Perceptual inference and learning

Collège de France 2008

Abstract

We start with a statistical formulation of Helmholtz's ideas about neural energy to furnish a model of perceptual inference and learning that can explain a remarkable range of neurobiological facts. Using constructs from statistical physics it can be shown that the problems of inferring what cause our sensory inputs and learning causal regularities in the sensorium can be resolved using exactly the same principles. Furthermore, inference and learning can proceed in a biologically plausible fashion. The ensuing scheme rests on Empirical Bayes and hierarchical models of how sensory information is generated. The use of hierarchical models enables the brain to construct prior expectations in a dynamic and context-sensitive fashion. This scheme provides a principled way to understand many aspects of the brain's organization and responses.

Overview

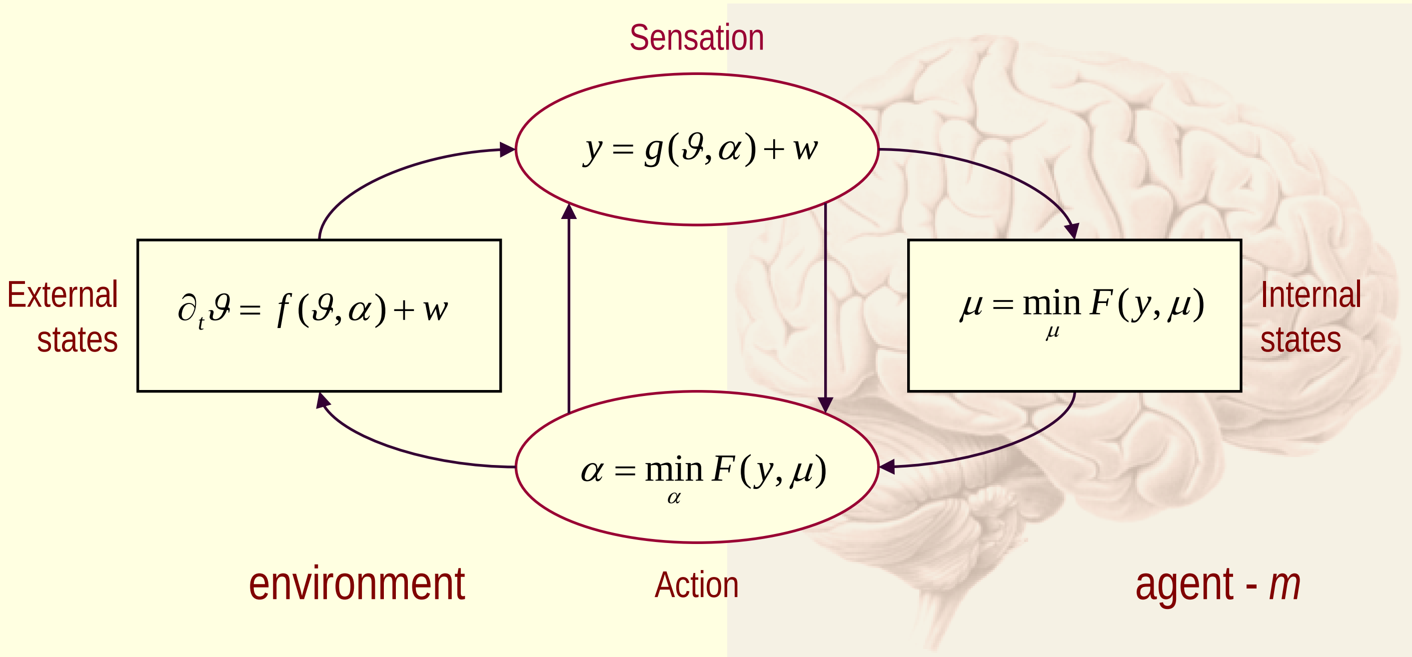
Inference and learning under the free energy principle
- Hierarchical Bayesian inference

A simple experiment

Bird songs (inference)
- Structural and dynamic priors
- Prediction and omission
- Perceptual categorisation

Bird songs (learning)
- Repetition suppression
- The mismatch negativity

Exchange with the environment



Separated by a Markov blanket

The free-energy principle

$$F = -\left\langle \ln p(y(\alpha), \vartheta \mid m) \right\rangle_q + \left\langle \ln q(\vartheta) \right\rangle_q \geq -\ln p(y \mid m)$$

Action to minimise a bound on surprise

$$F = -\left\langle \ln p(y(\alpha) \mid \vartheta, m) \right\rangle_q + D(q \,\|\, p(\vartheta))$$

$$\alpha = \min_{\alpha} F$$

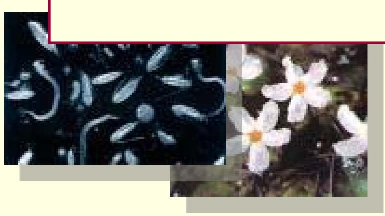
$$= \max_{\alpha} \left\langle \ln p(y(\alpha) \mid \vartheta, m) \right\rangle_q$$

Perception to optimise the bound

$$F = -\ln p(y \mid m) + D(q(\vartheta; \mu) \,\|\, p(\vartheta \mid y))$$

$$\mu = \min_{\mu} F \Rightarrow$$

$$q(\vartheta; \mu) \rightarrow p(\vartheta \mid y)$$



The ensemble density and its parameters

$$q(\vartheta; \mu) = q(u; \mu_u) q(\theta; \mu_\theta) q(\gamma; \mu_\gamma)$$

Perceptual inference	Perceptual learning	Perceptual uncertainty
$\mu_u = \min_{\mu} F$	$\mu_\theta = \min_{\mu} F$	$\mu_\gamma = \min_{\mu} F$

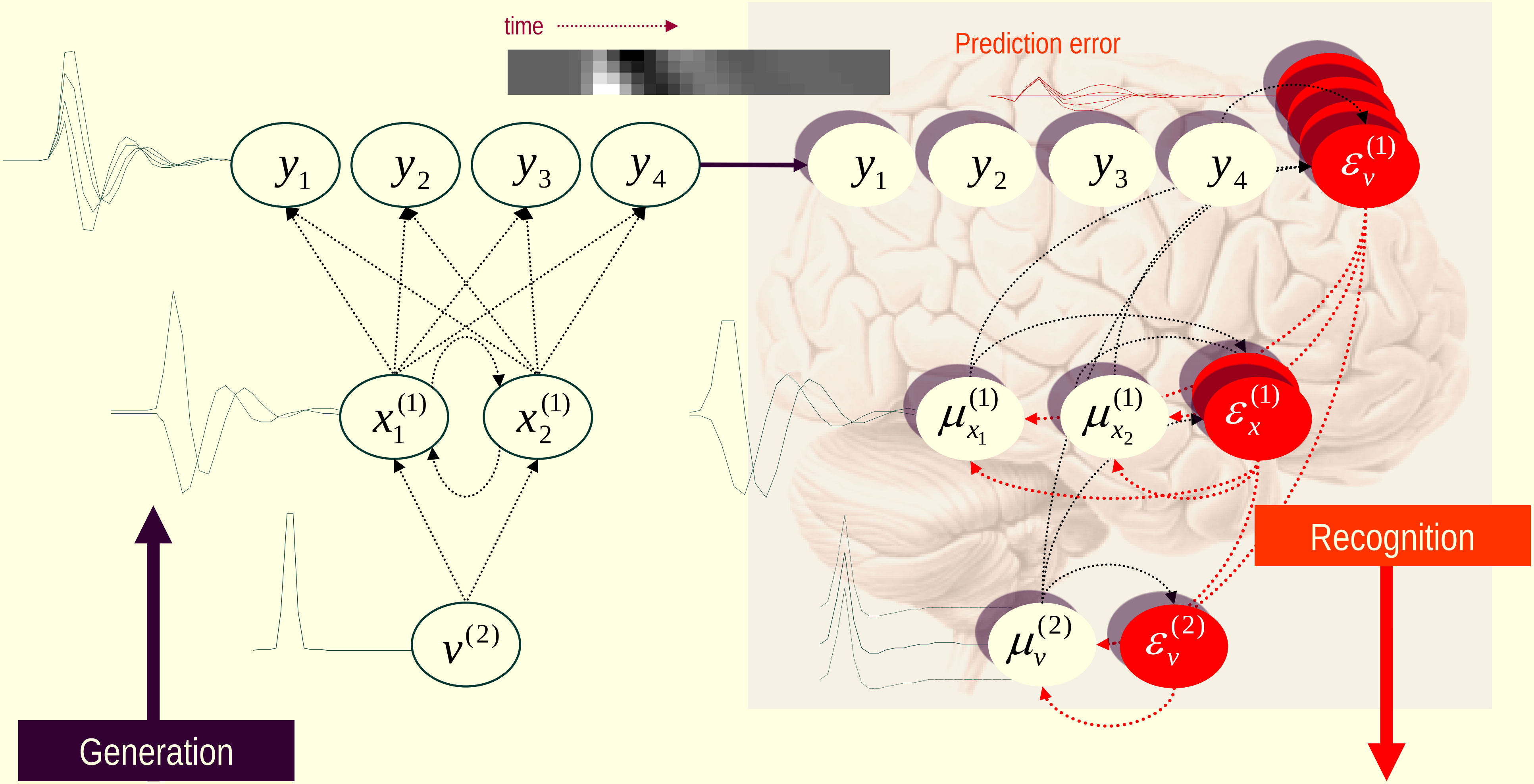
Hierarchical models and message passing

Top-down messages | Bottom-up messages

$$v^{(i)} = g(x^{(i)}, v^{(i+1)}) + \varepsilon_v^{(i)}$$
$$\partial_t x^{(i)} = f(x^{(i)}, v^{(i+1)}) + \varepsilon_x^{(i)}$$

$$\varepsilon_v^{(i)} = \mu_v^{(i)} - g(\mu_x^{(i)}, \mu_v^{(i+1)})$$
$$\varepsilon_x^{(i)} = \partial_t \mu_x^{(i)} - f(\mu_x^{(i)}, \mu_v^{(i+1)})$$

$$\partial_t \mu_v^{(i)} = -\partial_{v\varepsilon^{(i-1)}} F \varepsilon^{(i-1)} - \partial_{v\varepsilon^{(i)}} F \varepsilon^{(i)}$$
$$\partial_t \mu_x^{(i)} = -\partial_{x\varepsilon^{(i)}} F \varepsilon^{(i)}$$



Empirical Bayes and hierarchical models

D-Step
Perceptual inference

Bottom-up — Lateral — Top-down

$$\partial_t \mu_v^{(i)} = -\partial_v \varepsilon_u^{(i-1)T} \mu_\gamma^{(i-1)} \varepsilon_u^{(i-1)} - \mu_\gamma^{(i)} \varepsilon_u^{(i)}$$

$$\varepsilon_v^{(i)} = \mu_v^{(i)} - g(\mu_x^{(i)}, \mu_v^{(i+1)})$$

Recurrent message passing among neuronal populations, with top-down predictions changing to suppress bottom-up prediction error

E-Step
Perceptual learning

$$\partial_t \mu_\theta^{(i)} = -\left\langle \partial_\theta \varepsilon_u^{(i)T} \mu_\gamma^{(i-1)} \varepsilon_u^{(i)} \right\rangle$$

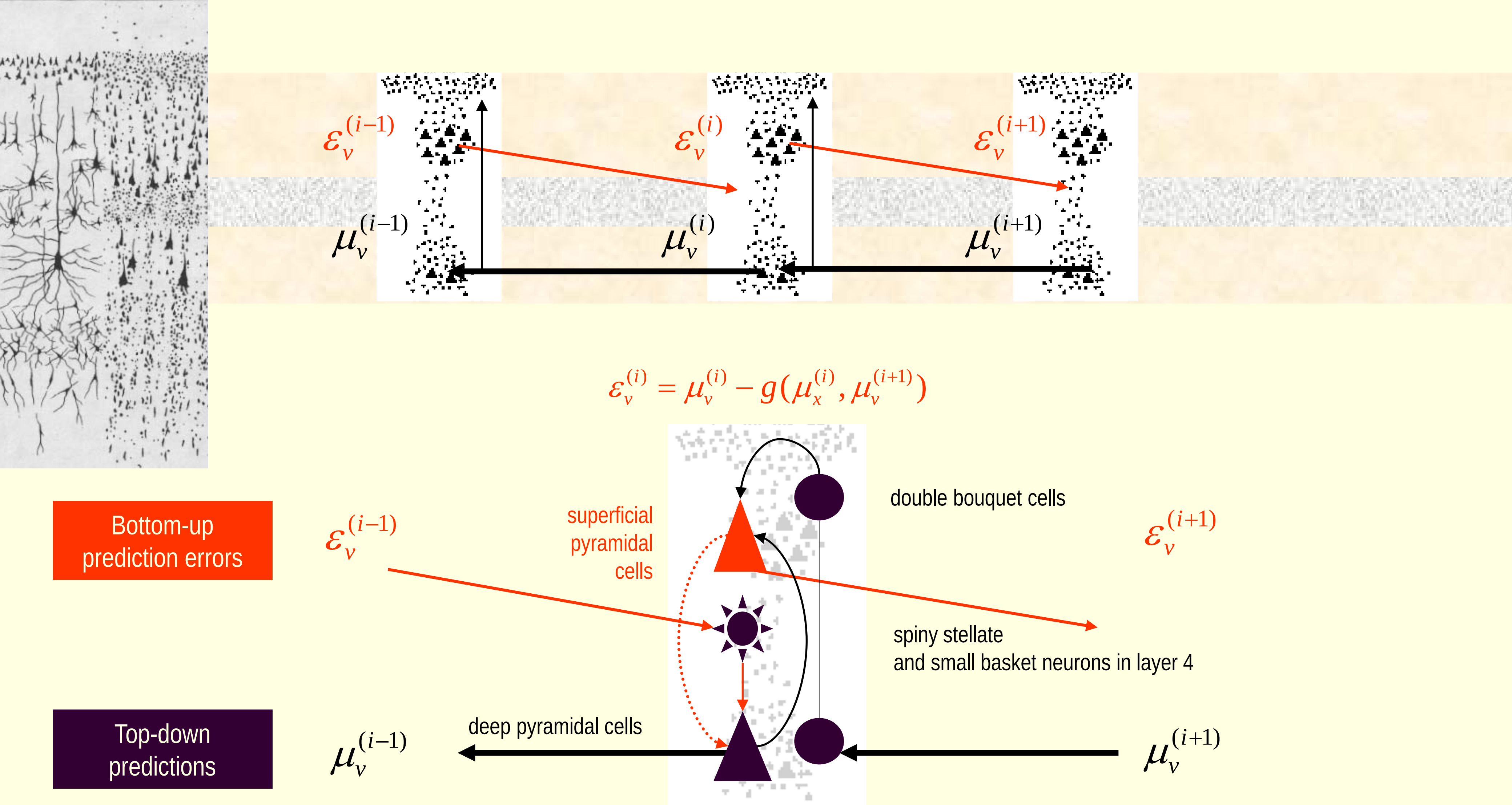
Associative plasticity, modulated by precision

M-Step
Perceptual uncertainty

$$\partial_t \mu_\gamma^{(i)} = \mu_\gamma^{(i)-1} - \varepsilon_u^{(i)T} \varepsilon_u^{(i)}$$

Encoding of precision through classical neuromodulation or plasticity in lateral connections

Friston K Kilner J Harrison L A free energy principle for the brain. J. Physiol. Paris. 2006



$$\varepsilon_v^{(i)} = \mu_v^{(i)} - g(\mu_x^{(i)}, \mu_v^{(i+1)})$$

$$\partial_t \mu_v^{(i)} = -\partial_v \varepsilon_u^{(i-1)T} \mu_\gamma^{(i-1)} \varepsilon_u^{(i-1)} - \mu_\gamma^{(i)} \varepsilon_u^{(i)}$$

Neural implementation in cortical hierarchies (c.f. evidence accumulation models)

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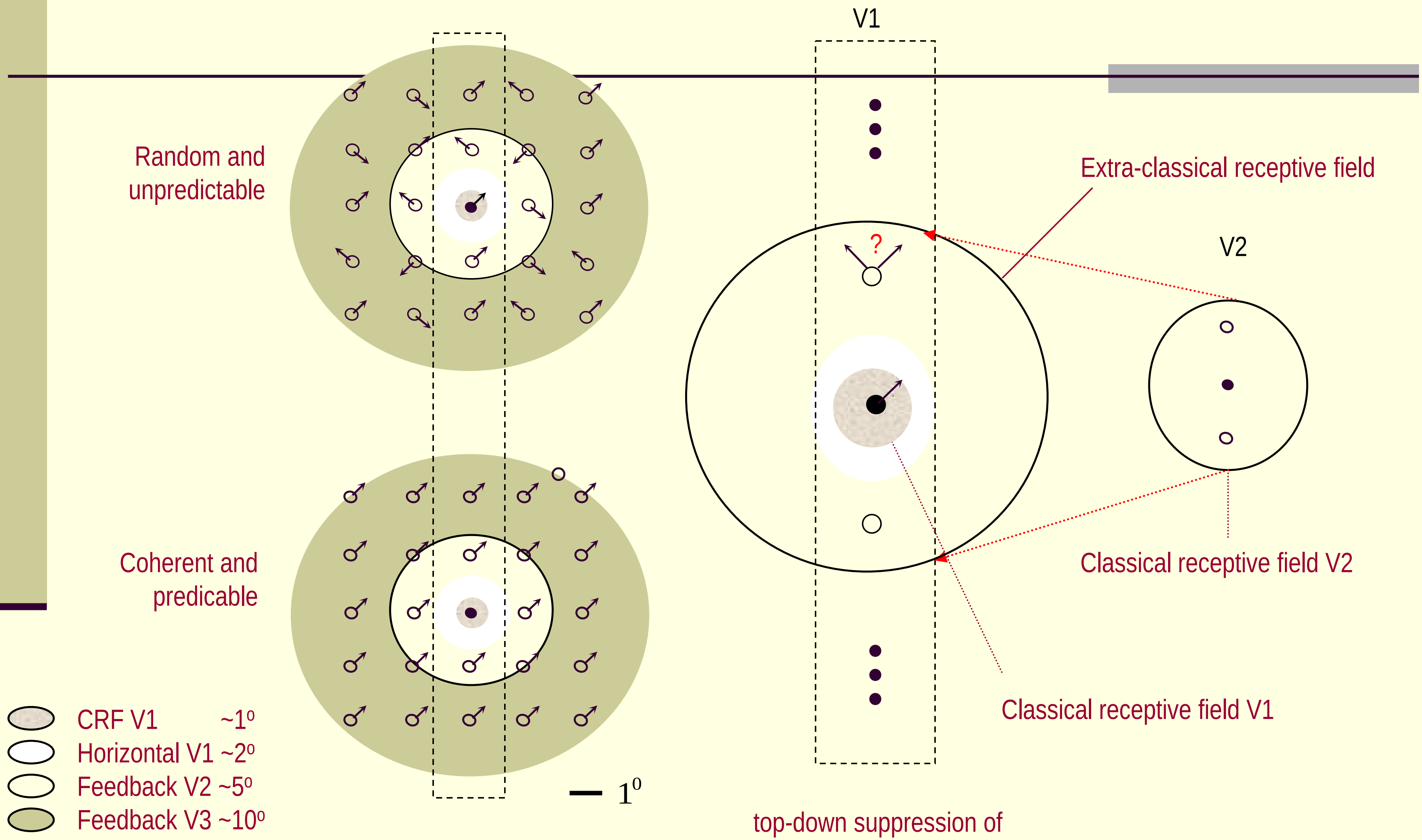
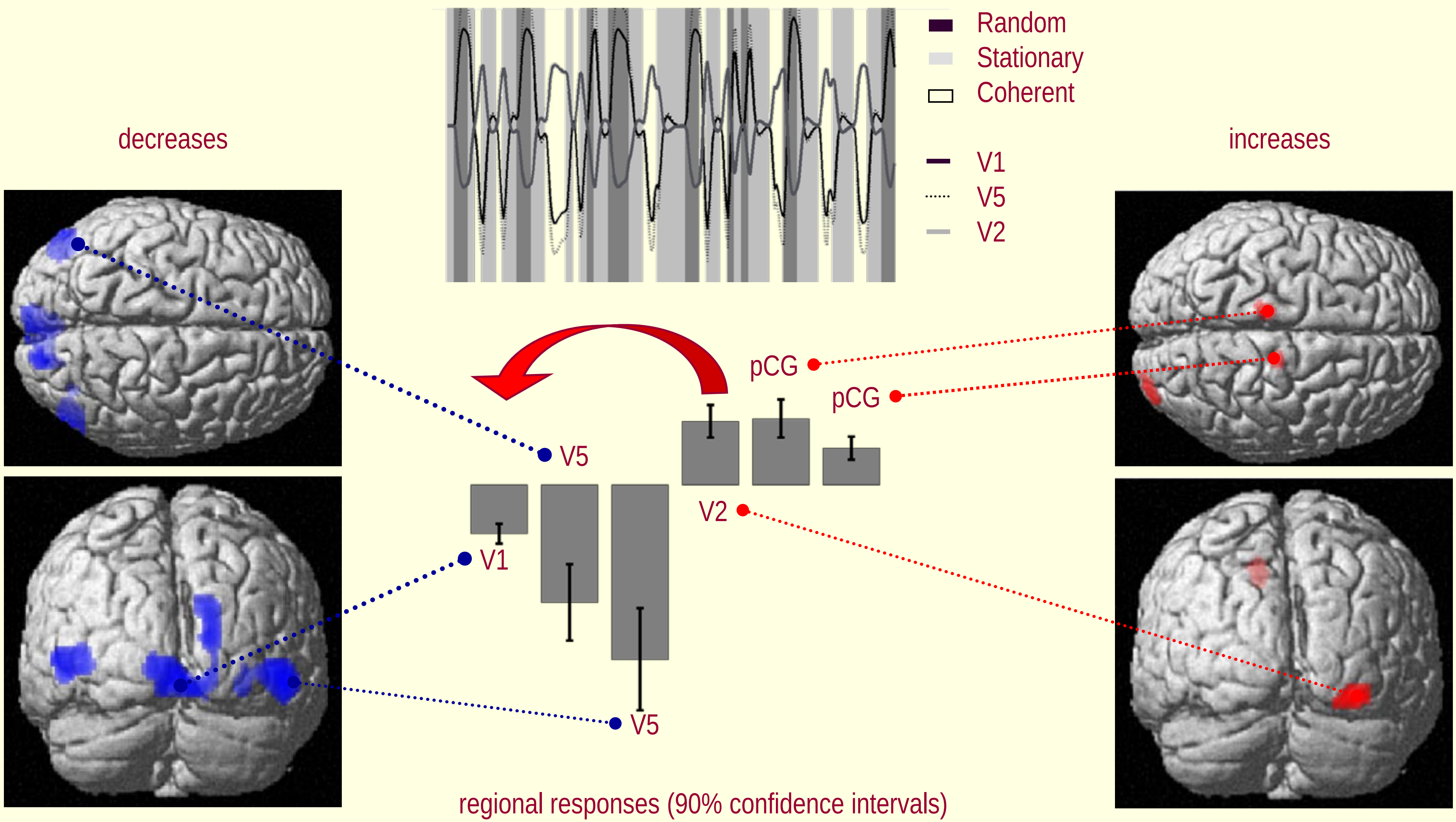
A brain imaging experiment with sparse visual stimuli



Angelucci et al

top-down suppression of prediction error when coherent?

Suppression of prediction error with coherent stimuli



Harrison et al NeuroImage 2006

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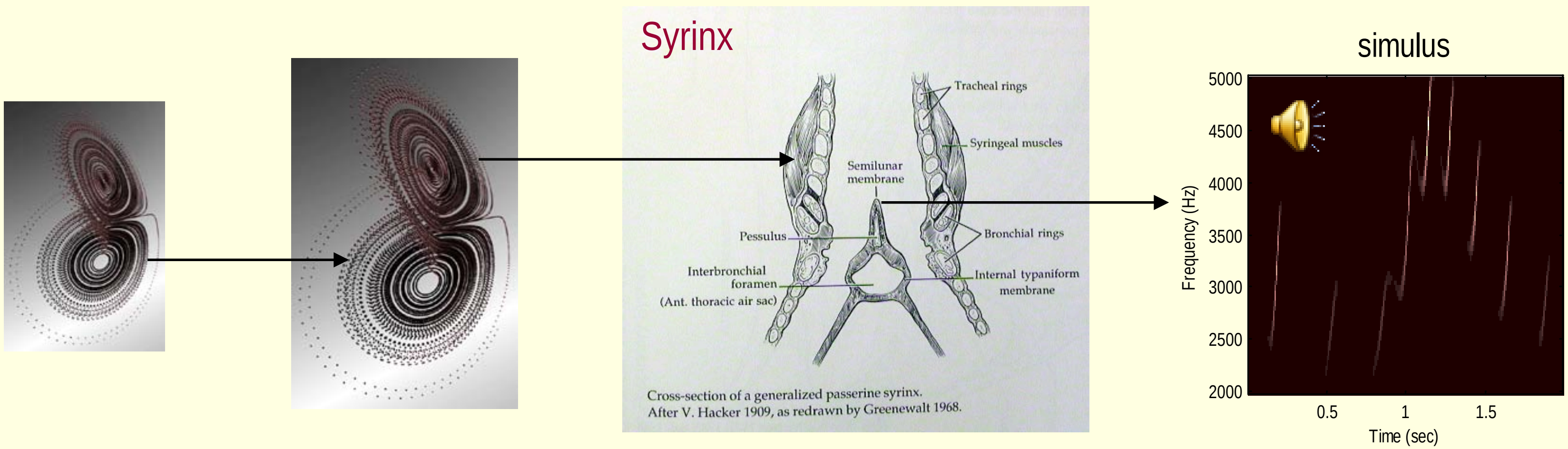
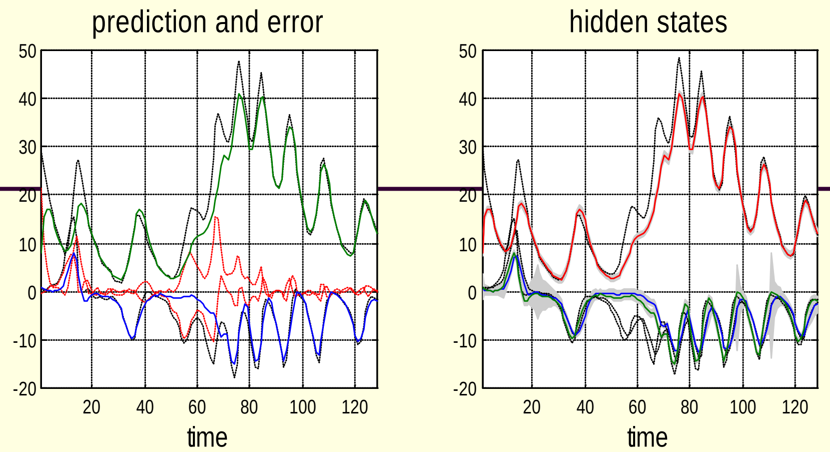
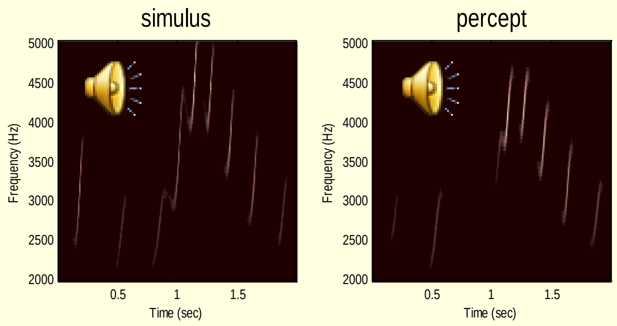
Synthetic song-birds

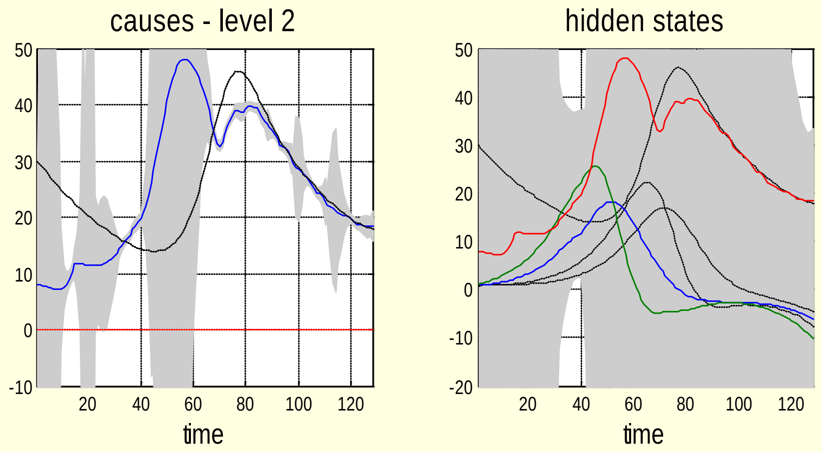


Neuronal hierarchy

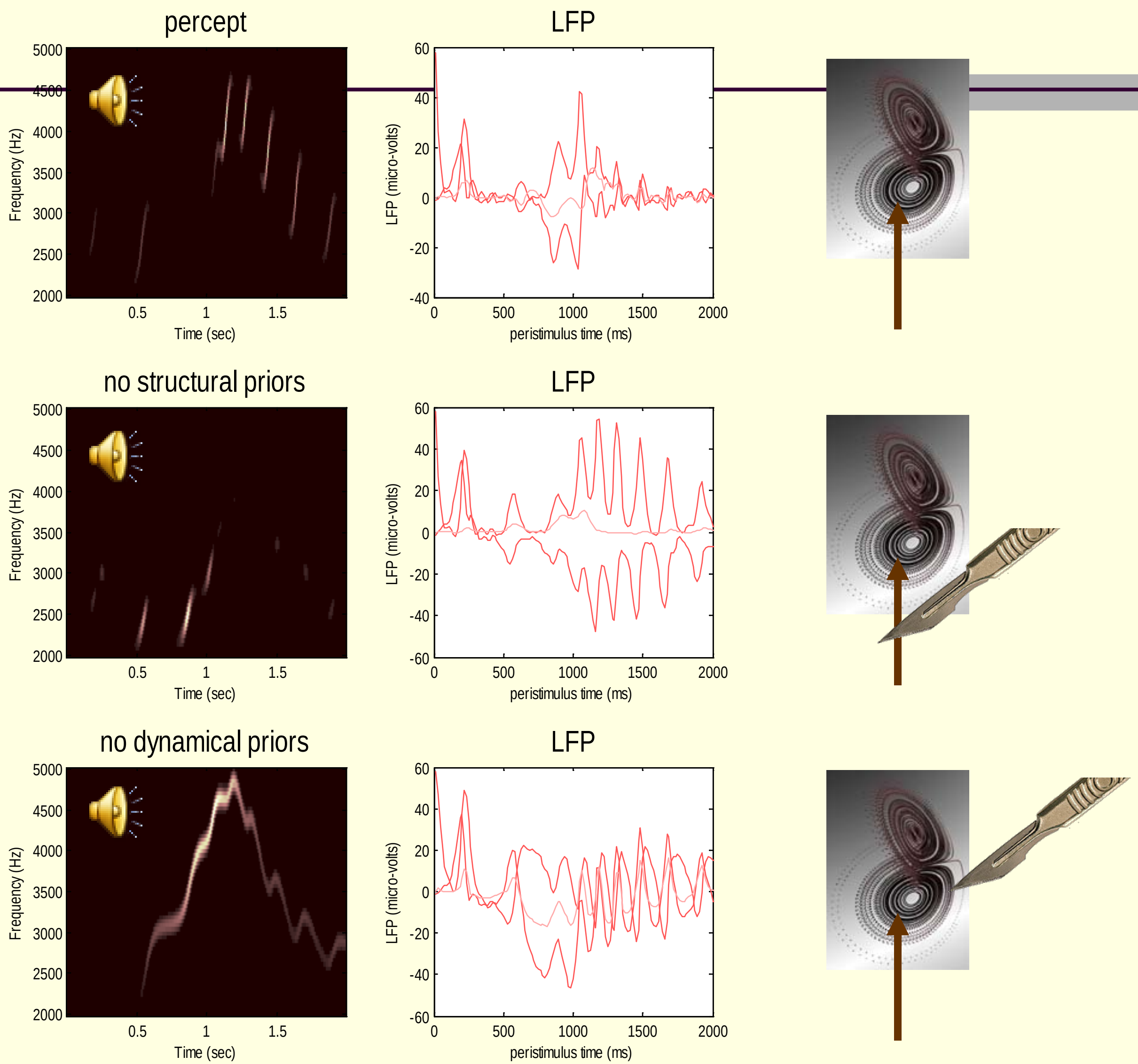


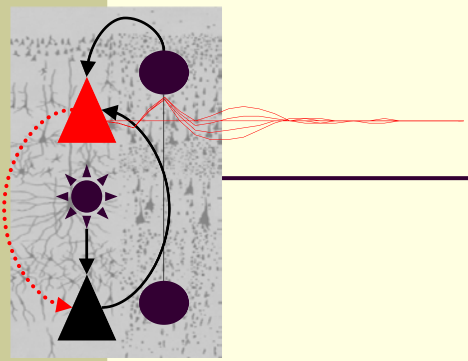
Song recognition with DEM

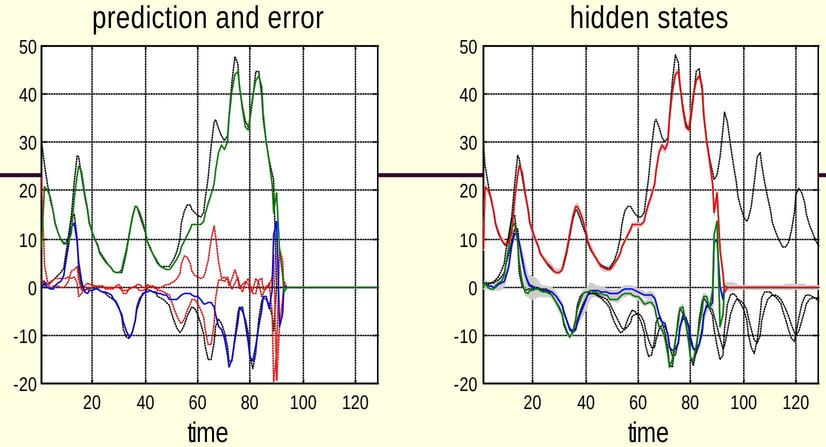




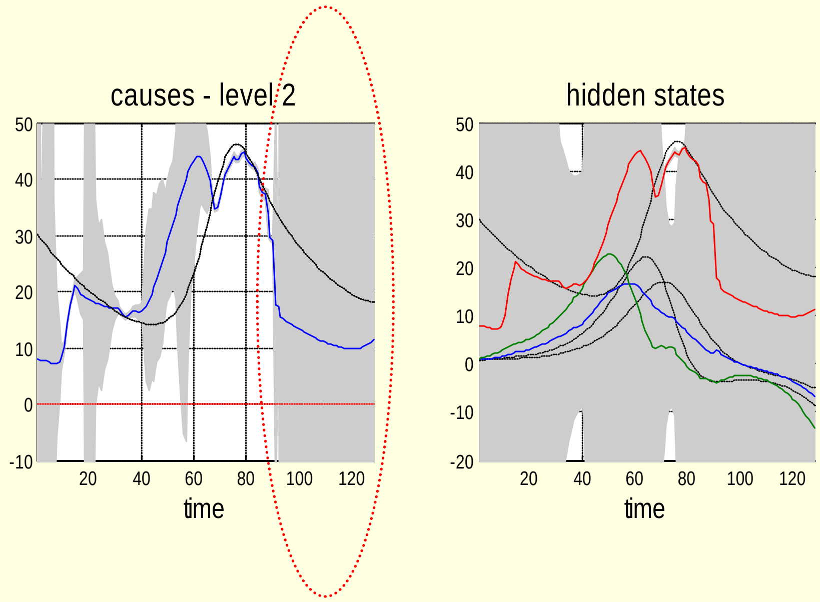
… and broken birds



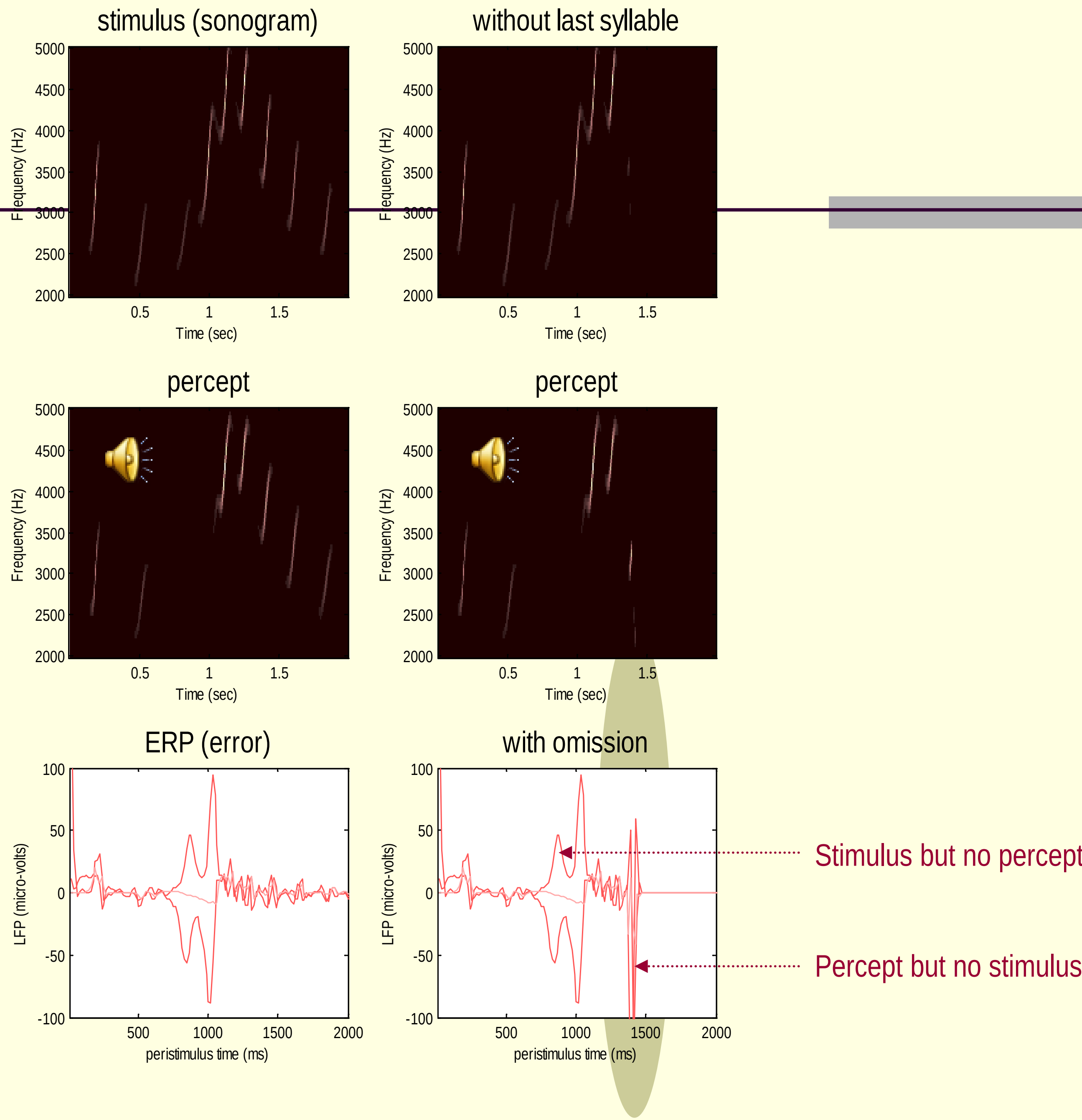




… omitting the last chirps



omission and violation of predictions



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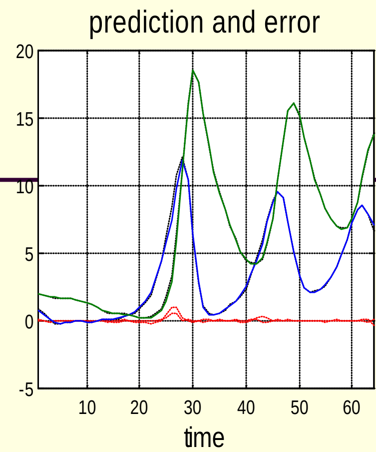
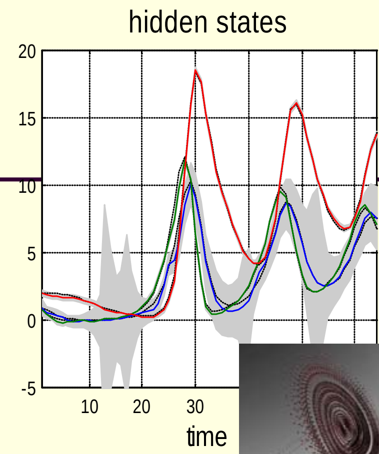


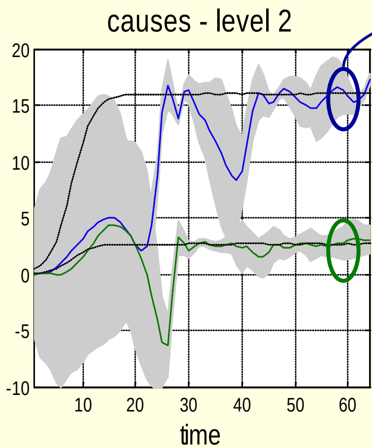


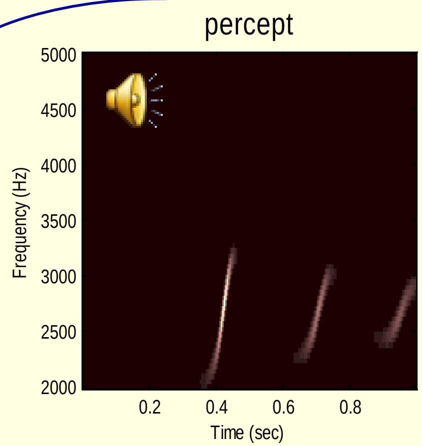
A simple song

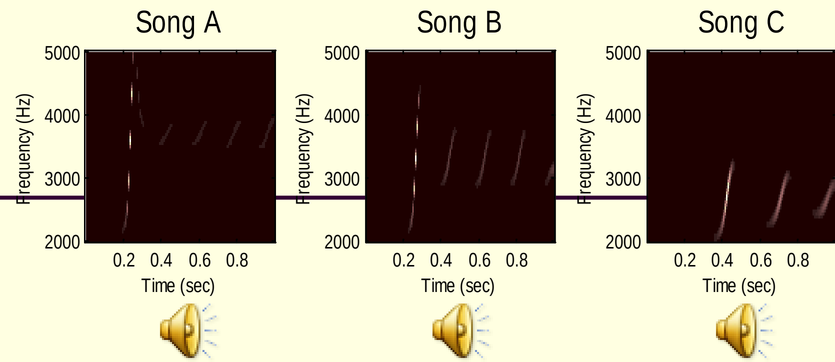
$$f(x) = \begin{bmatrix} 18x_2 - 18x_1 \\ v_1 x_1 - 2x_3 x_1 - x_2 \\ 2x_1 x_2 - v_2 x_3 \end{bmatrix}$$

Encoding sequences in terms of attractor manifolds

$$v(t)$$

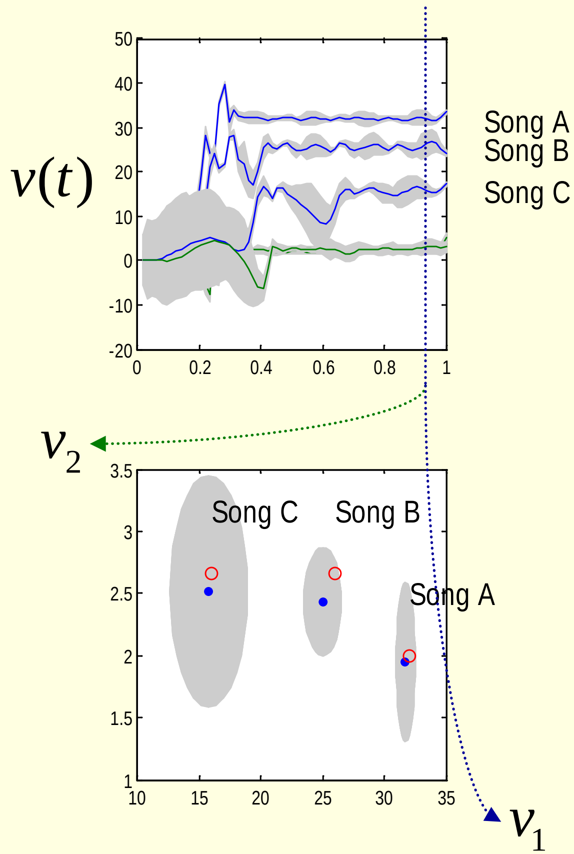






Categorizing sequences

90% confidence regions



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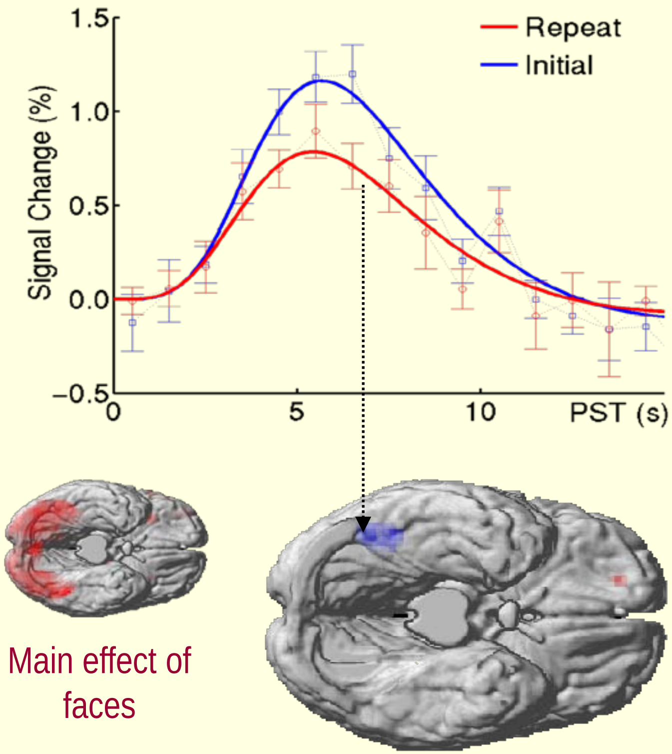
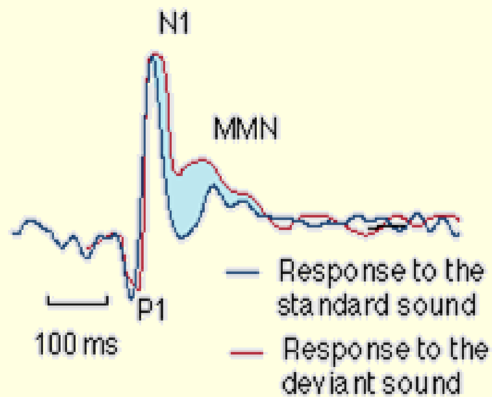
Repetition suppression and the MMN



Main effect of faces

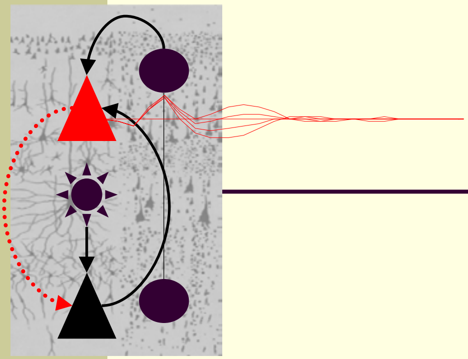
Suppression of inferotemporal responses to repeated faces

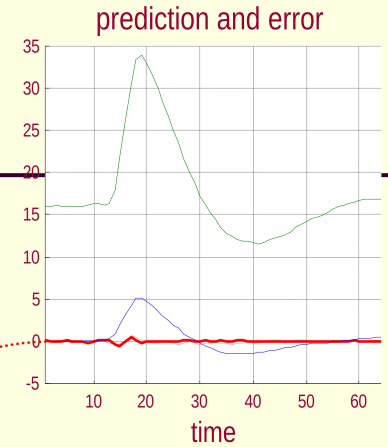


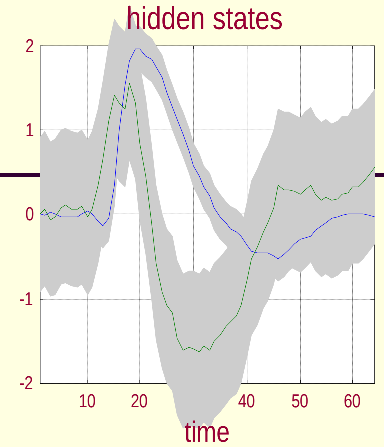
The MMN is an enhanced negativity seen in response to any change (deviant) compared to the standard response.

Henson *et al* 2000

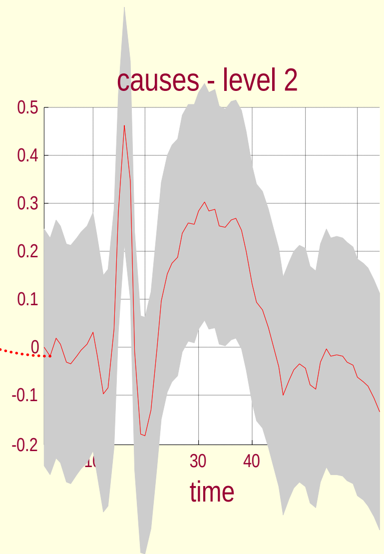
A simple chirp

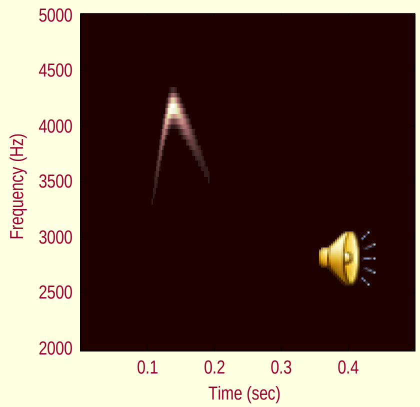




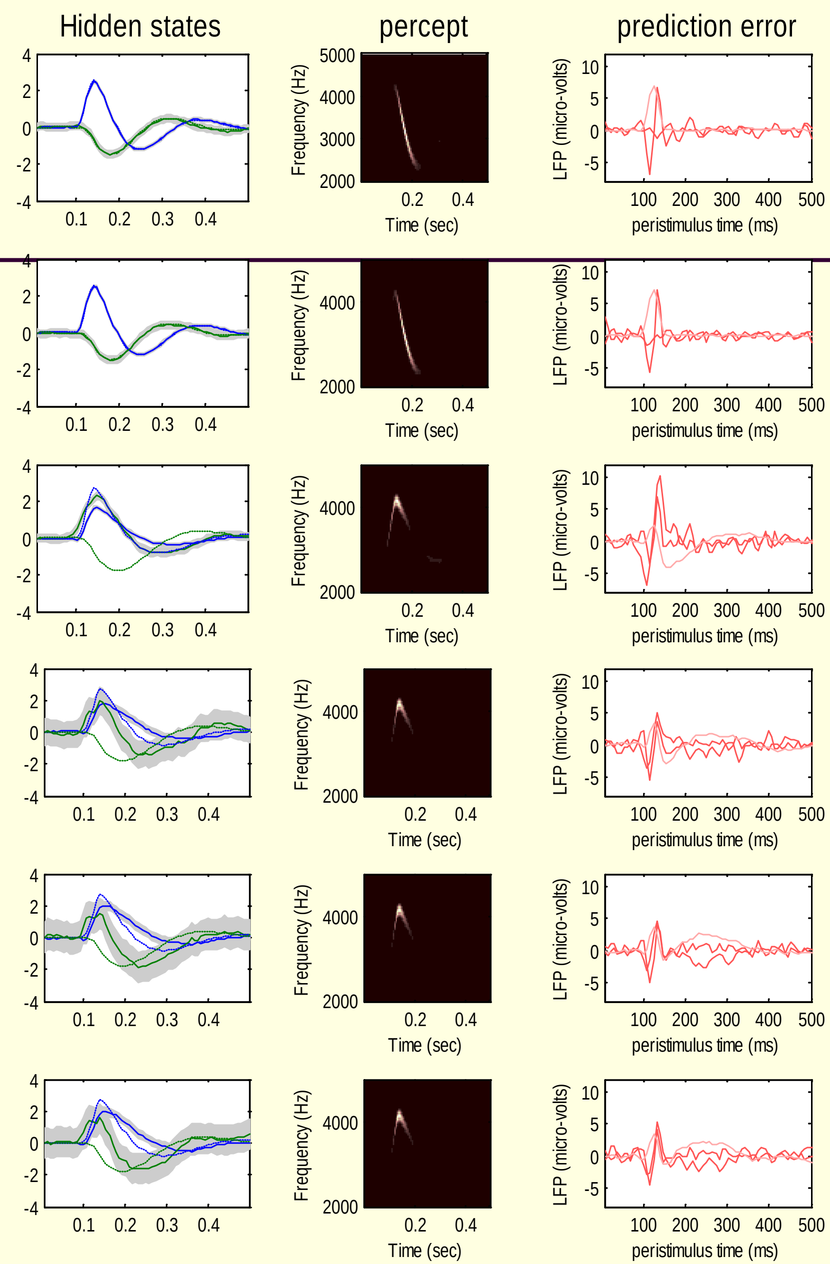


Prediction error encoded by superficial pyramidal cells





Simulating ERPs to repeated chirps



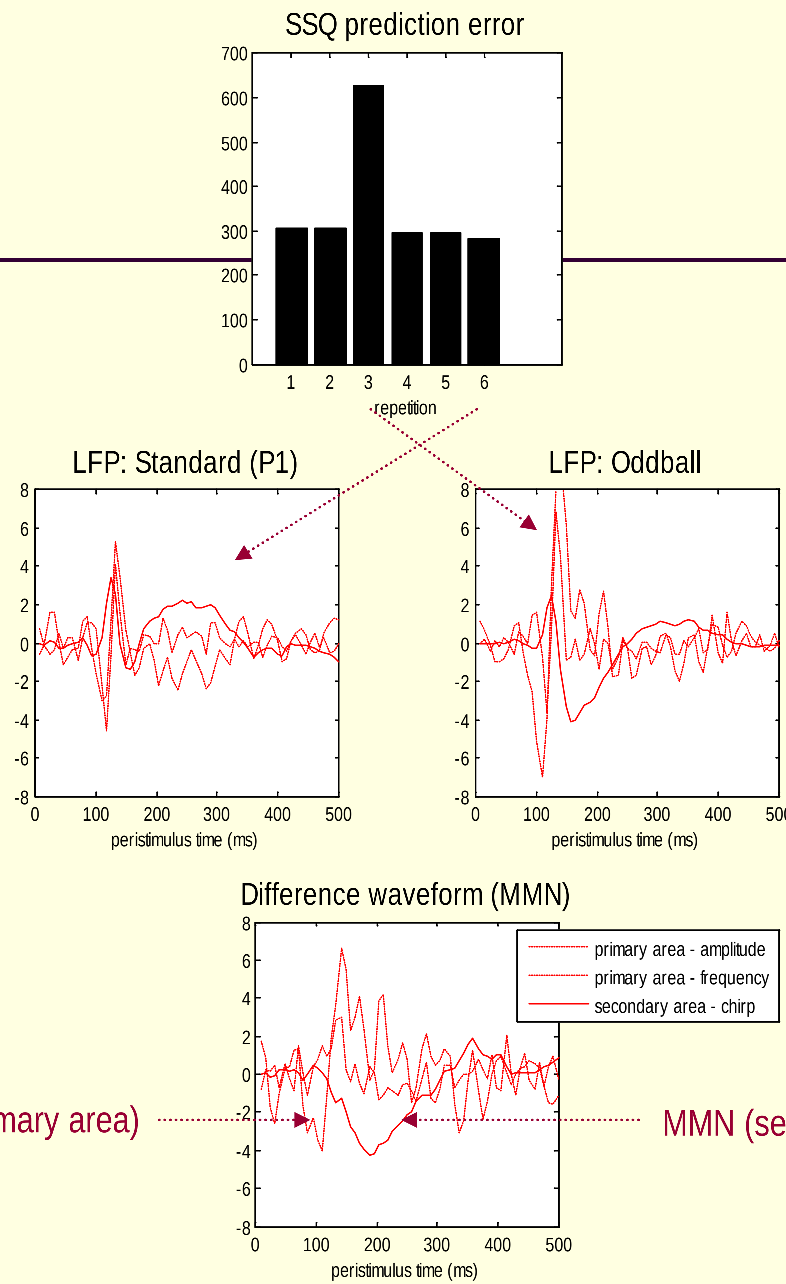
$$\mu_u = \min_\mu F$$

Perceptual inference: suppressing error over peristimulus time

Perceptual learning: suppression over repetitions

$$\mu_\theta = \min_\mu F$$

The MMN



Last presentation
(after learning)

First presentation
(before learning)

Enhanced N1 (primary area)

MMN (secondary area)

P300 (tertiary area)?

Summary

- A free energy principle can account for several aspects of action and perception
- The architecture of cortical systems speak to hierarchical generative models
- Estimation of hierarchical dynamic models corresponds to a generalised deconvolution of inputs to disclose their causes
- This deconvolution can be implemented in a neuronally plausible fashion by constructing a dynamic system that self-organises when exposed to inputs to suppress its free energy
- Minimisation of free energy proceeds over many spaces, including the state of a model (perception), its parameters (learning), its hyperparameters (salience and attention) and the model itself (selection in somatic or evolutionary time).