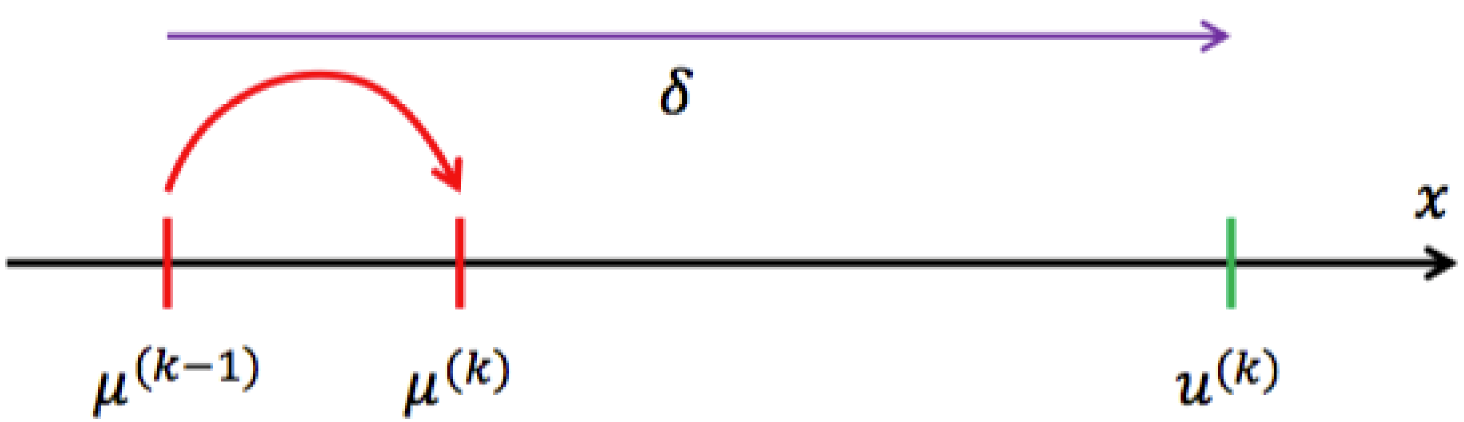
Translational Neuromodeling Unit

Rescorla-Wagner Learning:

Learning Rate

Belief Update

$$\Delta\mu^{(k)} \propto \alpha\delta$$



Example of a hierarchical model

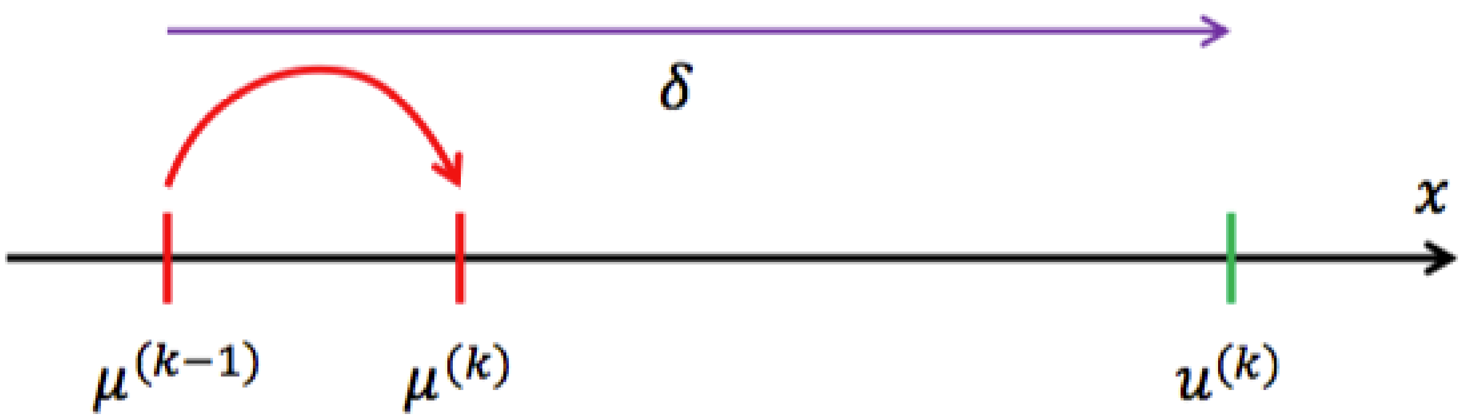
Hierarchical Gaussian Filter :

Weight

Belief Update

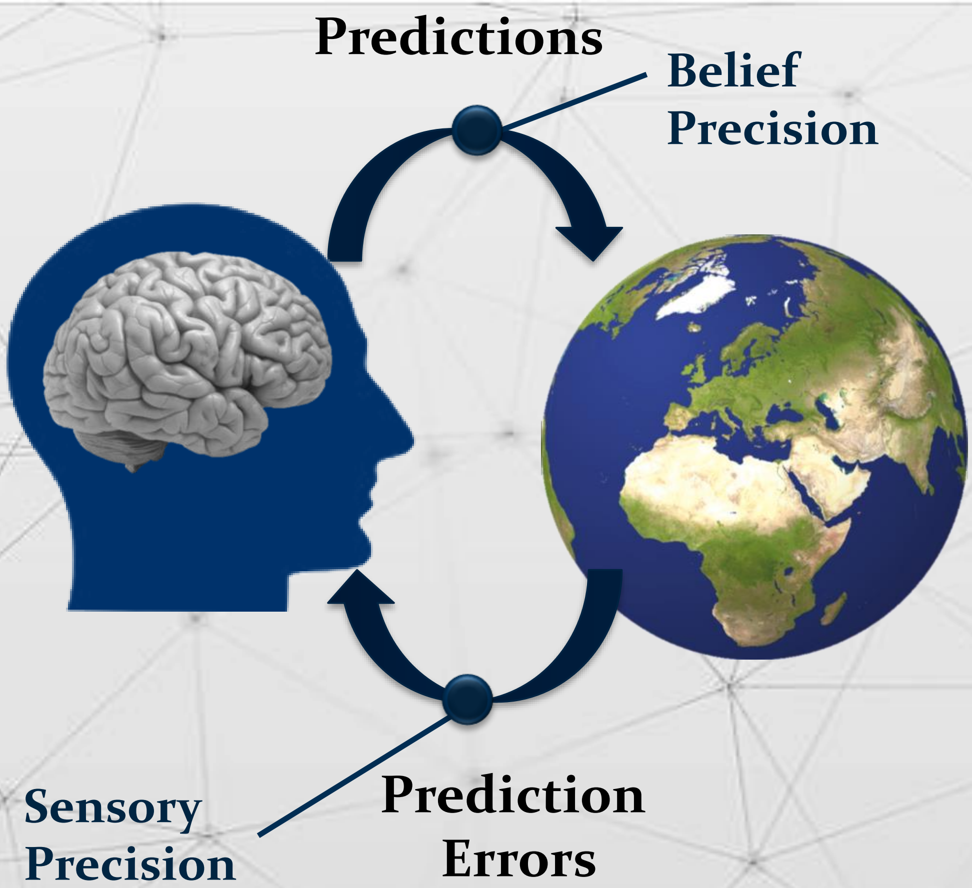
$$\Delta\mu^{(k)} \propto \frac{\hat{\pi}_{i-1}^{(k)}}{\pi_i^{(k)}}\delta$$

$$= \frac{how\ much\ we're\ learning\ here}{how\ much\ we\ already\ know}$$



Inference is Hierarchical

Translational Neuromodeling Unit



- Learning rate as precision-weighted prediction errors

Sensory Precision

$$\Delta\mu_i^{(k)} \propto \frac{\hat{\pi}_{i-1}^{(k)}}{\pi_i^{(k)}}\,\delta_{i-1}^{(k)} \quad \textbf{PE}$$

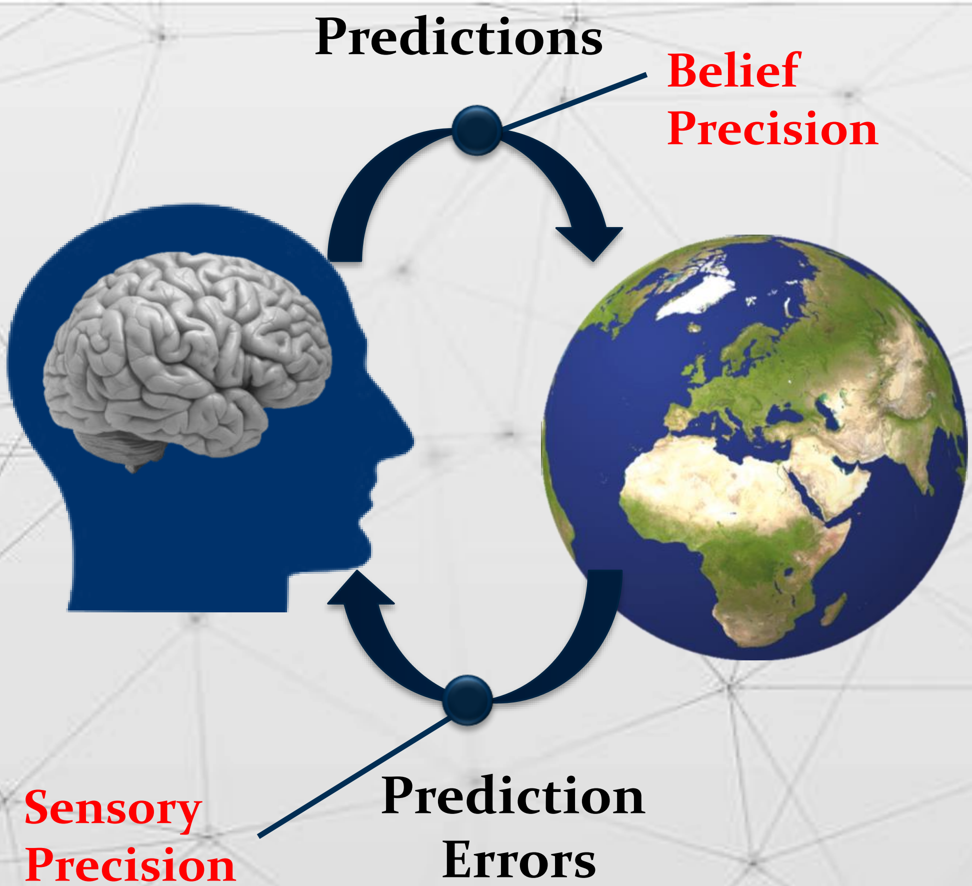
Belief Update

Belief Precision

Mathys et al., *Frontiers Human Neurosci* 2011

Inference is Hierarchical

Translational Neuromodeling Unit



- Learning rate as precision-weighted prediction errors

Sensory Precision

$$\Delta\mu_i^{(k)} \propto \frac{\hat{\pi}_{i-1}^{(k)}}{\pi_i^{(k)}} \delta_{i-1}^{(k)}$$

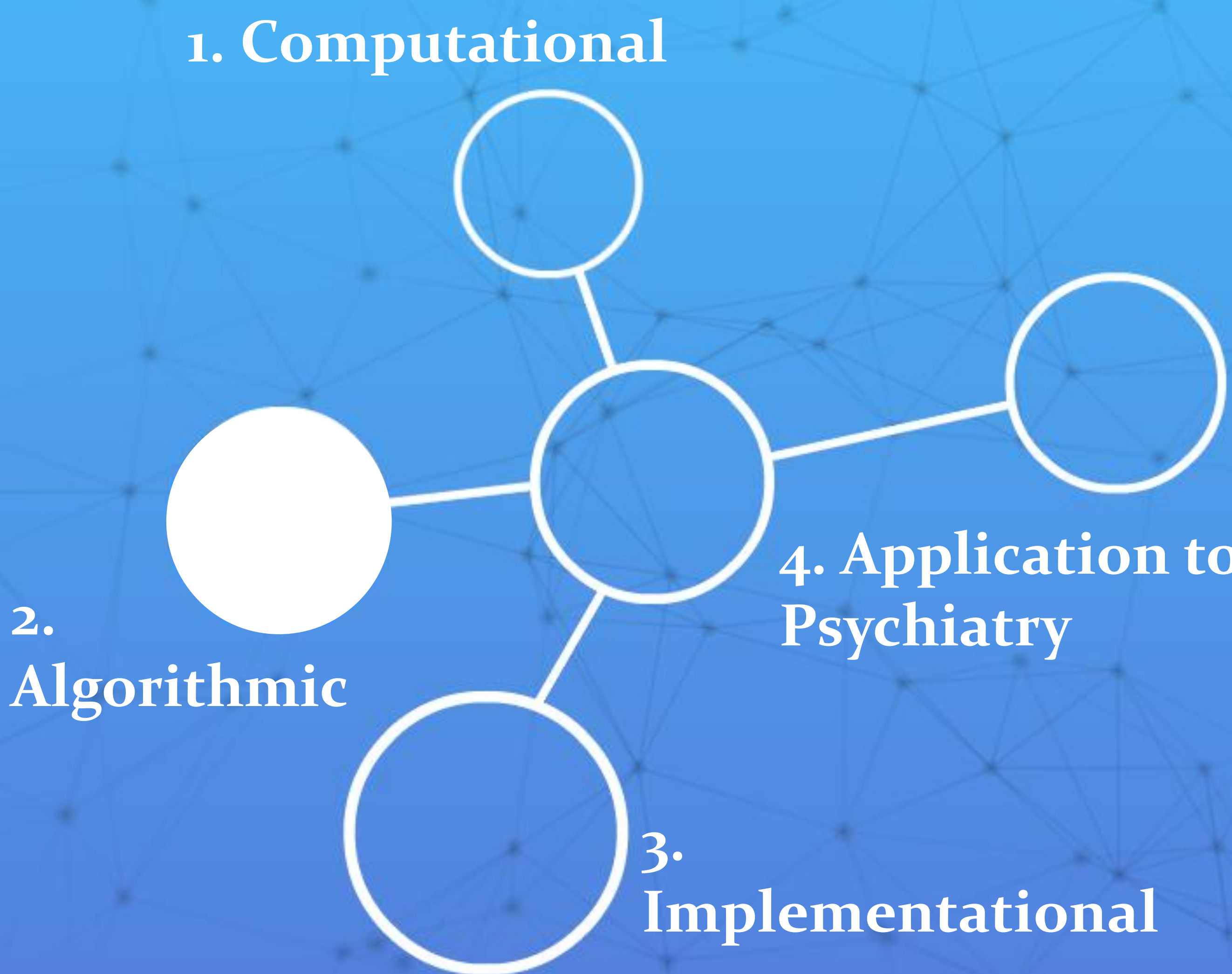
PE

Belief Update

Belief Precision

Mathys et al., *Frontiers Human Neurosci* 2011

Outline


1. Computational
2. Algorithmic
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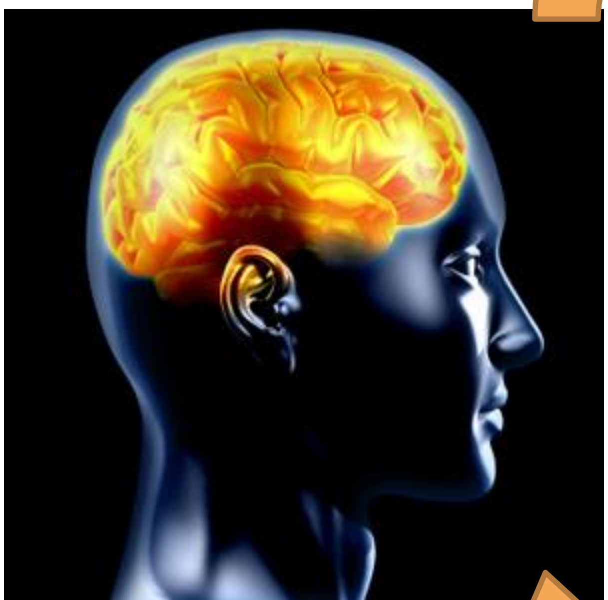
Perception (learning) via hierarchical interactions

Translational Neuromodeling Unit

Top-down;
Predictions

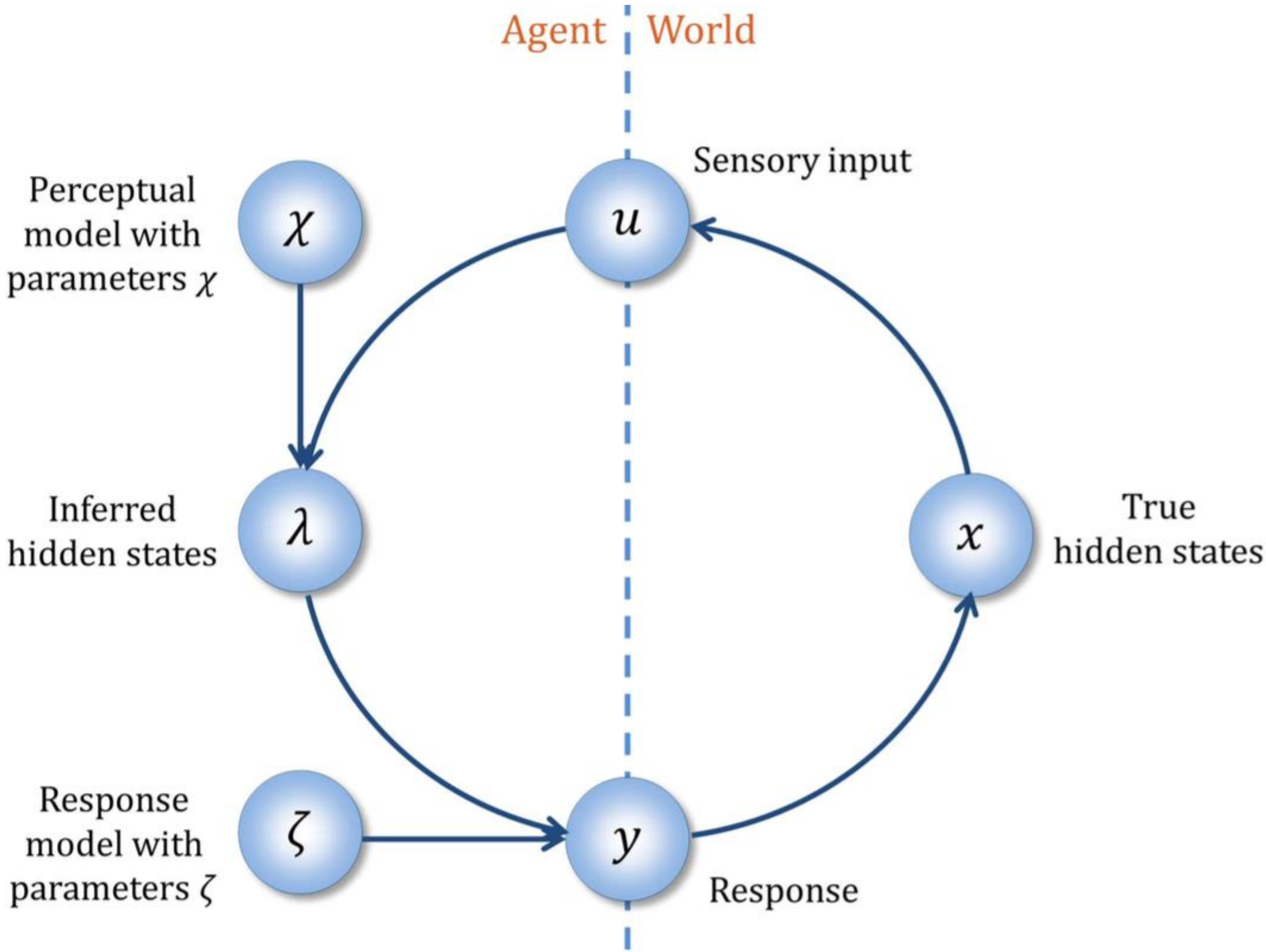


Filter

Update

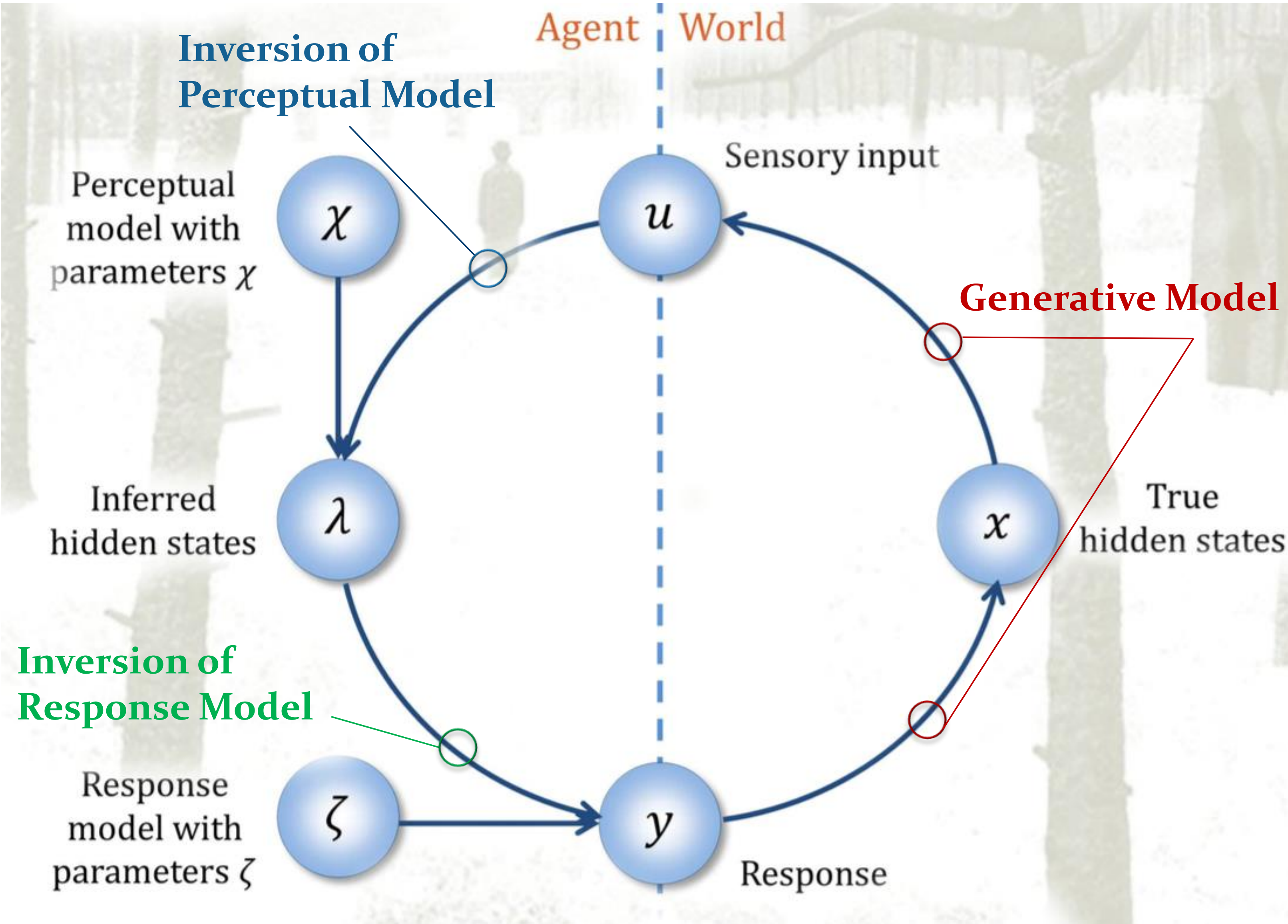
Bottom-up;
Sensations/Prediction Error

From perception to action



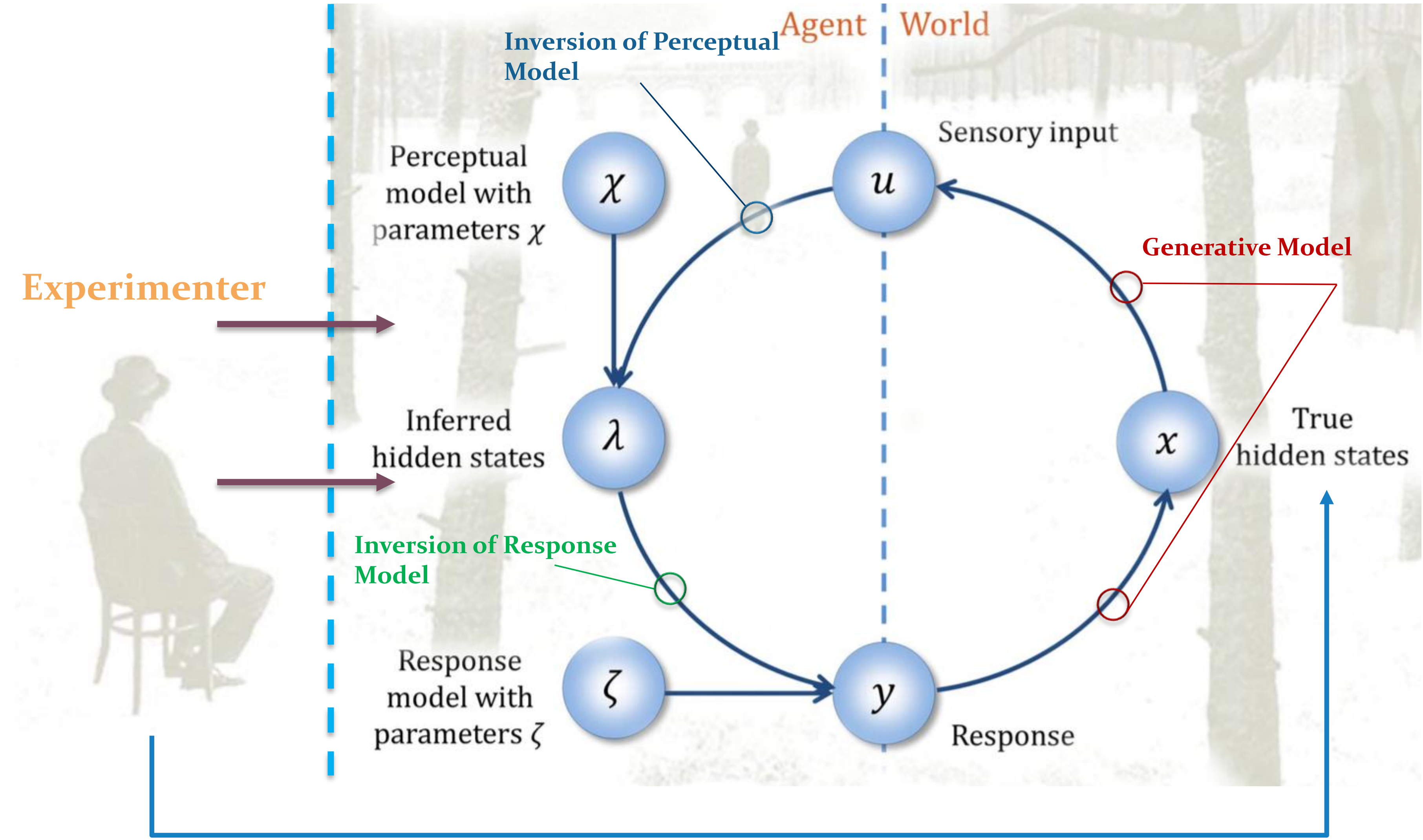
From perception to action

Translational Neuromodeling Unit



From perception to action to observation

Translational Neuromodeling Unit



Observing the observer

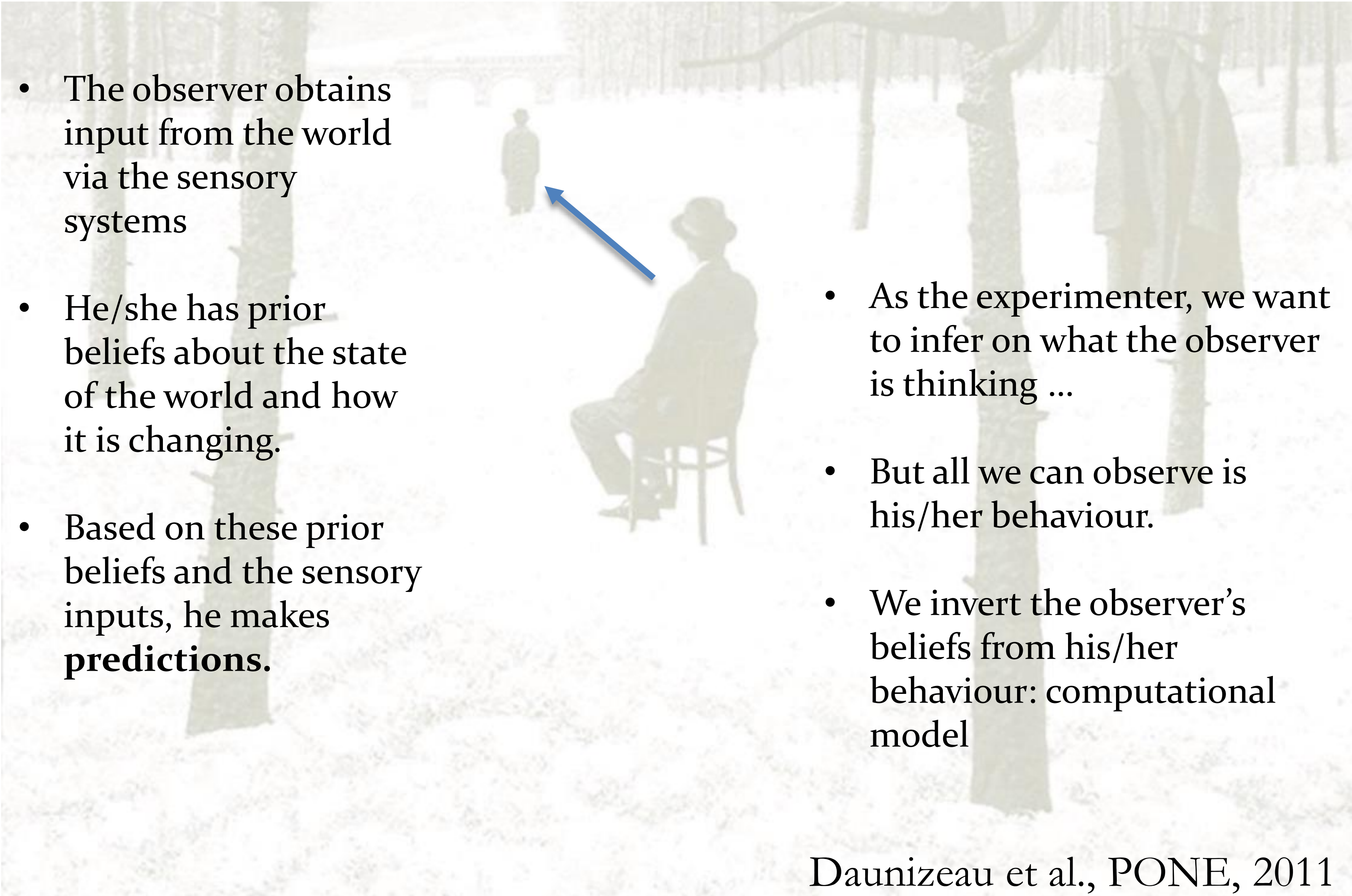
Translational Neuromodeling Unit

- The observer obtains input from the world via the sensory systems
- He/she has prior beliefs about the state of the world and how it is changing.
- Based on these prior beliefs and the sensory inputs, he makes **predictions.**

Daunizeau et al., PONE, 2011

Observing the observer

Translational Neuromodeling Unit



- The observer obtains input from the world via the sensory systems
- He/she has prior beliefs about the state of the world and how it is changing.
- Based on these prior beliefs and the sensory inputs, he makes **predictions.**

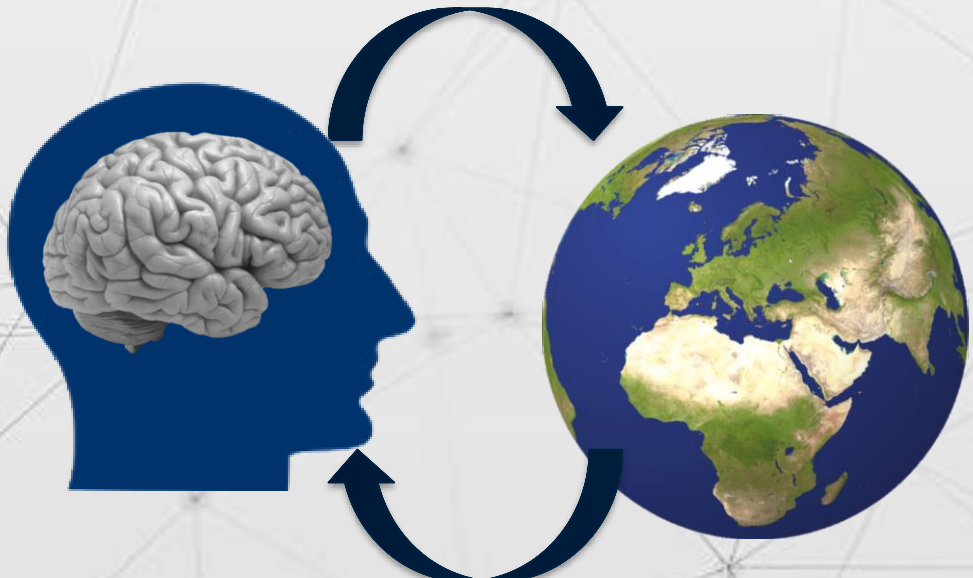
- As the experimenter, we want to infer on what the observer is thinking ...
- But all we can observe is his/her behaviour.
- We invert the observer's beliefs from his/her behaviour: computational model

Daunizeau et al., PONE, 2011

Bayesian Models

The Bayesian Brain

Predictions



Prediction Errors

- The brain is an inference machine
- Conceptualise beliefs as probability distributions
- Updates via Bayes' rule:

Prior Belief **Sensory Data**

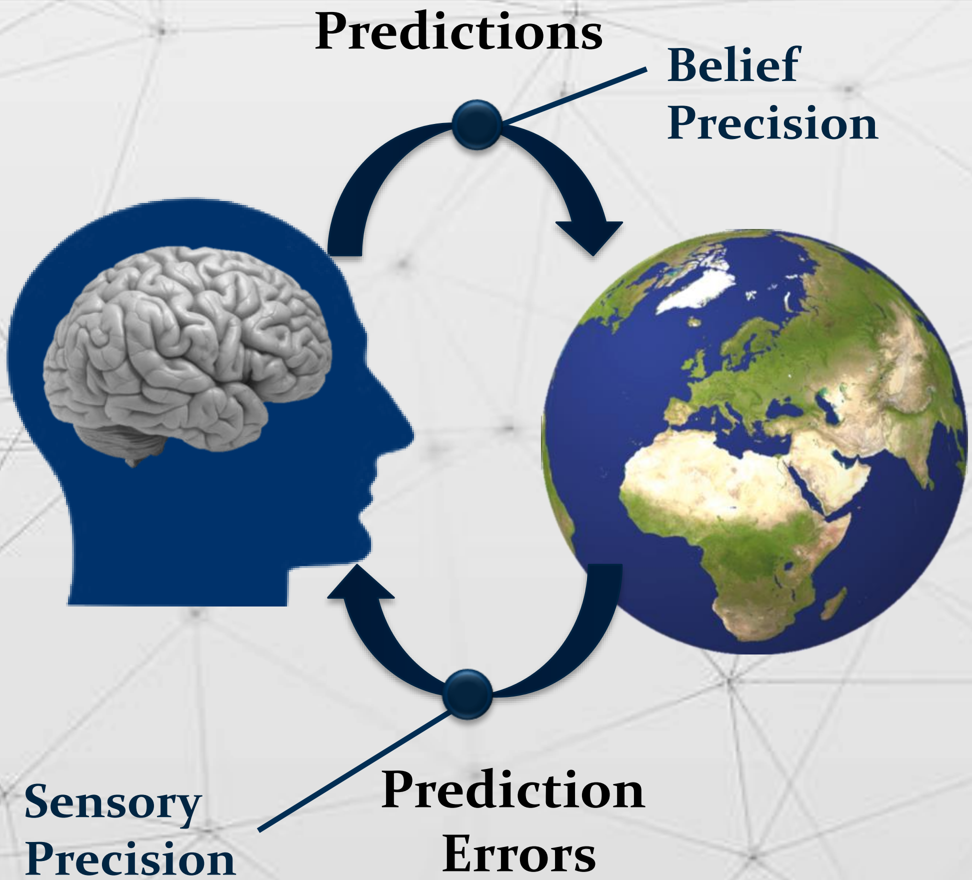
$$p(\Theta|y,m) = \frac{p(\Theta|m)p(y|\Theta,m)}{\int p(\Theta|m)p(y|\Theta,m)d\Theta}$$

Posterior Belief **Evidence**

Hierarchical Gaussian Filter

Translational Neuromodeling Unit

Hierarchy



- Updates as precision-weighted prediction errors

Sensory Precision

$$\Delta\mu_i^{(k)} \propto \frac{\hat{\pi}_{i-1}^{(k)}}{\pi_i^{(k)}} \delta_{i-1}^{(k)}$$

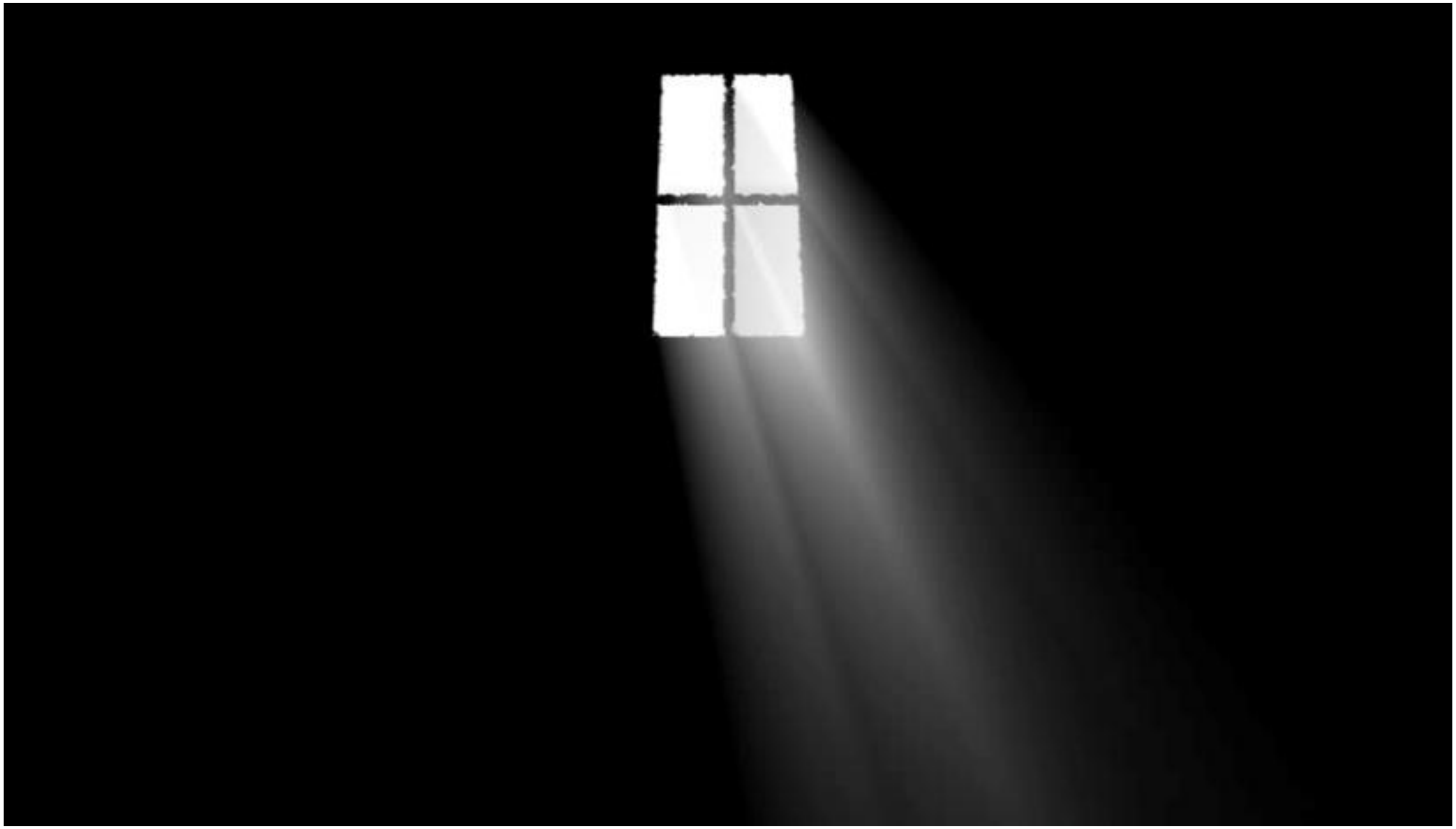
PE

Belief Update

Belief Precision

Mathys et al., *Frontiers Human Neurosci* 2011
Mathys et al., *Frontiers Human Neurosci* 2014

Dark Room Experiment



The hierarchical Gaussian filter (HGF): a computationally tractable model for individual learning under uncertainty

Translational Neuromodeling Unit

Level 3: Phasic volatility

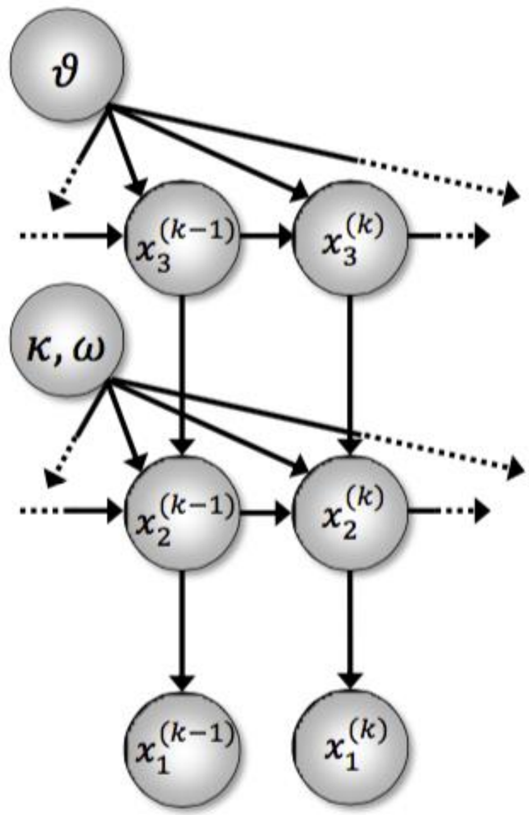
$$p\left(x_3^{(k)}\right) \sim \mathcal{N}\left(x_3^{(k-1)}, \vartheta\right)$$

Level 2: Tendency towards category 1

$$p\left(x_2^{(k)}\right) \sim \mathcal{N}\left(x_2^{(k-1)}, e^{\left(\kappa x_3^{(k-1)} + \omega\right)}\right)$$

Level 1: Stimulus category

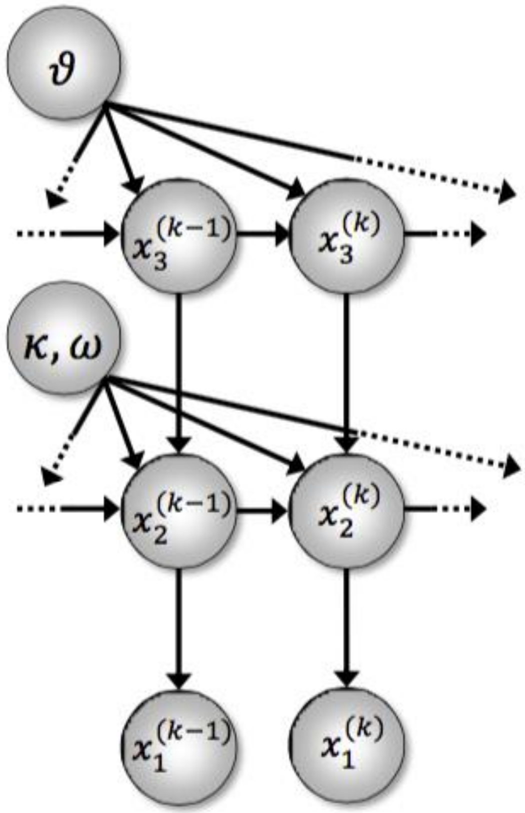
$$p(x_1 = 1) = \frac{1}{1 + e^{-x_2}}$$

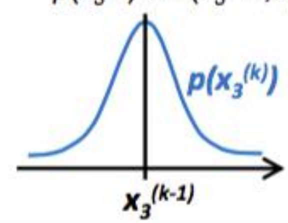
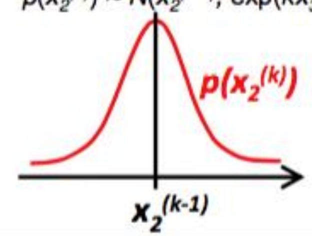
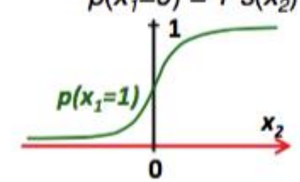


Mathys et al., *Front Hum Neurosci*, 2011

The hierarchical Gaussian filter (HGF): a computationally tractable model for individual learning under uncertainty

Translational Neuromodeling Unit



State of the world	Model	
Log-volatility x_3 of tendency	Gaussian random walk with constant step size ϑ	$p(x_3^{(k)}) \sim N(x_3^{(k-1)}, \vartheta)$ 
Tendency x_2 towards category "1"	Gaussian random walk with step size $\exp(\kappa x_3+\omega)$	$p(x_2^{(k)}) \sim N(x_2^{(k-1)}, \exp(\kappa x_3+\omega))$ 
Stimulus category x_1 ("0" or "1")	Sigmoid transformation of x_2	$p(x_1=1) = s(x_2)$ $p(x_1=0) = 1-s(x_2)$ 

Mathys et al., *Front Hum Neurosci*, 2011

HGF: Variational inversion and update equations

Translational Neuromodeling Unit

- Inversion proceeds by introducing a mean field approximation and fitting quadratic approximations to the resulting variational energies.

- This leads to simple one-step update equations for the sufficient statistics (mean and precision) of the approximate Gaussian posteriors of the hidden states x_i.

- The updates of the means have the same structure as value updates in Rescorla-Wagner learning:

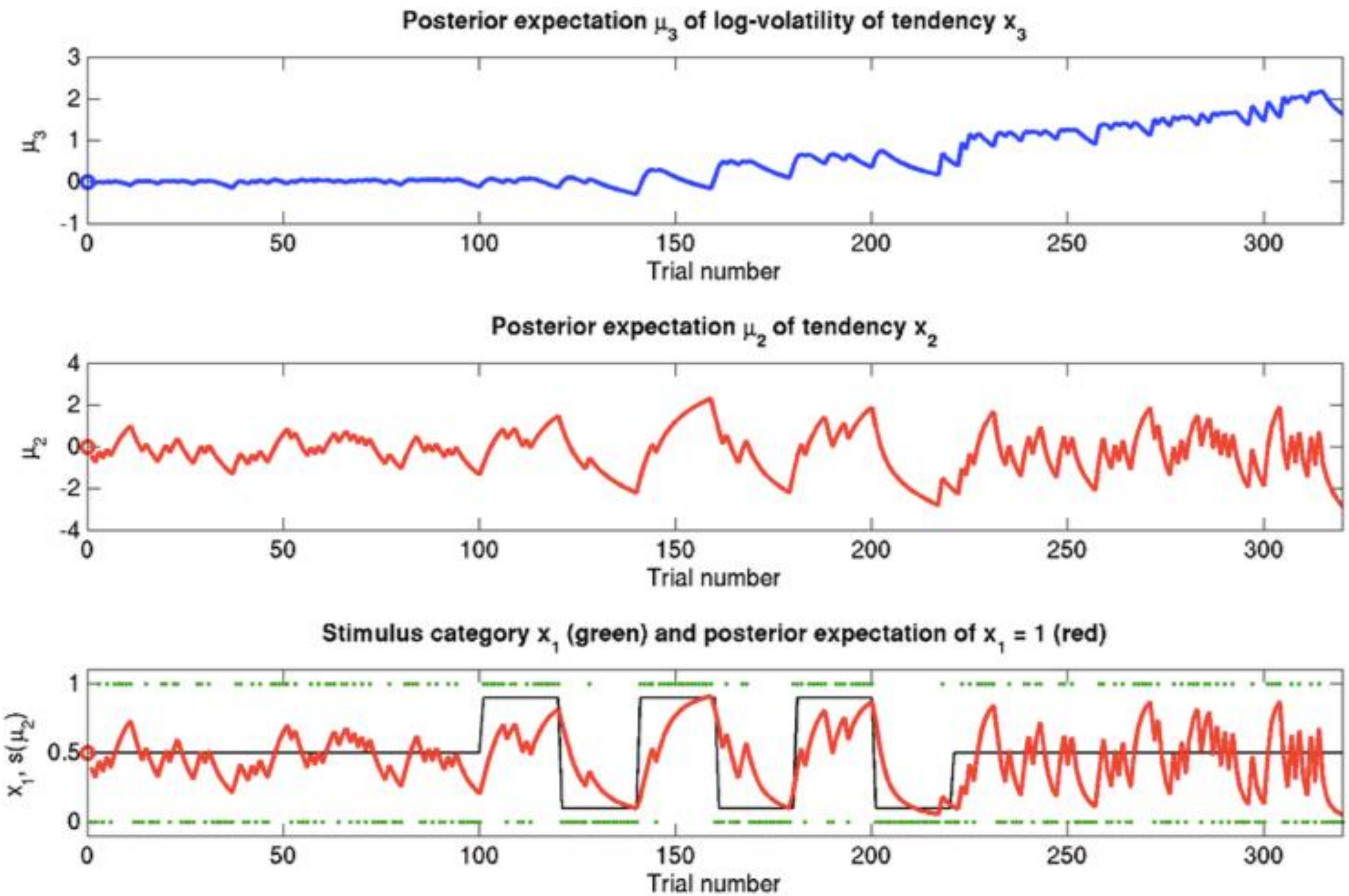
$$\Delta\mu_i = \boxed{\frac{\hat{\pi}_{i-1}}{\pi_i}} \delta_{i-1}$$

Prediction Error

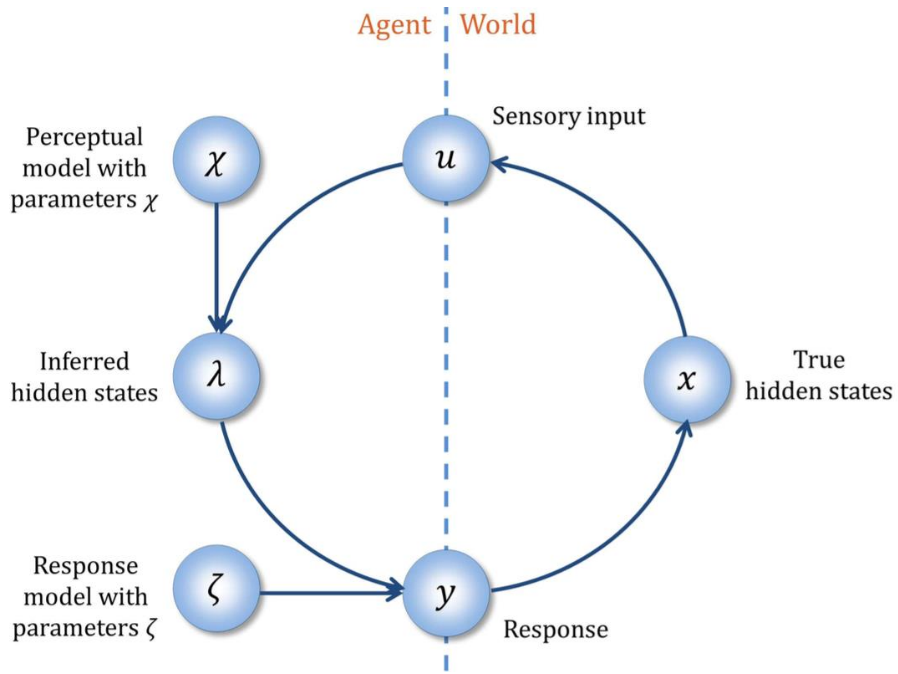
Precisions determine the learning rate

Hierarchical Learning

Simulations: $\vartheta = 0.5,\ \omega = -2.2,\ \kappa = 1.4$



From perception to action



- In behavioural tasks, we observe actions a
- How do we use them to infer on beliefs λ?
- Answer: we invert (estimate) a **response model**

Example of a simple response model

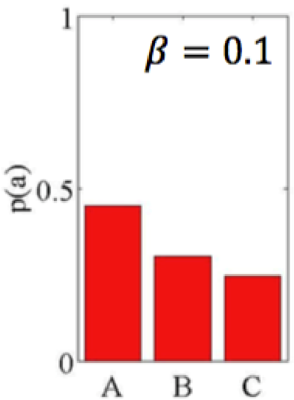
Translational Neuromodeling Unit

- Options A, B and C have values: $v_A = 8, v_B = 4, v_C = 2$
- We translate these values into action probabilities via a *Softmax* function:

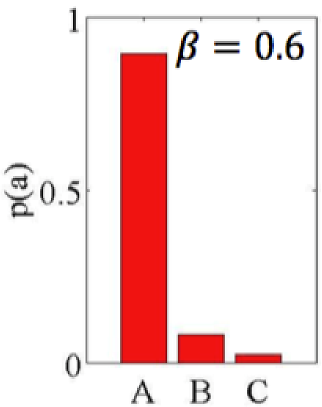
$$p(a = A) = \frac{e^{\beta v_A}}{e^{\beta v_A} + e^{\beta v_B} + e^{\beta v_C}}$$

- Parameter β determines sensitivity to value differences:

low β



high β

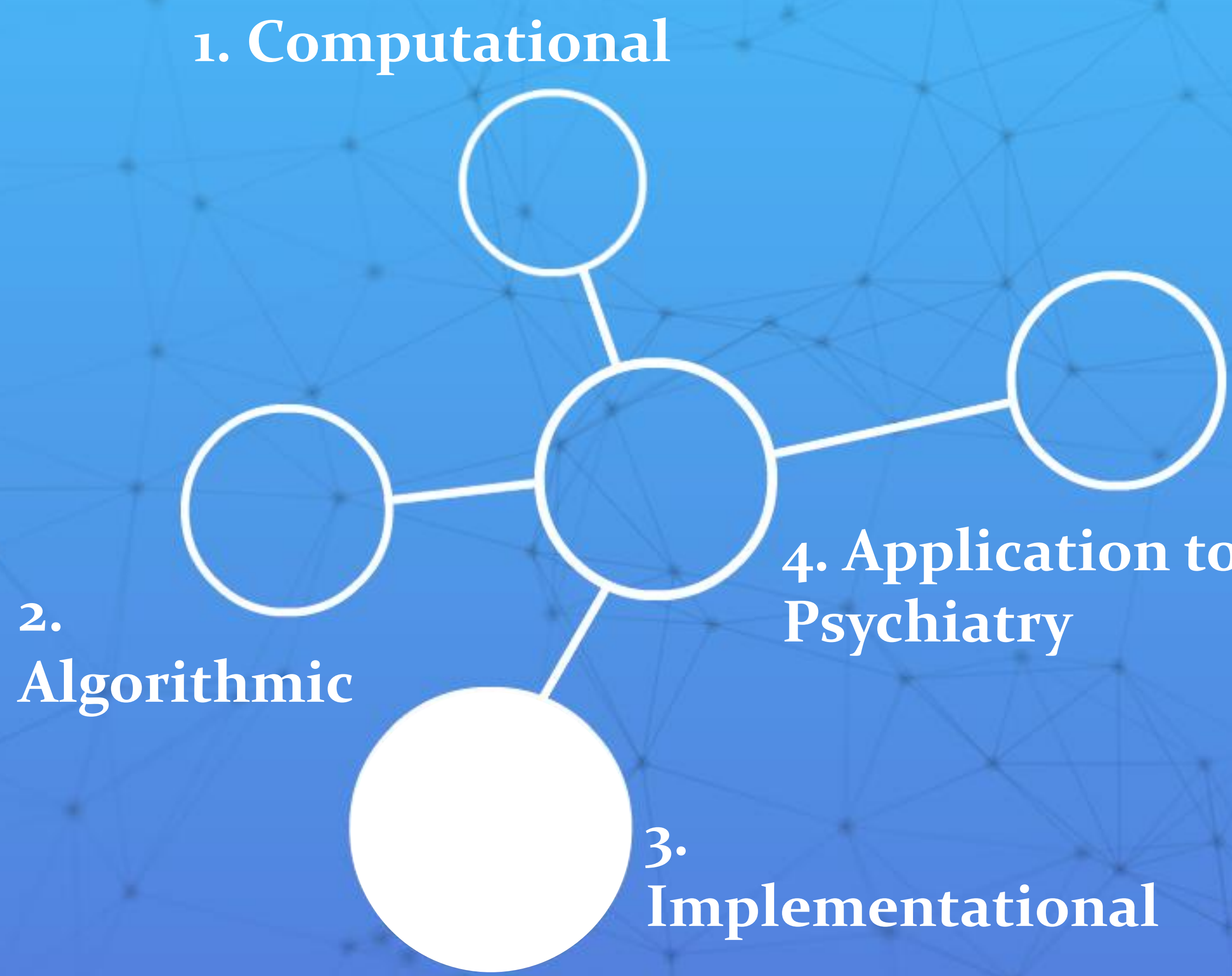


All the necessary ingredients

Translational Neuromodeling Unit

- Perceptual model (updates based on prediction errors)
- Value function (inferred state to action value)
- Response model (action value to response probability)

Outline


1. Computational
2. Algorithmic
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4. Application to Psychiatry

Computational fMRI: The advantage

The question event-related/block designs answer:

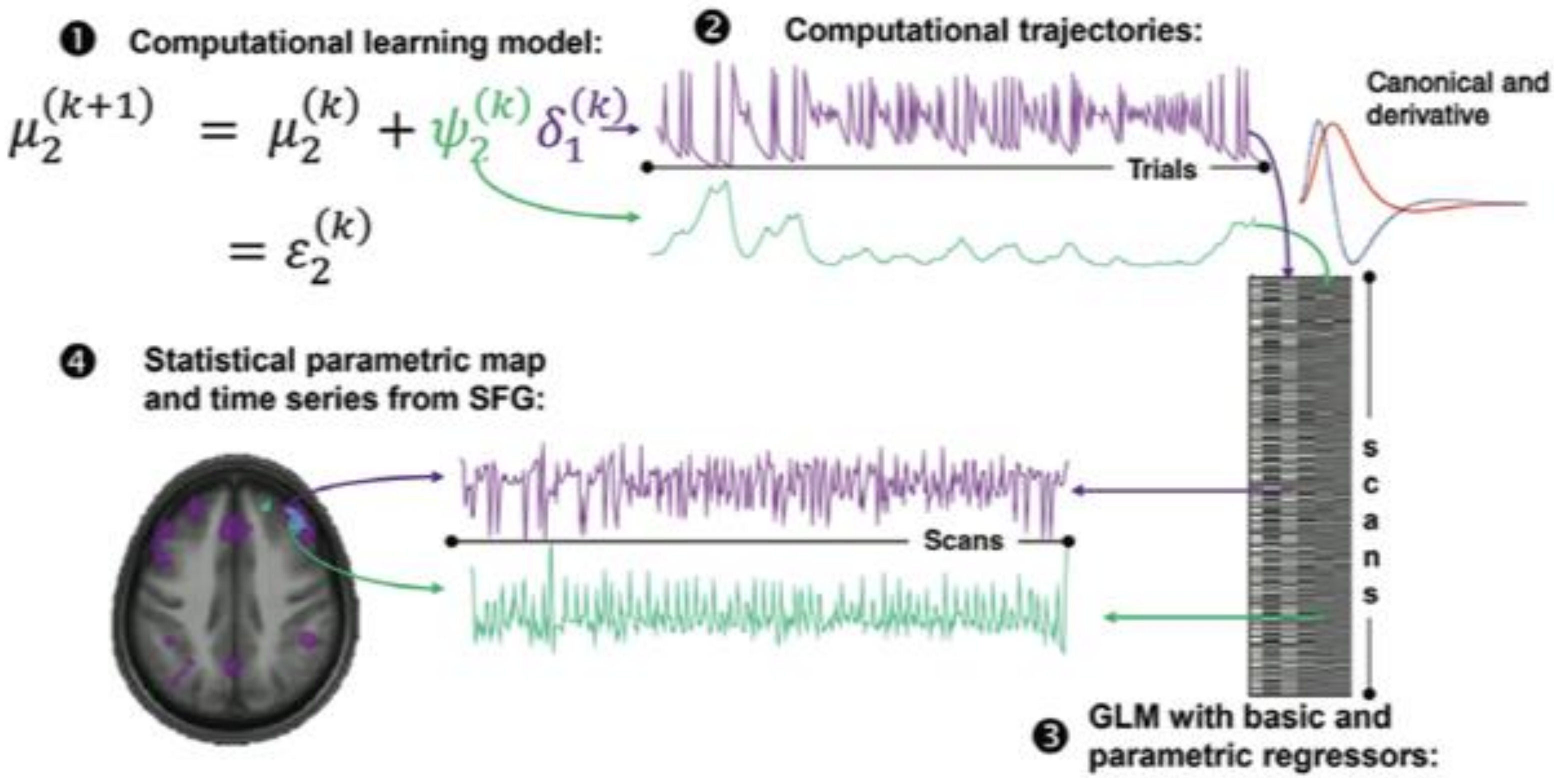
- Where in the brain do particular experimental conditions elicit BOLD responses?

The question model-based fMRI answers:

- How (i.e., by activation of which areas) does the brain implement a particular cognitive process?

It is able to do so because its regressors correspond to particular cognitive processes instead of experimental conditions.

Computational fMRI analyses of neuromodulation



Iglesias et al., 2016

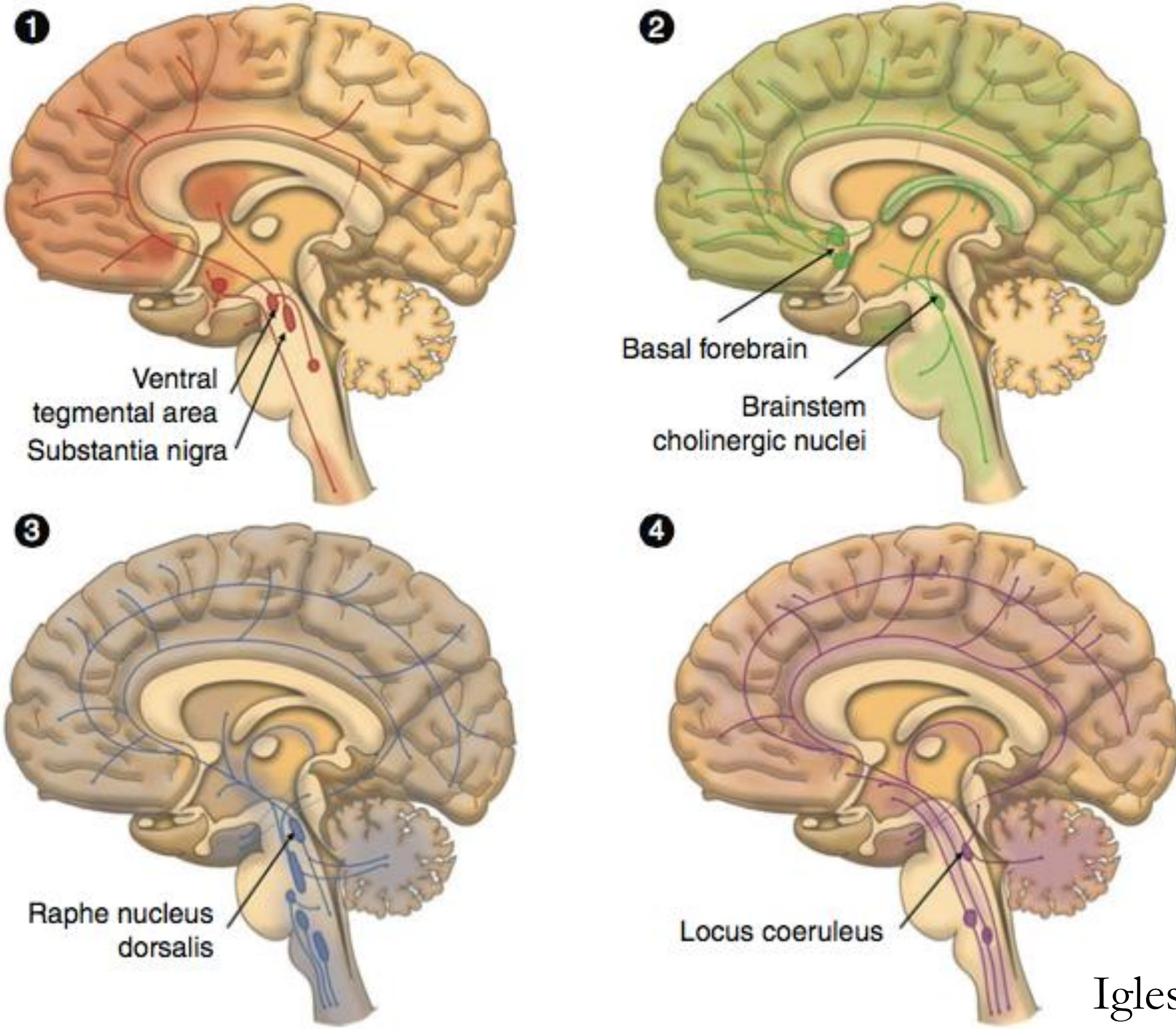
Computational fMRI analyses of neuromodulation

Dopamine

Acetylcholine

Serotonin

Noradrenaline

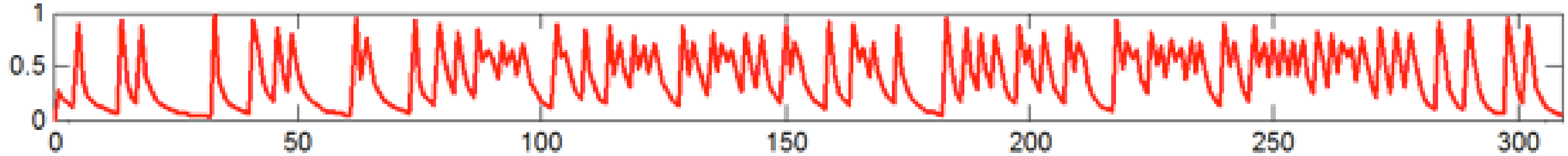


Iglesias et al., 2016

Application of the HGF: Two types of PEs

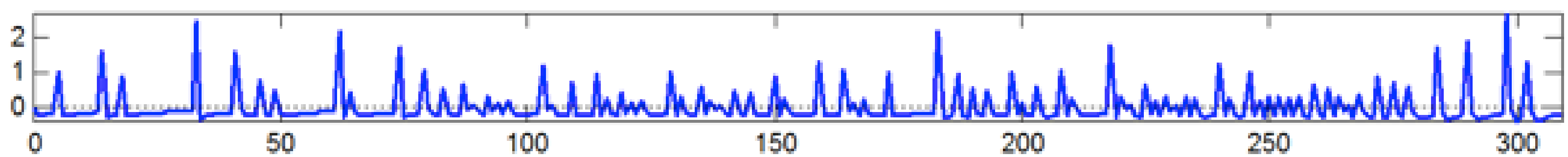
Translational Neuromodeling Unit

1. Outcome PE



ϵ_2

2. Cue-Outcome Contingency PE

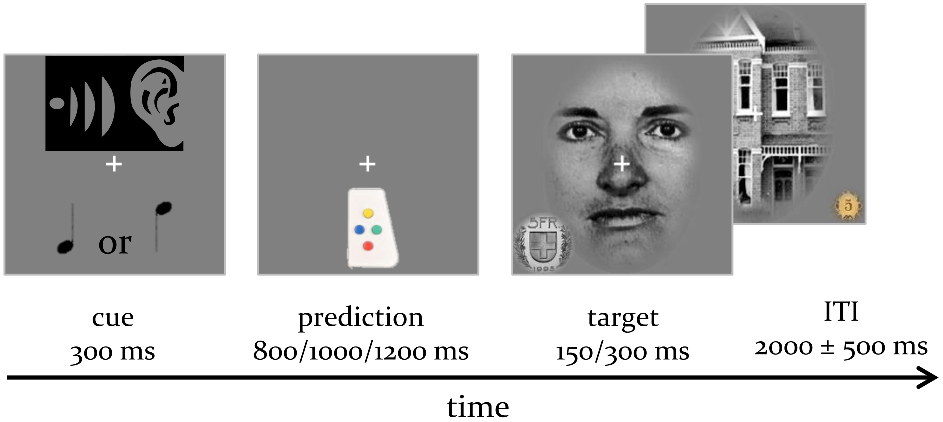


ϵ_3

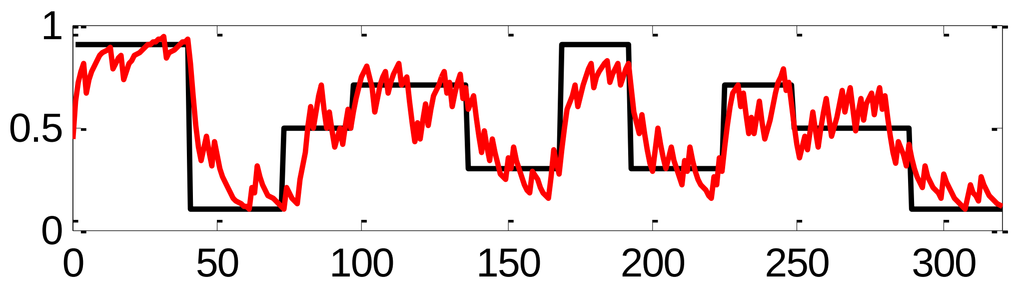
Iglesias et al., *Neuron*, 2013

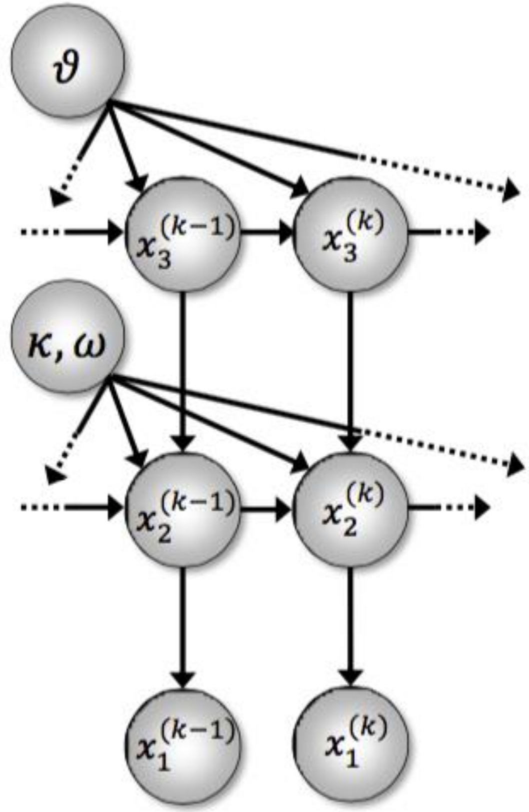
Application of the HGF: Sensory Learning

Translational Neuromodeling Unit



Changes in cue strength (black), and posterior expectation of visual category (red)



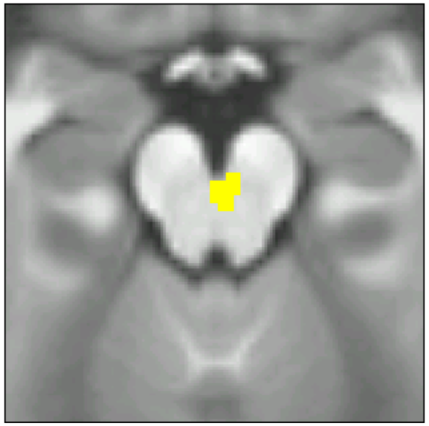


Iglesias et al., *Neuron*, 2013

Application of the HGF: Representation of precision-weighted PEs

Translational Neuromodeling Unit

1. Outcome PE

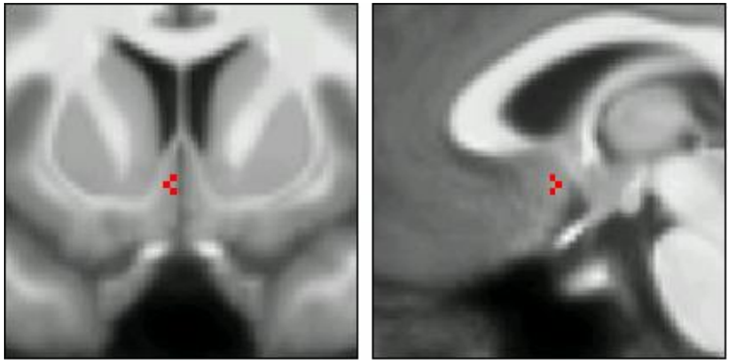


z = -18

- right VTA

Dopamine

2. Probability PE



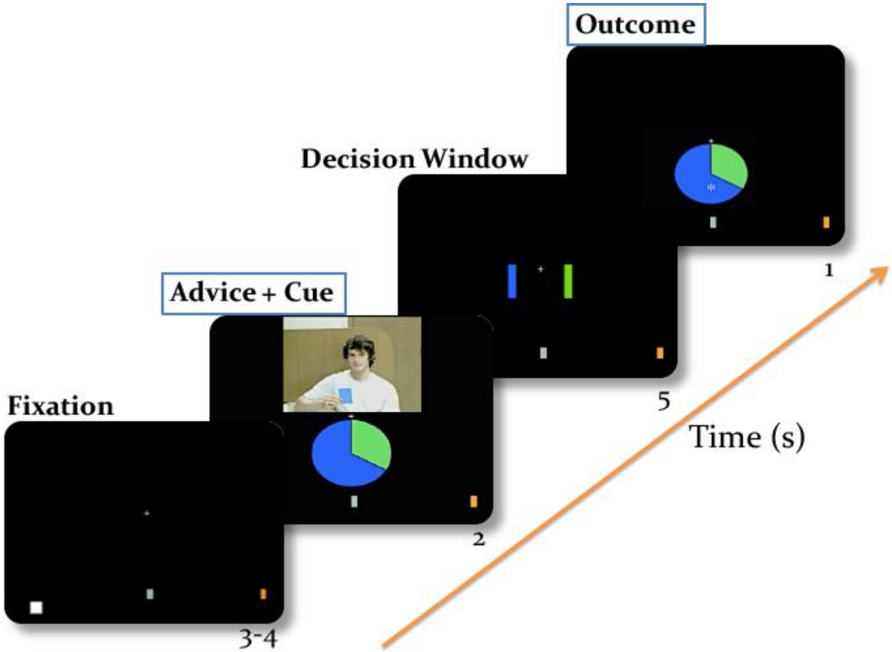
- left basal forebrain

Acetycholine

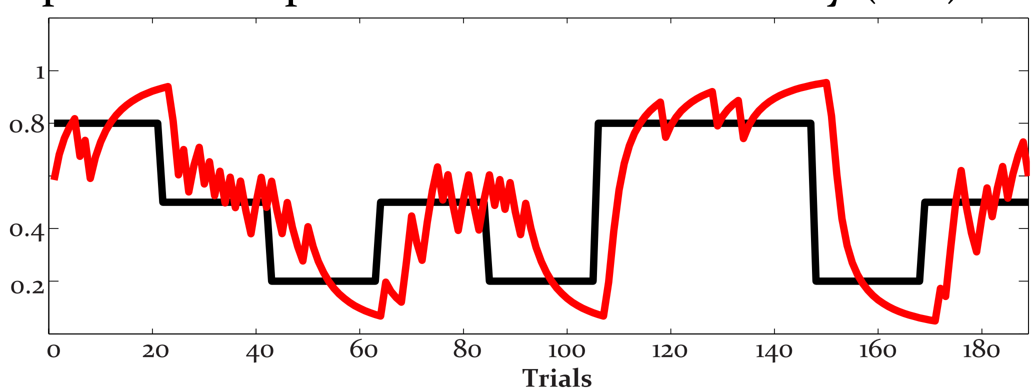
Iglesias et al., *Neuron*, 2013

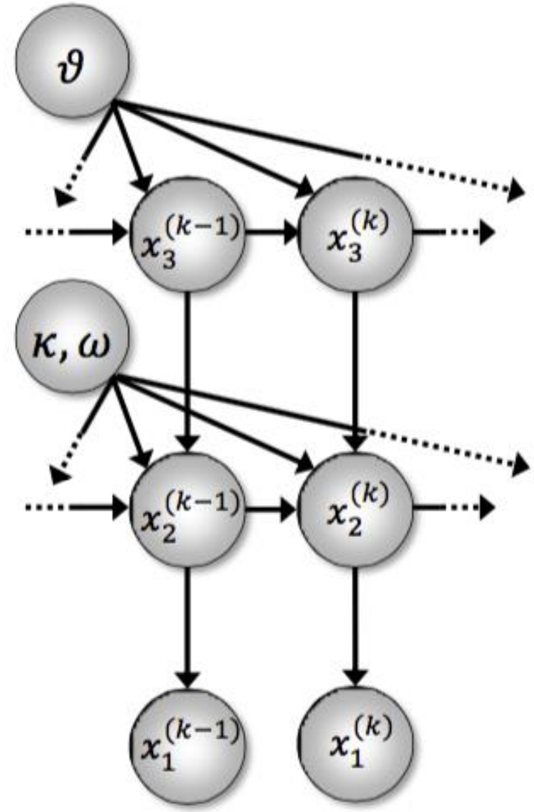
Application of the HGF: Social Learning

Translational Neuromodeling Unit



Changes in advice accuracy (black), and posterior expectation of adviser fidelity (red)



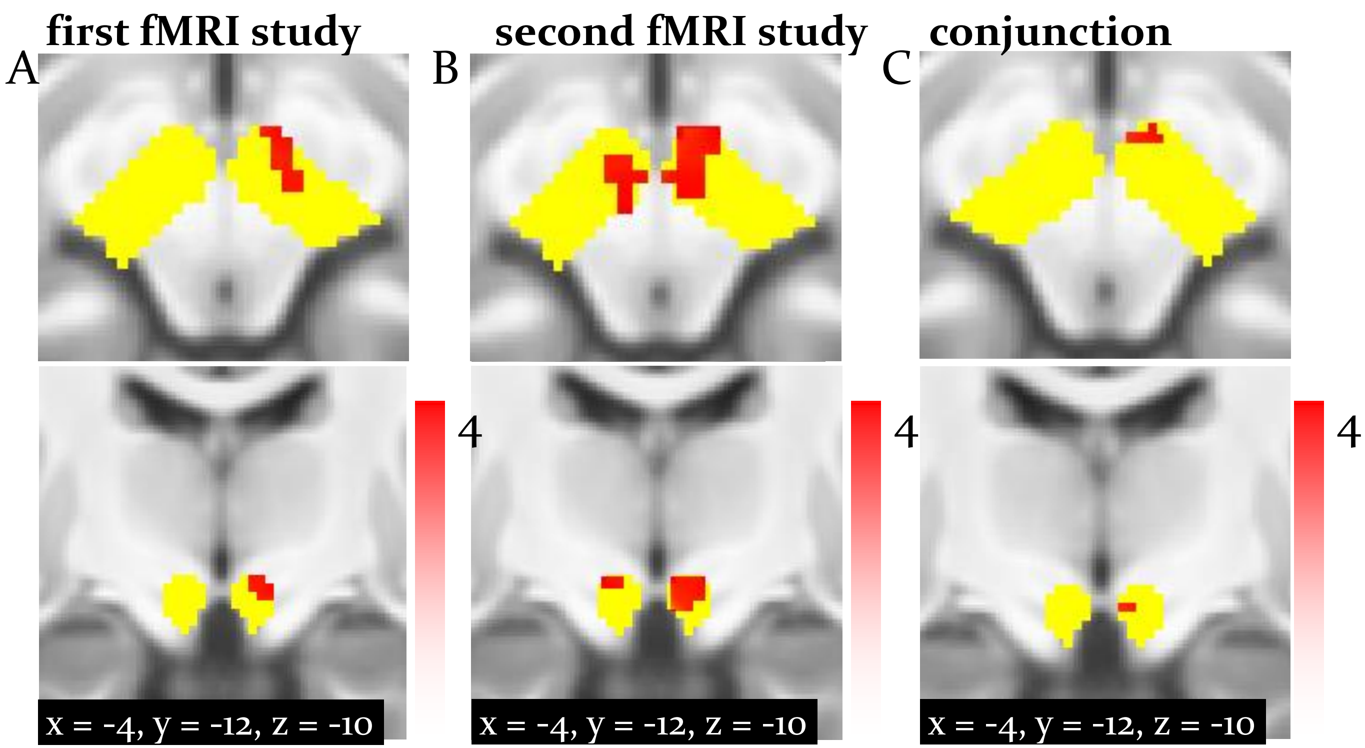


Diaconescu et al., *SCAN*, 2017

Representation of precision-weighted PEs in the social domain

Translational Neuromodeling Unit

1. Outcome PE

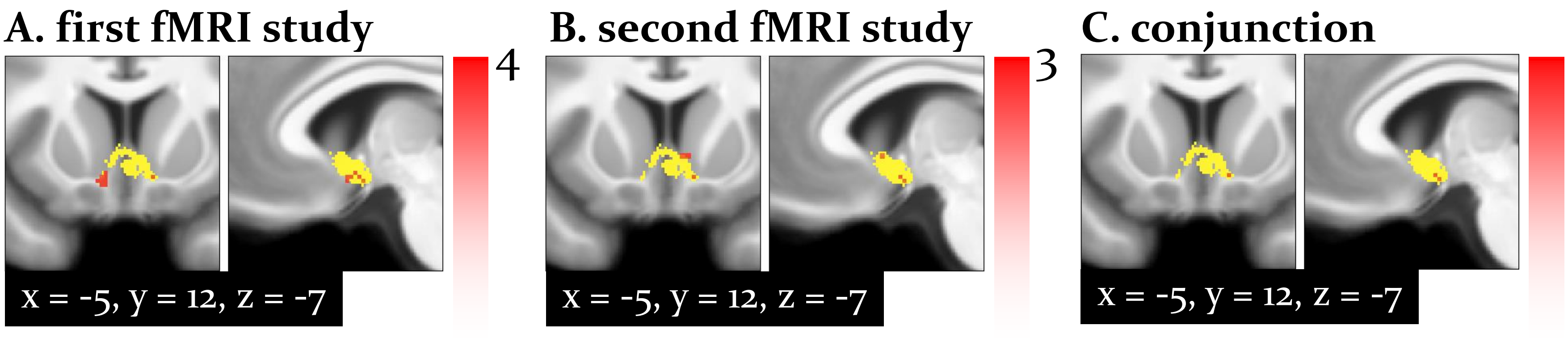


Diaconescu et al., *SCAN*, 2017

Representation of precision-weighted PEs in the social domain

Translational Neuromodeling Unit

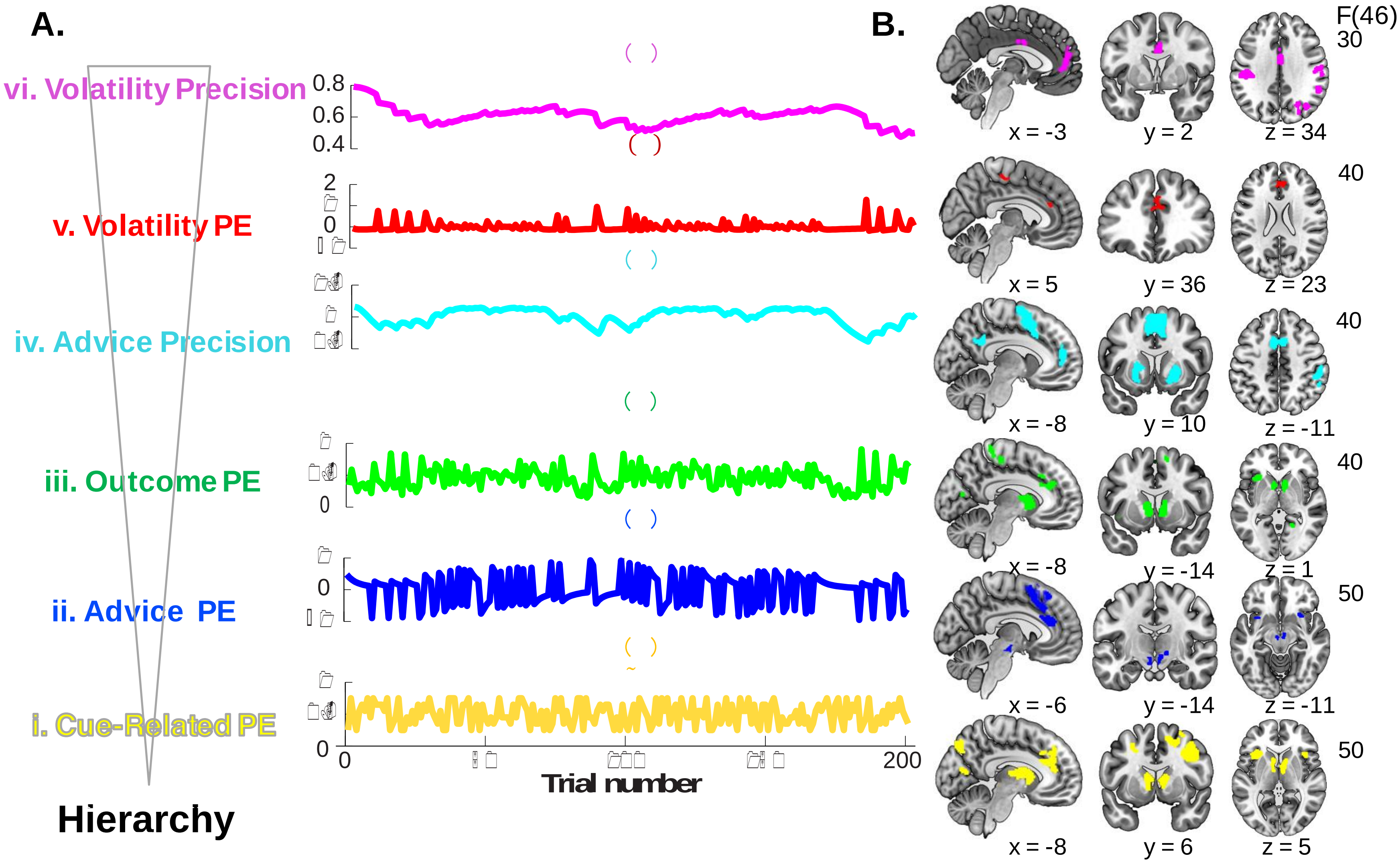
2. Probability PE



Diaconescu et al., *SCAN*, 2017

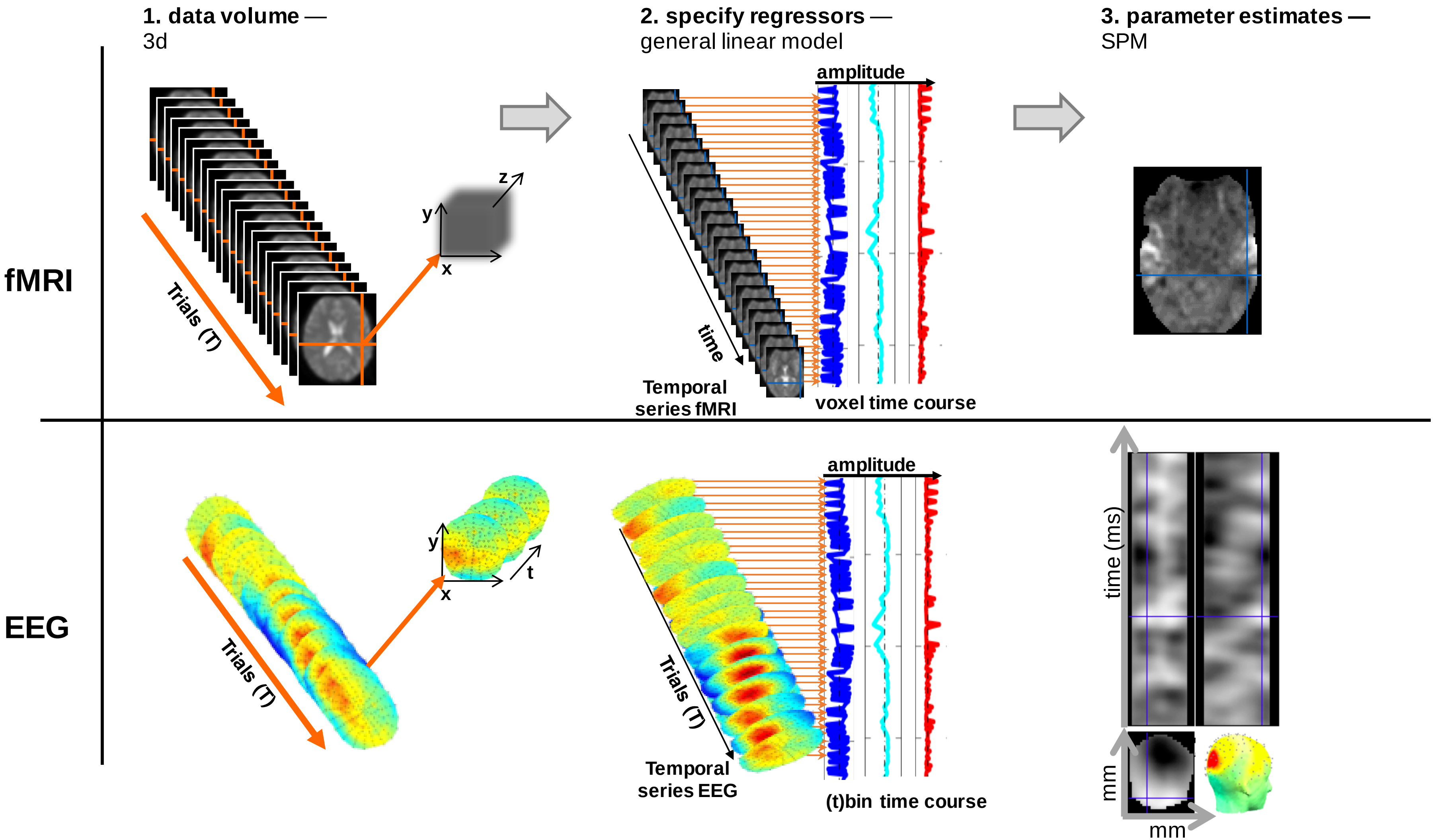
Computational hierarchy & its neural signature

Translational Neuromodeling Unit



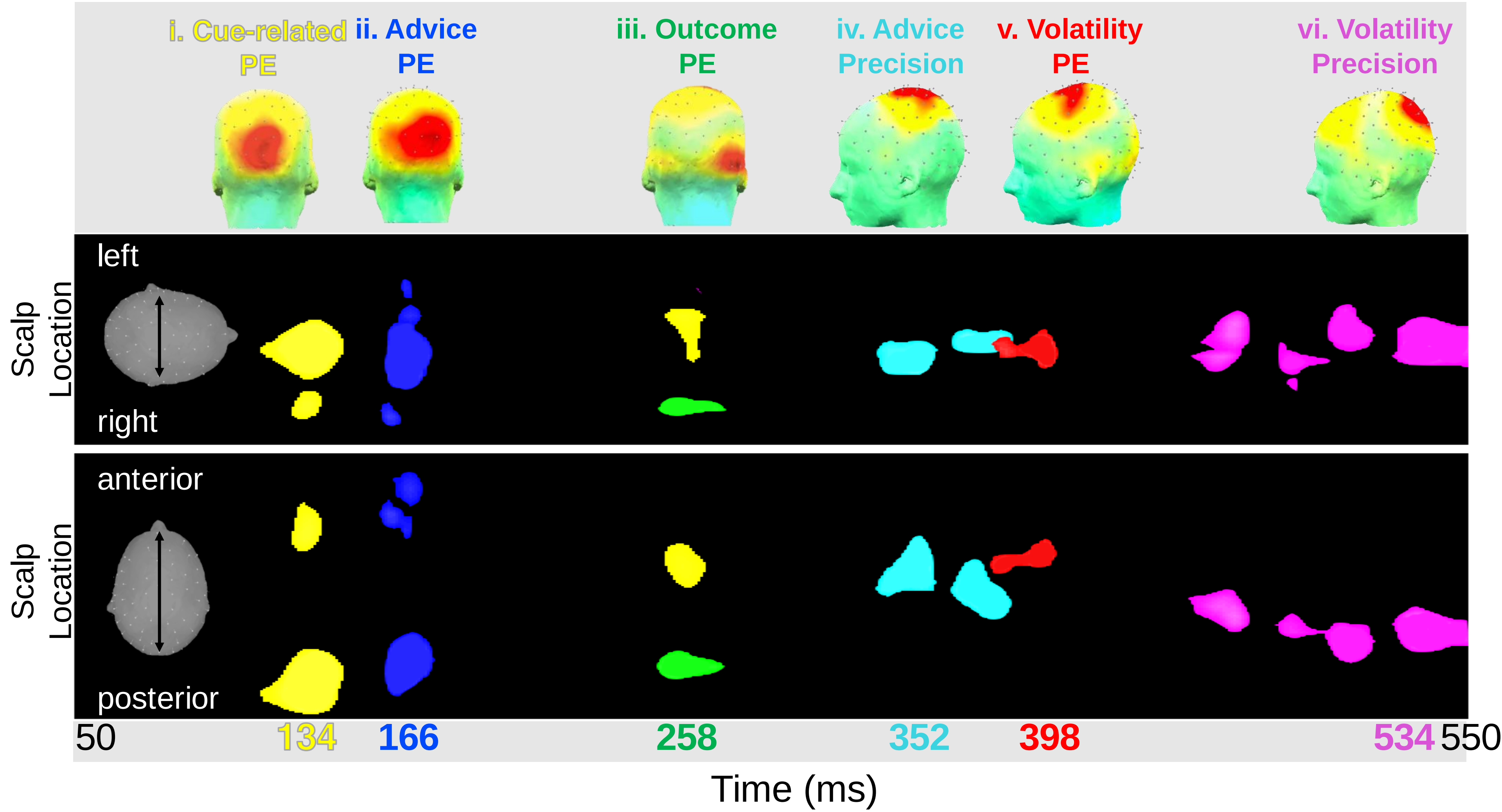
Diaconescu et al., *Under Revision*

Analogy to electrophysiological data



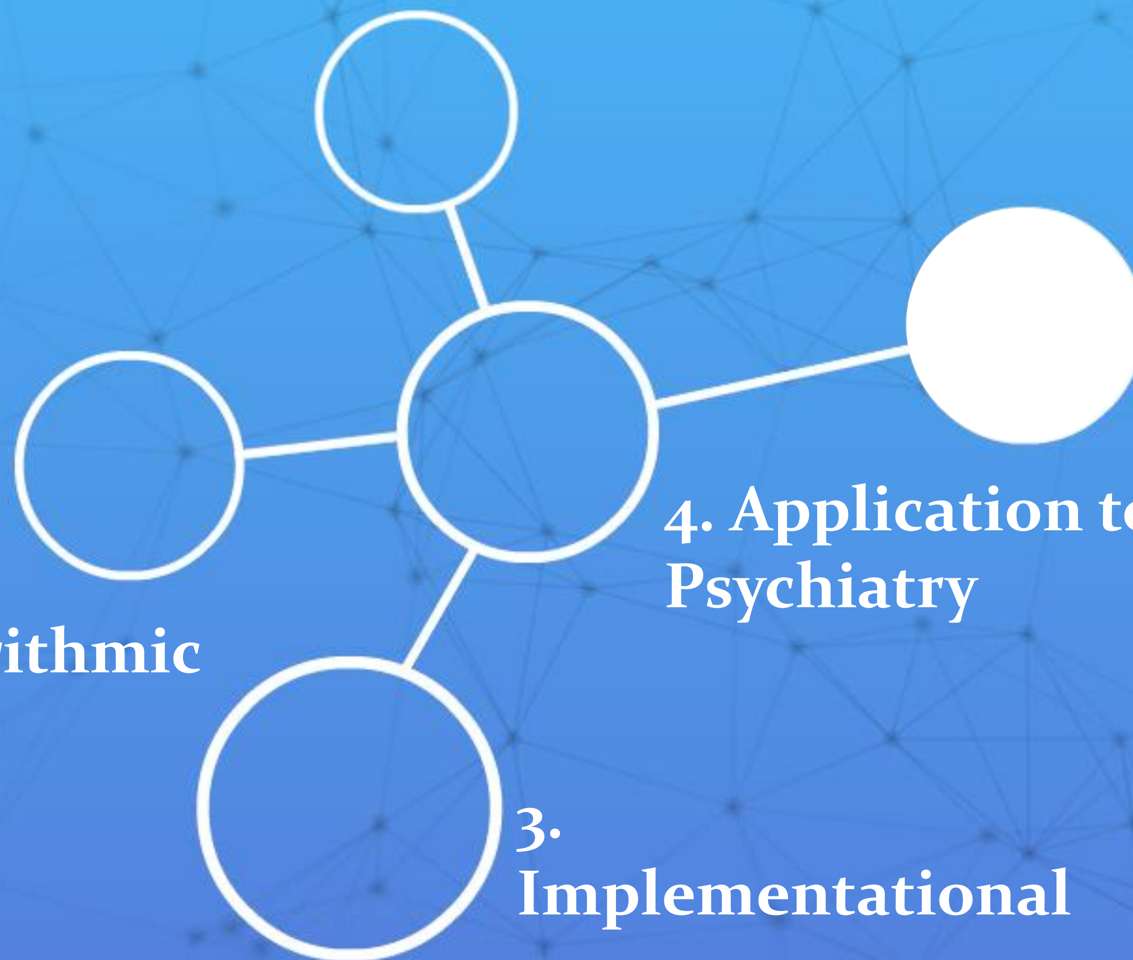
Diaconescu et al., *Under Revision*

Temporal hierarchy



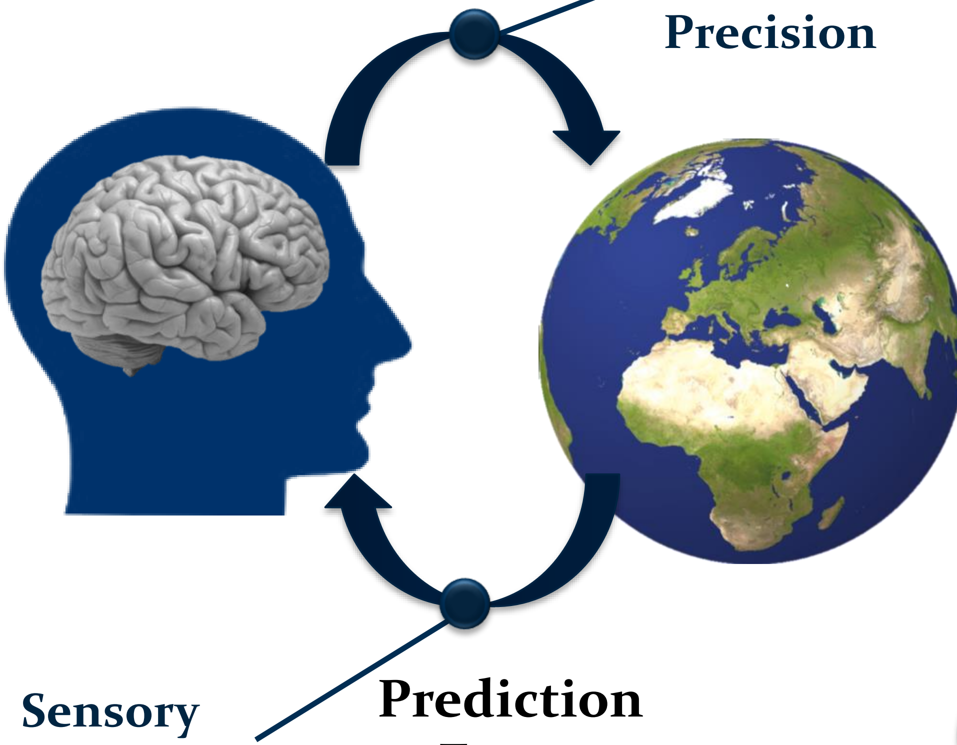
Diaconescu et al., *Under Revision*

Outline


1. Computational
2. Algorithmic
3. Implementational
4. Application to Psychiatry

Hierarchical Gaussian Filter

Translational Neuromodeling Unit

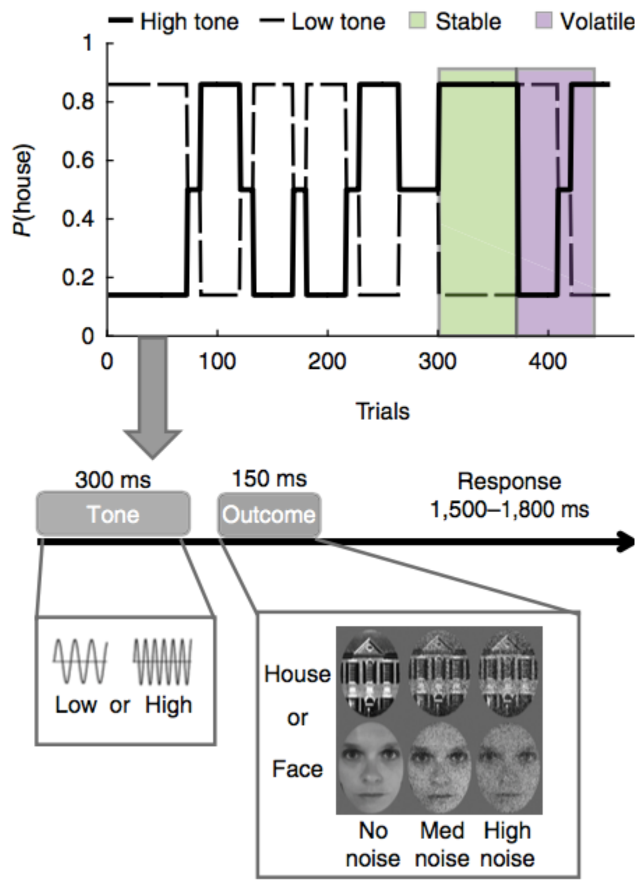


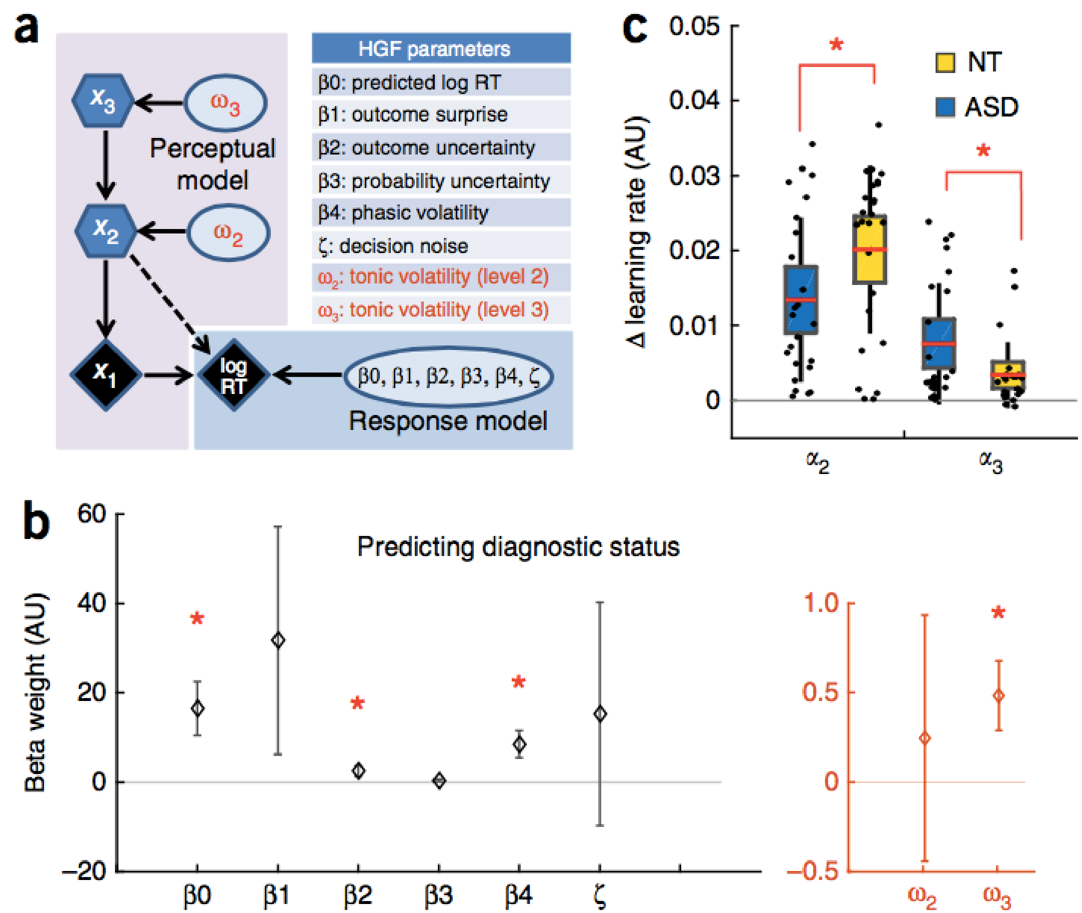
$$\underbrace{\Delta\mu_i^{(k)}}_{\text{Belief Update}} \propto \frac{\overbrace{\hat{\pi}_{i-1}^{(k)}}^{\text{Sensory Precision}}}{\underbrace{\pi_i^{(k)}}_{\text{Belief Precision}}} \underbrace{\delta_{i-1}^{(k)}}_{\text{PE}}$$

Mathys et al., *Frontiers Human Neurosci* 2011
Mathys et al., *Frontiers Human Neurosci* 2014

Autism

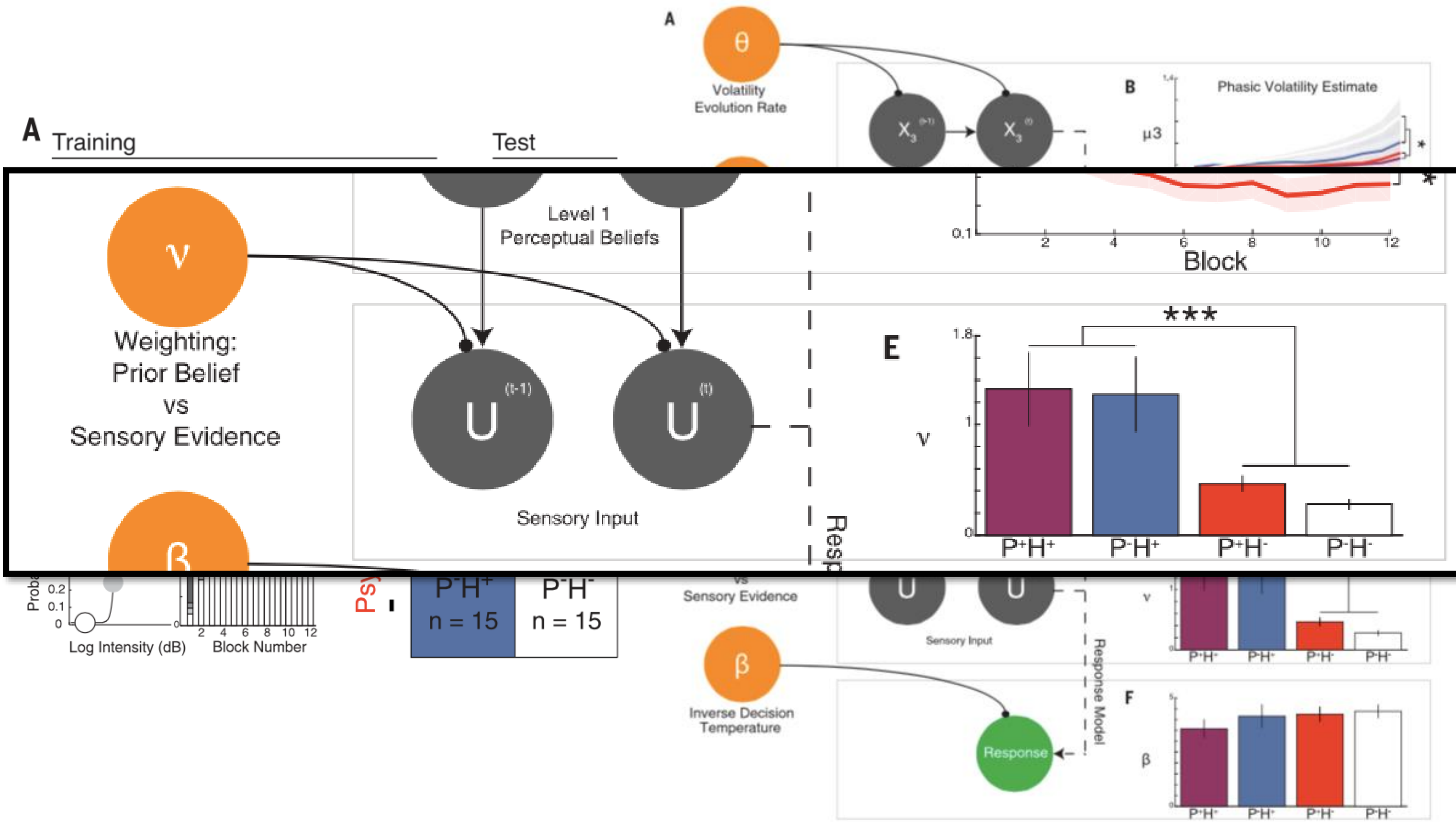
Translational Neuromodeling Unit





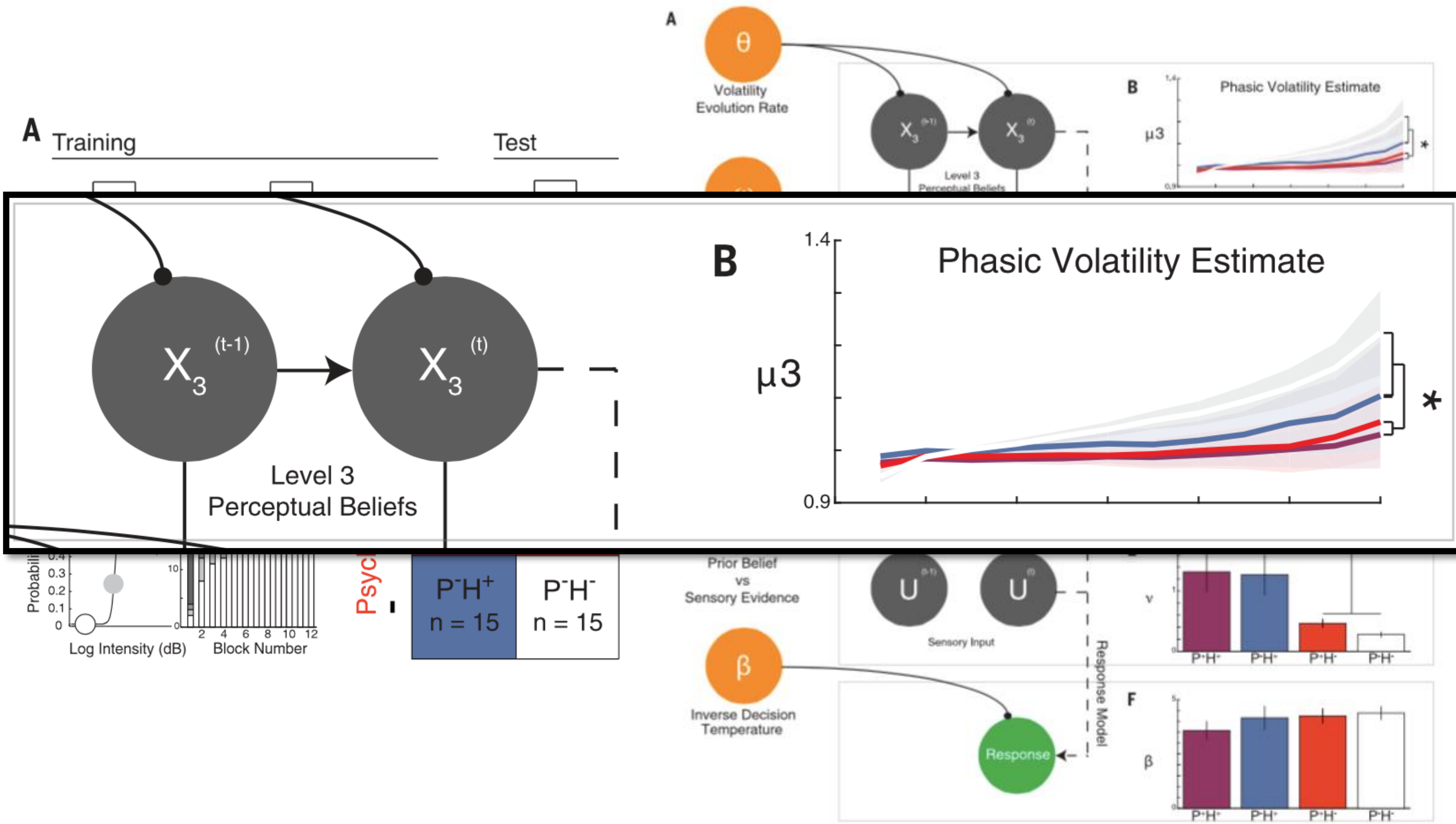
Lawson et al., *Nature Neuroscience*, 2017

Psychosis & Hallucinations



Powers et al., *Science*, 2017

Psychosis & Hallucinations



Powers et al., *Science*, 2017

Conclusion

Translational Neuromodeling Unit

Autism

$$\underbrace{\Delta\mu_i^{(k)}}_{\text{Belief Update}} \propto \frac{\overbrace{\hat{\pi}_{\mathrm{i-1}}^{(k)}}^{\text{Sensory Precision}}}{\underbrace{\pi_i^{(k)}}_{\text{Belief Precision}}} \delta_{i-1}^{(k)} \text{PE}$$

3rd level of the hierarchy

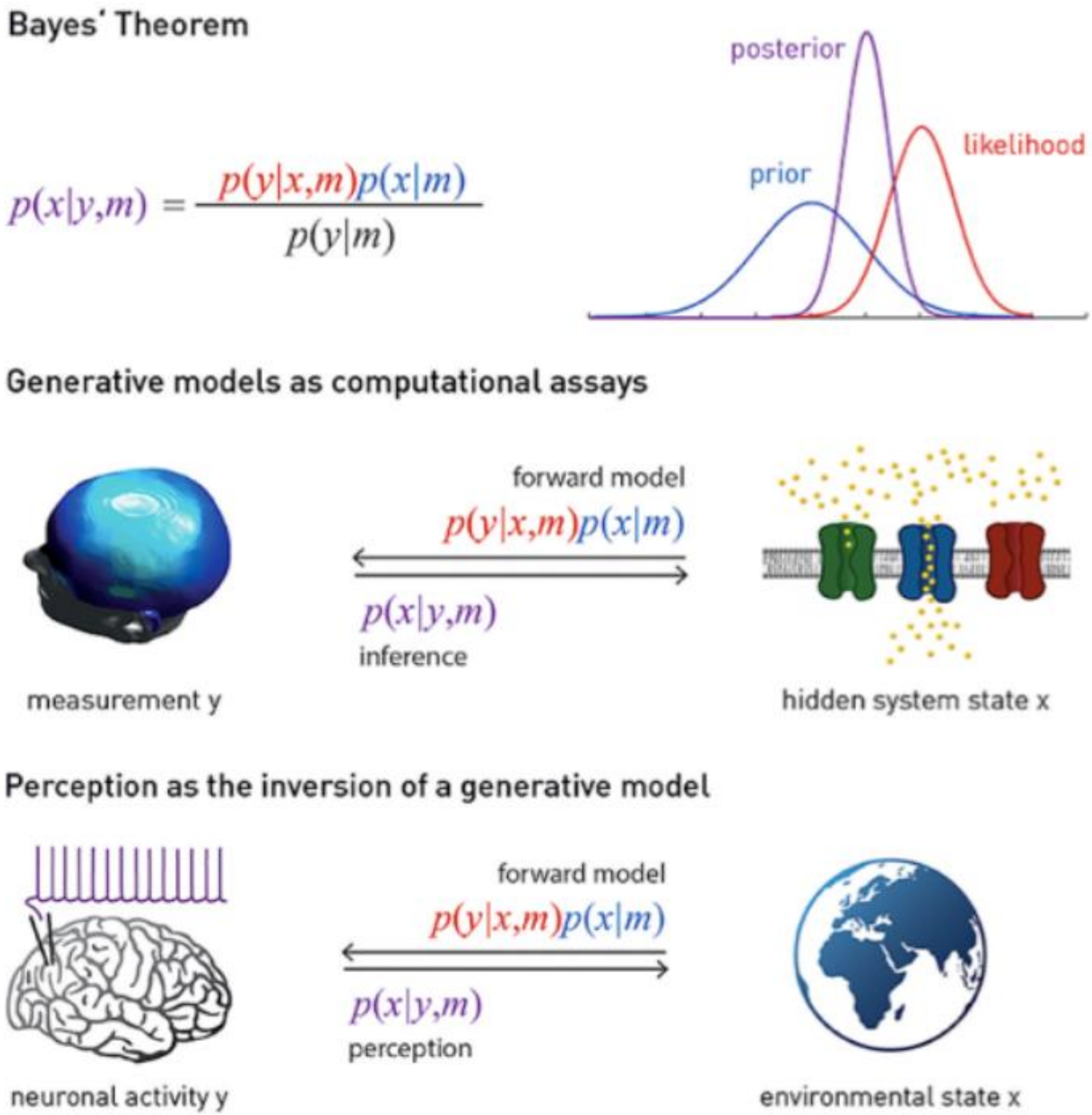
Psychosis

$$\underbrace{\Delta\mu_i^{(k)}}_{\text{Belief Update}} \propto \frac{\overbrace{\hat{\pi}_{\mathrm{i-1}}^{(k)}}^{\text{Sensory Precision}}}{\underbrace{\boldsymbol{\pi_i^{(k)}}}_{\text{Belief Precision}}} \delta_{i-1}^{(k)} \text{PE}$$

2nd level of the hierarchy

Translational Neuromodeling Unit

Take-Home Message



Stephan et al., *Frontiers Human Neurosci* 2016

References

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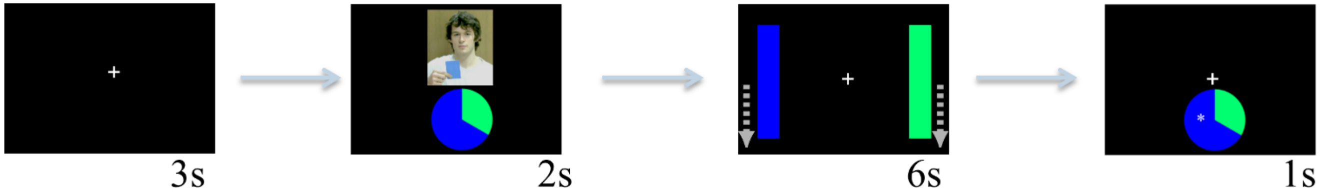
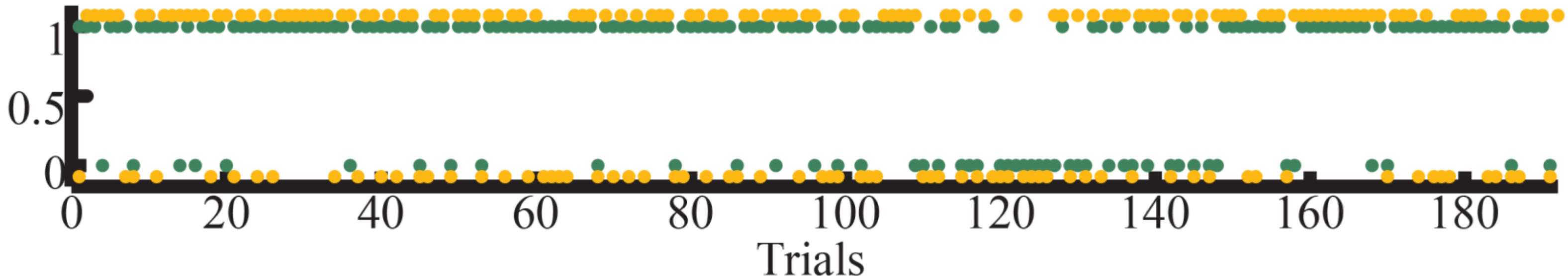
How do we construct regressors that correspond to cognitive processes and use them in SPM?

Translational Neuromodeling Unit

1. Pass individual subject trial history into SPM:



Response y (orange=1 advice was taken), input u (green=1 advice was accurate)



How do we construct regressors that correspond to cognitive processes and use them in SPM?

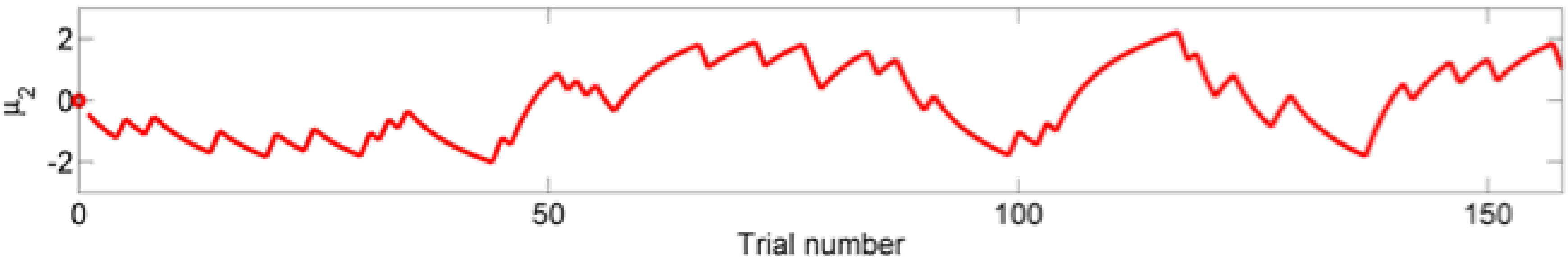
Translational Neuromodeling Unit

2. Estimated subject-by-subject model parameters:
   - Model Inversion:

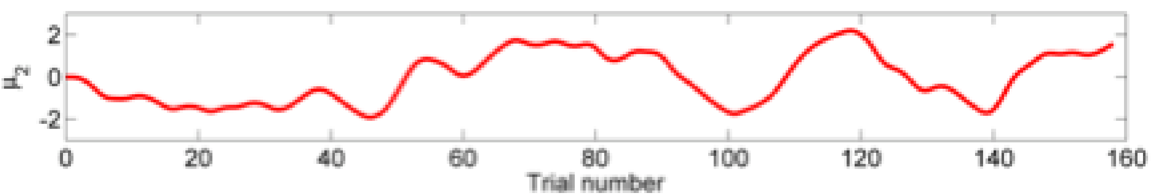
```
runnning model/param combination 4 of 546
Irregular trials: none
Ignored trials: none
Irregular trials: none

Optimizing...

Calculating the negative free energy...

Results:
     mu2_0: 1.0665
     sa2_0: 1.4966
     mu3_0: 1
     sa3_0: 1
        ka: 0
        om: -10
        th: 1.0000e-18
         p: [1.0665 1.4966 1 1 0 -10 1.0000e-18]
    ptrans: [1.0665 0.4032 1 0 -22.3327 -10 -34.5388]

       ze1: 0.8816
       ze2: 48.0000
         p: [0.8816 48.0000]
    ptrans: [2.0073 3.8712]

Negative free energy F: -82.9603
```

How do we construct regressors that correspond to cognitive processes and use them in SPM?

3. Generate model-based time-series:



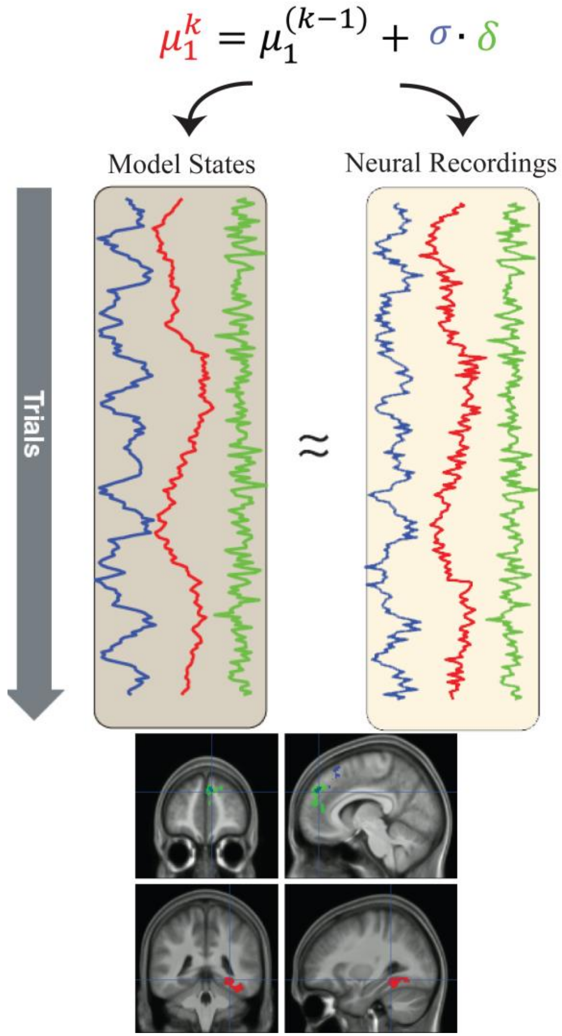
3. Convolve them with HRF:



Adapted from O'Doherty et al., 2007

How do we construct regressors that correspond to cognitive processes and use them in SPM?

5. Construct your GLM:



Adapted from Behrens et al., 2010

Estimate: single subject

Translational Neuromodeling Unit

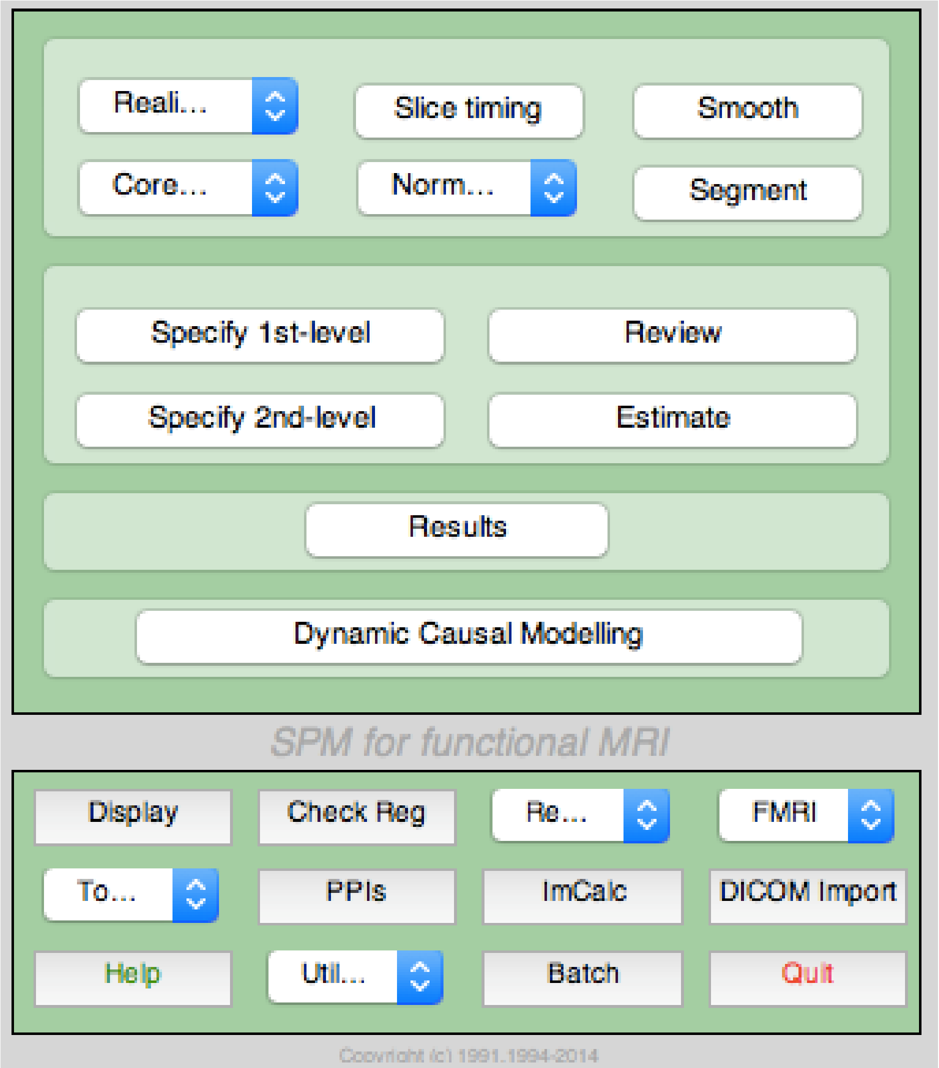
6. First-level analysis:
   - Load your regressors:

```
reg1 =

    [1x189 double]
    [1x189 double]
    [1x189 double]
```

```
mu1hat         <1x189 double>
positive_PE    <1x189 double>
```

Estimate: single subject

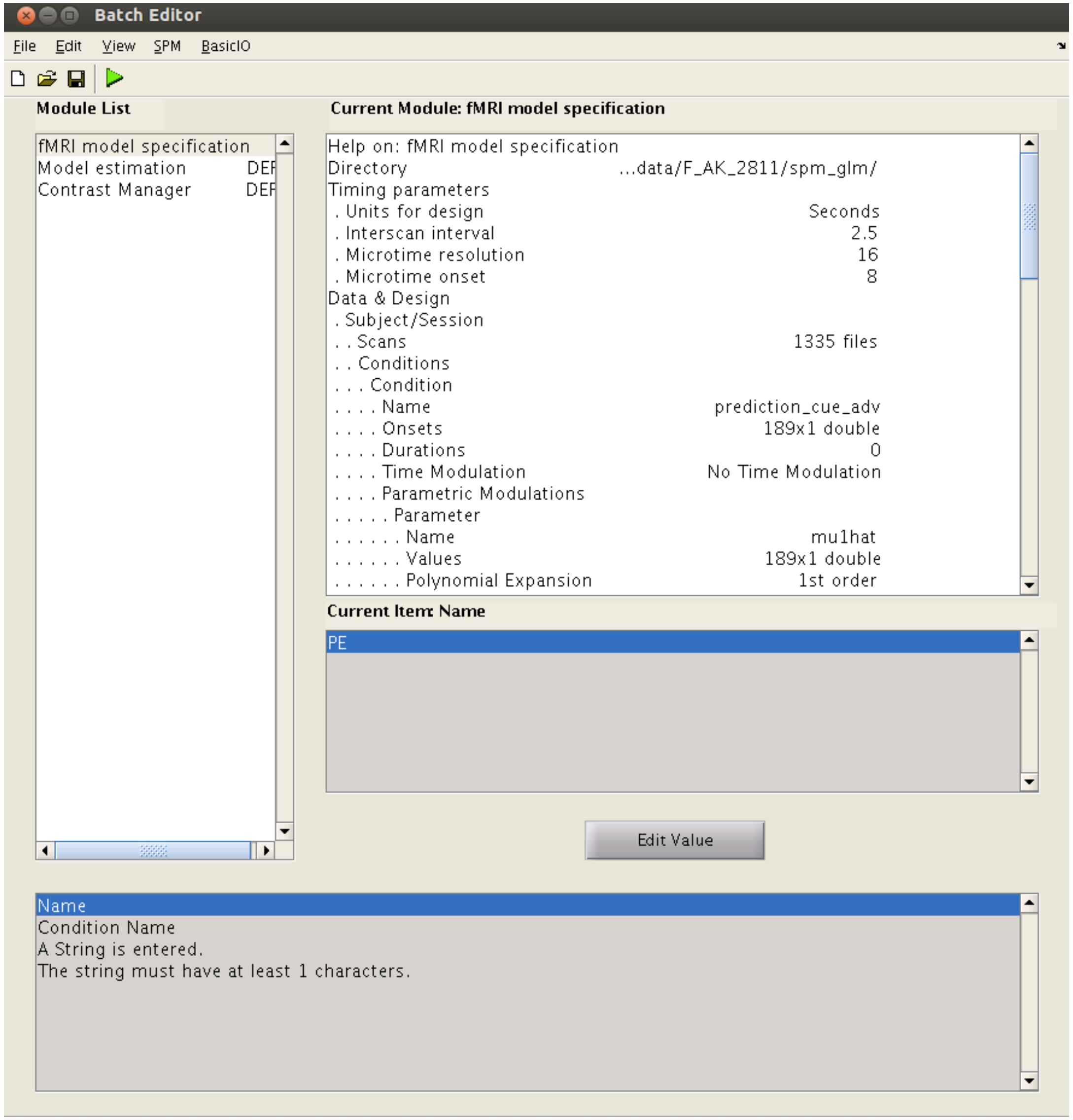
6. First-level analysis:
   - Open SPM: Specify first level analysis



Estimate: single subject

Translational Neuromodeling Unit

6. First-level analysis:
   - Load Design matrix into Batch editor



Estimate: single subject

6. First-level analysis:
   - Examine results:
     - PE