

# Joint Modelling of Behavioural and Brain Imaging Data

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## **Foundational research in AI, Mach Learning, Natural Comp:**

- learning theory
- state space models and dynamical systems
- coevolutionary dynamics, population based approaches to optimisation

## **Methodology advancements:**

- metric learning
- blending modelling with machine learning

## **Inter- and cross-disciplinary research (extract science from data):**

- astronomy
- cognitive neuroscience
- biomedical sciences
- computational finance

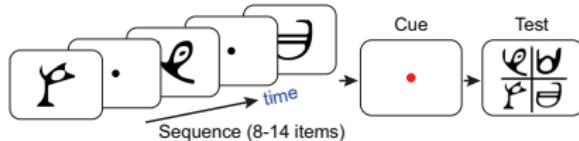
# Behavioral experiment

- 4 abstract symbols (retaining no semantic meaning/relationships)
- participants exposed to symbolic series over this alphabet generated by 0-, 1st- or 2nd- order Markov models.
- Markov models (actually VLMM) constructed in a hierarchical manner (to study possible transfer of information)
- after seeing a block of symbols there is a gap - participants are asked to predict what comes next (choose one of the 4 symbols presented in the screen in randomized positions).

Kourtzi, Wang, Shen, Tino, Welchman. *The Journal of Neuroscience*, 37(35), pp. 8412-8427, 2017.

# Experimental setup

a

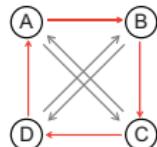


b

*Level-0: Zero-order model*

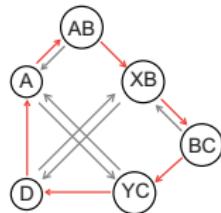
	A	B	C	D
A	0.18	0.72	0.05	0.05
B				
C				
D				

*Level-1: First-order model*



		Target			
		A	B	C	D
Context	A	0.8	0.2		
	B		0.8	0.2	
	C	0.2			0.8
	D	0.8	0.2		

*Level-2: Second-order model*



		Target			
		A	B	C	D
Context	A	0.8	0.2		
	D	0.8	0.2		
	AB	0.2	0.8		
	XB		0.8	0.2	
	BC	0.2	0.8		
	YC			0.8	

# Questions to investigate

- would like to investigate
  - transfer of knowledge across levels
  - transfer of learning capabilities across levels
  - higher level groupings of participants
  - strategies for coping with increasingly complex stimuli (environment) - probability matching/maximization
- BUT - sparse data difficult to capture - each participant saw a different series of symbols, albeit generated from the same source
- difficult to approach in a standard ML framework
- describe each participant (data item) by an associated model that captures his/her learning behaviour

# Model that Tracks Participants' Learning

- Mixture of Markov models of order  $k = 0, 1, 2$
- Predictive distribution for the  $t$ -th gap item:

$$p(s_t | s_{t-2}s_{t-1}) = \textcolor{blue}{w_0} \cdot p_0(s_t | \emptyset) + \textcolor{blue}{w_1} \cdot p_1(s_t | s_{t-1}) + \textcolor{blue}{w_2} \cdot p_2(s_t | s_{t-2}s_{t-1})$$

- Probability vector  $\mathbf{w}$  is of central importance. Its time evolution  $\mathbf{w}_t$  shows how a participant learned the correct set of contexts
- Bayesian approach to update  $\mathbf{w}_t$ .

# Quantification Measures on the Models

- How well did a participant learn the underlying source?

$$\text{KL}(\mathcal{M}^{true,k} \parallel \mathcal{M}_t^{tracking,k}) = \sum_{c \in Context^k} p^k(c) \cdot \text{KL} \left( p^k(\cdot|c) \parallel p_t^k(\cdot|c) \right)$$

- Probability maximization? To what degree?

$$\text{KL}(\mathcal{M}^{max,k} \parallel \mathcal{M}_t^{tracking,k}) = \sum_{c \in Context^k} p^k(c) \cdot \text{KL} \left( p^{max,k}(\cdot|c) \parallel p_t^k(\cdot|c) \right)$$

where

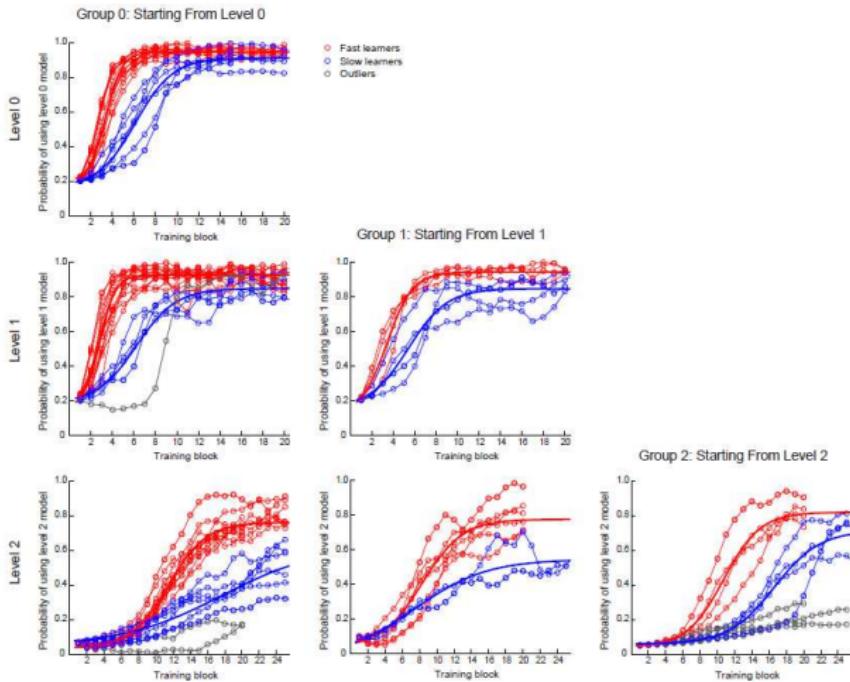
$$p^{max,k}(s|c) = \begin{cases} \approx 1 & s = s^{\max} \\ \approx 0 & \text{otherwise} \end{cases} \quad \text{with} \quad s^{\max} = \underset{s}{\operatorname{argmax}} p^k(s|c).$$

- Probability maximization or matching?

$$\mathcal{D}_t^{strategy} = \text{KL}(\mathcal{M}^{max,k} \parallel \mathcal{M}_t^{tracking,k}) - \text{KL}(\mathcal{M}^{true,k} \parallel \mathcal{M}_t^{tracking,k})$$

# Learning the Model Order

Figure 4



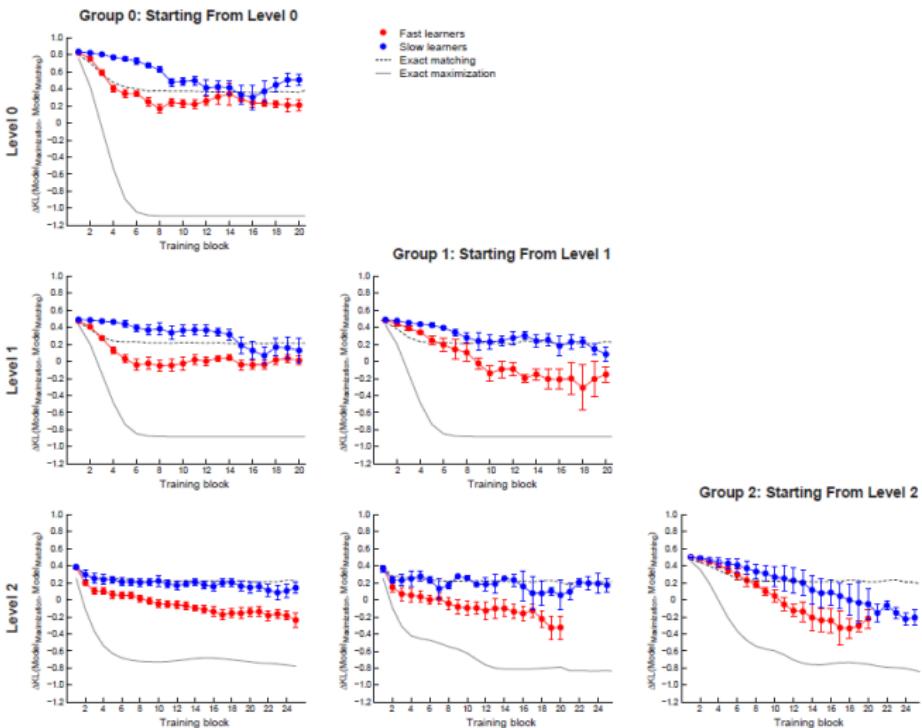
# Key Question

Does the participants grouping based on learning the **model order** carry on to other aspects of behavioural studies?

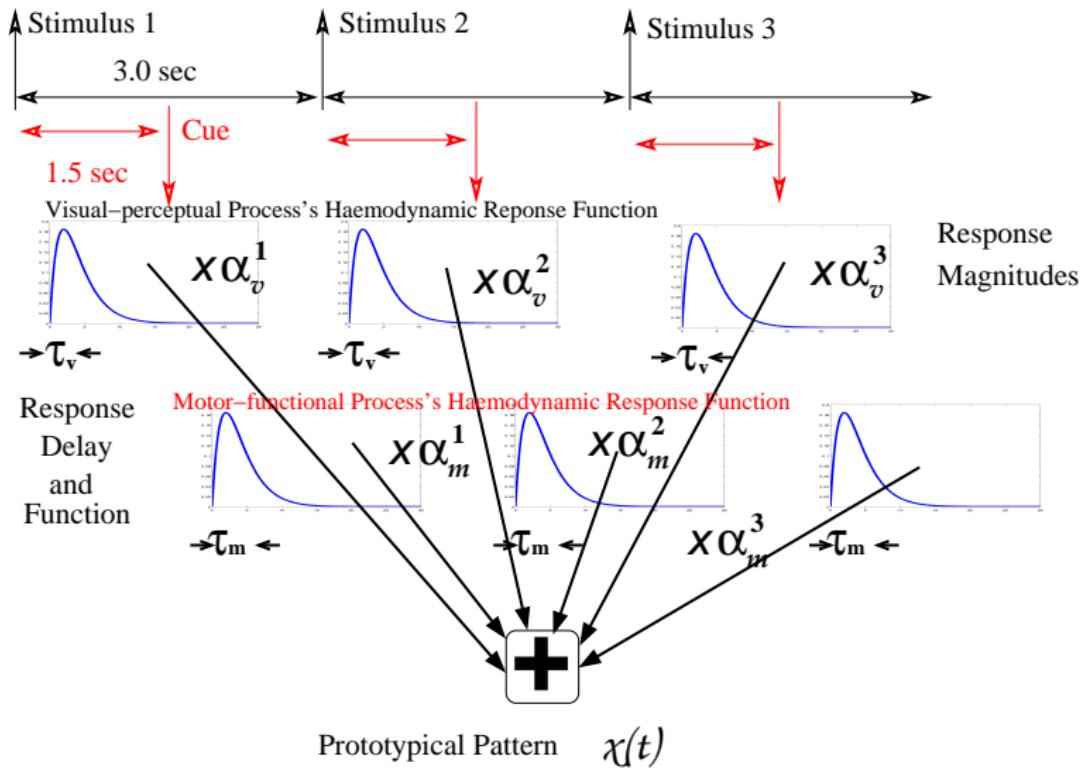
- transfer learning
- learning detailed source structure
- strategy choice (matching vs. maximization)

# Strategy Choice

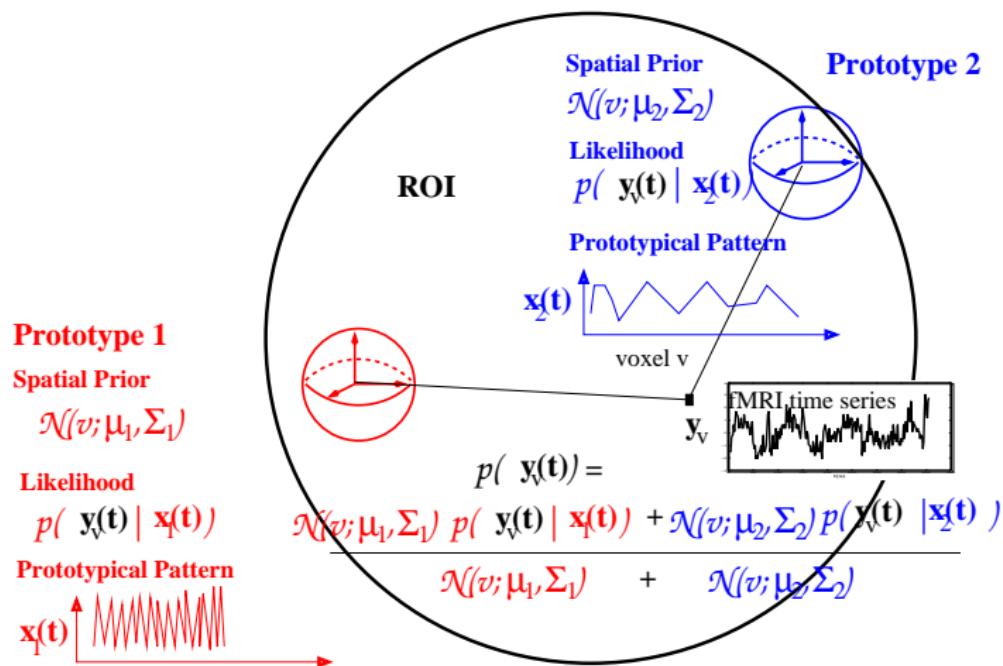
**Figure 6**



# fMRI signals in ROIs - HPM modelling



# Prototypes in space and time - ROI cortical activations



Shen, Mayhew, Kourtzi, Tino. Neuroimage, 84(1), pp. 657-671, 2014.

# Simultaneous brain imaging and behavioral measurements

## group level fMRI modelling

fast vs. slow learners

Bayesian formulation: **shared tight parameter priors in each group**

**hierarchy of common/individualized within-group modelling**

Shen, Alowadi, Wang, Kourtzi, Tino. Neural Comp, under review.

# Regions of Interest

## ■ Frontal lobe

- **MFG** - middle frontal gyrus: attentional control.
- **SFG** - superior frontal gyrus: coordination with sensory system.

Both involved in learning, in particular, in sequential organization and self-monitoring of actions.

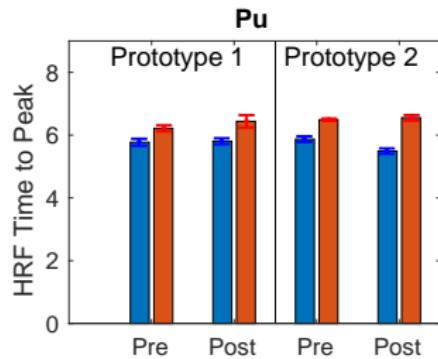
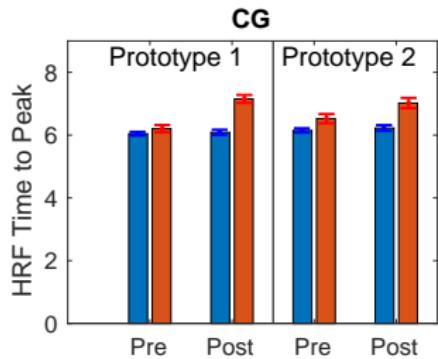
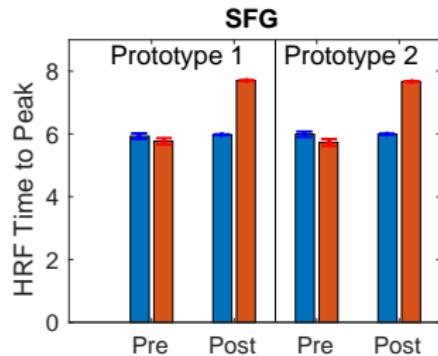
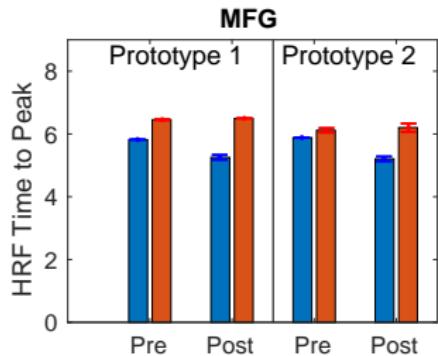
## ■ Limbic system

- **CG** - cingulate gyrus: integral part of the limbic system involved with emotion formation and processing, implicit learning and memory. Influential in linking motivational outcomes to behavior.

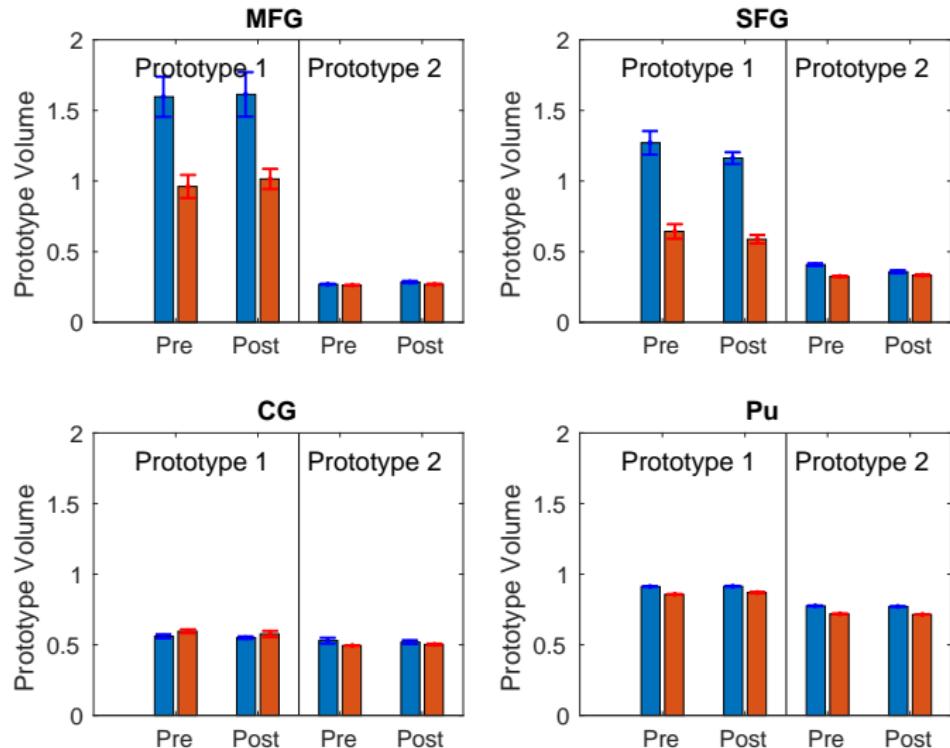
## ■ Basal ganglia

- **Pu** - putamen (lat. nutshell): Sub-cortical (dorsal stratum) associated with motor control, cognition, emotions and learning.

# HRF - time-to-peak



# Prototype volume



# ROI homogeneity

