# uai2011

The 27th Conference on Uncertainty in Artificial Intelligence Active Inference and Uncertainty

Karl Friston

#### Abstract

In this presentation, I will rehearse the free-energy formulation of action and perception, with a special focus on the representation of uncertainty: The free-energy principle is based upon the notion that both action and perception are trying to minimise the surprise (prediction error) associated with sensory input. In this scheme, perception is the process of optimising sensory predictions by adjusting internal brain states and connections; while action is regarded as an adaptive sampling of sensory input to ensure it conforms to perceptual predictions (this is known as active inference). Both action and perception rest on an optimum representation of uncertainty, which corresponds to the precision of prediction error. Neurobiologically, this may be encoded by the postsynaptic gain of prediction error units. I hope to illustrate the plausibility of this framework using simple simulations of cued, sequential, movements. Crucially, the predictions driving movements are based upon a hierarchical generative model that infers the context in which movements are made. This means that we can temporarily confuse agents by changing the context (order) in which cues are presented. These simulations provide a (Bayes-optimal) simulation of contextual uncertainty and set-switching that can be characterised in terms of behaviour and electrophysiological responses. Interestingly, one can lesion the encoding of precision (postsynaptic gain) to produce pathological behaviours that are reminiscent of those seen in Parkinson's disease. I will use this as a toy example of how information theoretic approaches to uncertainty may help understand action selection and set-switching



UNCERTAINTY, ansen seale (2005)



"Objects are always imagined as being present in the field of vision as would have to be there in order to produce the same impression on the nervous mechanism" - Hermann Ludwig Ferdinand von Helmholtz





**Geoffrey Hinton** 



Thomas Bayes

From the Helmholtz machine to the Bayesian brain and self-organization



Richard Feynman



Hermann Haken





# Overview

**Ensemble dynamics** 

The free-energy principle

Entropy and equilibria Free-energy and surprise

Perception and generative models Hierarchies and predictive coding

PerceptionBirdsong and categorization<br/>Simulated lesions and perceptual uncertaintyActionCued reaching and affordance<br/>Simulated lesions and behavioral uncertainty



#### What is the difference between snowfall and a flock of birds?





Ensemble dynamics, clumping and swarming

#### ...birds (biological agents) stay in the same place

# They resist the second law of thermodynamics, which says that their entropy should increase

## But what is the entropy?

 $H = \int_{0}^{T} dt \mathcal{L}(t) = -\int p(\vartheta \mid m) \ln p(\vartheta \mid m) d\vartheta$  $\mathcal{L} = -\ln p(s \mid m)$ 

...entropy is just average surprise



This means biological agents self-organize to minimise surprise. In other words, to ensure they occupy a limited number of states (cf homeostasis).

But there is a small problem... agents cannot measure their surprise

$$s = \mathbf{g}(\vartheta)$$

But they can measure their free-energy, which is always bigger than surprise

$$F(t) \ge \mathcal{L}(t)$$

This means agents should minimize their free-energy. So what is free-energy?

# What is free-energy?

... free-energy is basically prediction error







Free-energy is a function of sensations and a proposal density over hidden causes

$$F(\tilde{s}, \tilde{\mu}) = Energy - Entropy = \mathbf{E}_{q}(G) + \mathbf{E}_{q}(\ln q(\vartheta \mid \tilde{\mu}))$$

and can be evaluated, given a generative model (Gibbs Energy) or likelihood and prior:

 $G(\tilde{s}, \vartheta) = -\ln p(\tilde{s}, \vartheta \mid m) = -\ln p(\tilde{s} \mid \vartheta, m) - \ln p(\vartheta \mid m)$ 

So what models might the brain use?

#### Hierarchal models in the brain





 $\vartheta \supset \{\tilde{x}(t), \tilde{v}(t), \theta, \Pi\}$ 

So how do prediction errors change predictions?



...by hierarchical message passing in the brain



cf., Predictive coding or Kalman-Bucy filtering



# Summary

Biological agents resist the second law of thermodynamics
They must minimize their average surprise (entropy)
They minimize surprise by suppressing prediction error (free-energy)
Prediction error can be reduced by changing predictions (perception)
Prediction error can be reduced by changing sensations (action)
Perception entails recurrent message passing in the brain to optimise predictions
Predictions depend upon the precision of prediction errors



## Overview

**Ensemble dynamics** 

The free-energy principle

Entropy and equilibria Free-energy and surprise

Perception and generative models Hierarchies and predictive coding

PerceptionBirdsong and categorization<br/>Simulated lesions and perceptual uncertaintyActionCued reaching and affordance<br/>Simulated lesions and behavioral uncertainty

# Making bird songs with Lorenz attractors







# Perceptual categorization



time (seconds)



#### Hierarchical (itinerant) birdsong: sequences of sequences





#### Simulated lesions and false inference LFP percept 60 LFP (micro-volts) 40 Frequency (Hz) $\dot{\tilde{\mu}}^{(v,i)} = \mathcal{D}\tilde{\mu}^{(v,i)} - \tilde{\varepsilon}_{v}^{(i)T}\xi^{(i)} - \xi^{(v,i+1)}$ 20 $\dot{\tilde{\mu}}^{(x,i)} = \mathcal{D}\tilde{\mu}^{(x,i)} - \tilde{\varepsilon}_x^{(i)T}\xi^{(i)}$ -20 -40 LFP no top-down messages 60 40 LFP (micro-volts) Frequency (Hz) $$\begin{split} \dot{\tilde{\mu}}^{(v,i)} &= \mathcal{D}\tilde{\mu}^{(v,i)} - \tilde{\varepsilon}_{v}^{(i)T}\xi^{(i)} - \xi^{(i)} \\ \dot{\tilde{\mu}}^{(x,i)} &= \mathcal{D}\tilde{\mu}^{(x,i)} - \tilde{\varepsilon}_{x}^{(i)T}\xi^{(i)} \end{split}$$ 20 -20 -40 -60 no lateral messages LFP 6 4( LFP (micro-volts) Frequency (Hz) $$\begin{split} \dot{\tilde{\mu}}^{(v,i)} &= \mathcal{D}_{\tilde{\nu}}^{(v,i)} - \tilde{\varepsilon}_{v}^{(i)T} \xi^{(i)} - \xi^{(v,i+1)} \\ \dot{\tilde{\mu}}^{(x,i)} &= \tilde{\mu}^{(x,i)} - \tilde{\varepsilon}_{x}^{(i)T} \xi^{(i)} \end{split}$$ 20 -20 -40 -60 L 0.5 1.5 500 1000 1500 2000 1 time (seconds) peristimulus time (ms)

#### no structural priors

no dynamical priors



## Overview

Ensemble dynamics

The free-energy principle

Entropy and equilibria Free-energy and surprise

Perception and generative models Hierarchies and predictive coding

PerceptionBirdsong and categorization<br/>Simulated lesions and perceptual uncertaintyActionCued reaching and affordance<br/>Simulated lesions and behavioral uncertainty











#### Dopamine and precision









#### Uncertainty and perseveration







salience



proprioception













#### Uncertainly, delusions and confusion











# Thank you

#### And thanks to collaborators:

Rick Adams Harriet Brown Jean Daunizeau Lee Harrison Stefan Kiebel James Kilner Jérémie Mattout Klaas Stephan

And colleagues:

Peter Dayan Jörn Diedrichsen Paul Verschure Florentin Wörgötter

And many others