# Postdoctoral Project:
# Toward a Unified Bayesian Model of Vision

Jonathan Vacher, jonathan.vacher@ens.fr

Département Mathématiques et Applications, École Normale Supérieure &
Unité de Neurosciences, Information et Complexité, CNRS

**Outline** Bayesian probability is a powerful tool to model information processing. In perceptual neuroscience, the brain is often viewed as an information processing machine [1]. In this context, the "Bayesian brain" hypothesis [9, 3] emerges naturally: sensory information builds up in the brain as a likelihood that is combined to an internal prior in order to detect, discriminate, take decisions, *etc.* Confronting such an hypothesis to experimental data is still a challenge, especially in neurophysiology. The Bayesian inference theory is rich and applies in many fields that involve data analysis. However, when applied to perceptual neuroscience the approaches are disparate because they highly depend on the experimental techniques used (electrophysiology, psychophysics, imaging). My project tackles the question of unifying the Bayesian brain models of vision to address both electrophysiological and psychophysical data. This project will help us gain a better understanding of what neural computations are. In addition, it provides a complete Bayesian model that implies systematic characterization of neural responses through generative models of textures and images.

## 1 Related works

**Ideal Bayesian Observer Model** Recent advances in the field of Bayesian modeling [13, 12, 11, 8] have justified the outcome and bias observed in psychophysical studies of vision. In order to explain how the brain processes sensory information, the Bayesian model assumes that the brain performs some abstract measurements interpreted as a likelihood. These measurements are subsequently biased by an internal prior that is able to explain observed sensory bias, see Figure 1. However, these psychophysics experiments are rarely combined to their neurophysiological counterparts, as explained in [9]. In this context, such a model can be perceived by experimentalists as a mathematical and abstract black box.

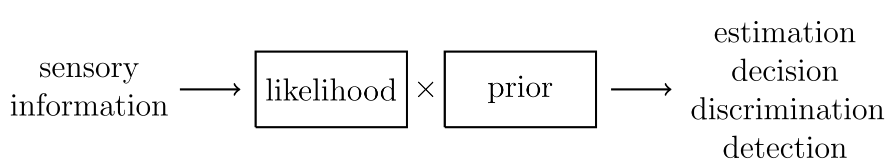


Figure 1: The basic principle of a Bayesian observer.

**Likelihood Functions Implemented by Neural Populations** In electrophysiology, work from the Movshon laboratory at NYU has focused on the computation made by neural populations: the main claim is that neurons implement likelihood functions through the combinations of their tuning curve and stimulus responses [7, 6]. In short, a stimulus $s$ elicits a number of spikes $m_i$ in neuron $i$ which has a characteristic response function $f_i$ called a tuning curve. In the case of Poisson spiking neurons, the number of spikes $m_i$ is generated from the Poisson law $P_{M_i|S}$ of parameter $f_i(s)$. The combination of the different neurons results in the computation of a likelihood function, see Figure 2. In this project, I would like to focus on two essential components: the question of the prior and that of the stimulus complexity (high dimensional movie stimulations).

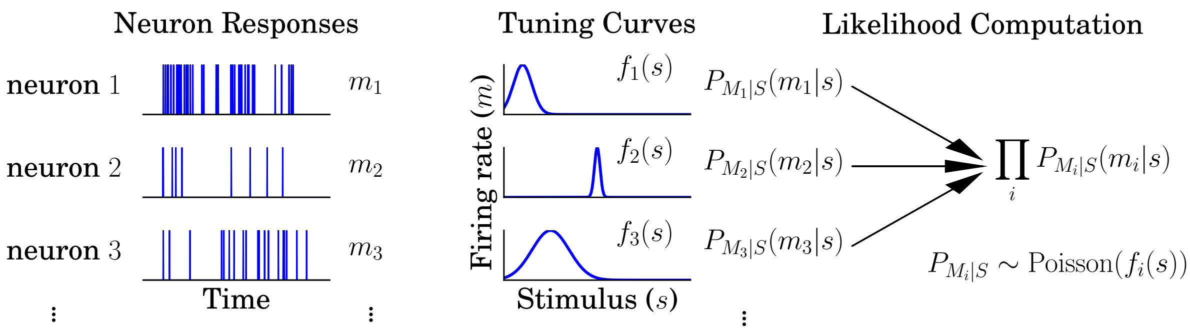


Figure 2: Neural implementation of likelihood computations.

**Priors Encoded in the Heterogeneity of Neural Populations** The recent work of Ganguli and Simoncelli [4] provides a framework that tackles in a mostly theoretical way the problem of how a prior is encoded in neural populations. In this work, the neurons implement a likelihood function. In addition, they assume that the tuning curves of neurons are distributed according to a certain law of density $d$, see Figure 3. By maximizing a lower bound of the mutual information between stimulus $s$ and the measurements of neurons $\mathbf{m} = (m_1, \ldots, m_n)$, they show that the prior (*ie* the density of $s$) is equal to the "tuning curve density" $d$ (see [4] for details). Yet, this result does not take into account the complexity of the stimulus and reduces neurons to their tuning curves.

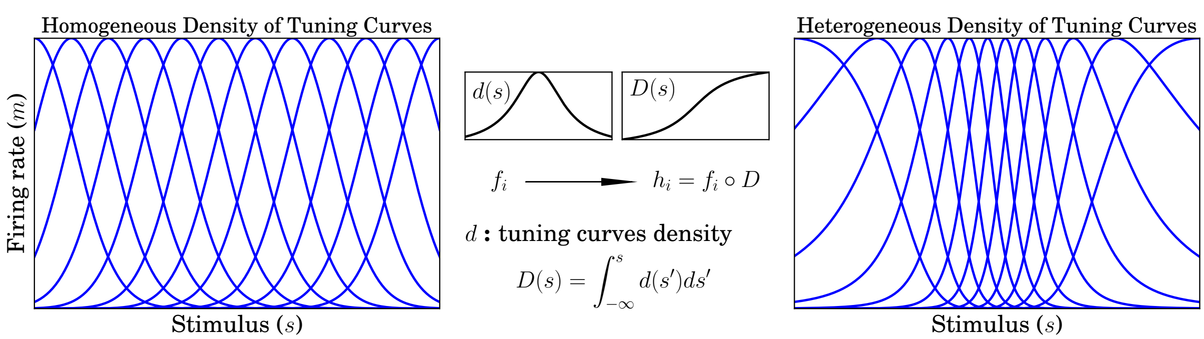


Figure 3: Density of tuning curves.

# 2 Working Program

In the related works, I identify three avenues. First, the lack of neurophysiological experiments that test the "Bayesian brain" hypothesis. Second, the simplifying assumption on the stimulus that discards its complexity. Third, following the simple stimulus, neurons are reduced to their tuning curves.

**Task 1: Take Back the Complexity of Visual Stimuli** The class of models I will develop in my project assumes an underlying generative model of images, see Figure 4. An image $i$ is generated with probability distribution $P_{I|S}$ parametrized by $s$ (for instance speed, spatial frequency, orientation). When presented to an ideal Bayesian observer, it elicits measurements of neurons $\mathbf{m} = (m_1, \ldots, m_n)$.

Typically $m_k$ is the spike counts of neuron $k$. Finally, the estimation $\hat{s}$ is computed from the combination of the measurements' distribution $P_{M_k|S}$ and of an internal prior $P_{\hat{S}}$. By requiring a generative model of

$$\begin{tikzcd} s \sim P_S \arrow[r] & i \sim P_{I|S} \arrow[r] & m_k \sim P_{M_k|I} \arrow[r] & \hat{s} \sim P_{\hat{S}|M_k} \end{tikzcd}$$

likelihood

$$P_{M_k|S} = \int_{\mathcal{I}} P_{M_k|I}(m_k|i) P_{I|S}(i|s) \mathrm{d}i \qquad P_{\hat{S}} = d$$

prior

Figure 4: The ideal Bayesian observer model that takes into account the stimulus complexity.

measurements knowing the stimulus, such models are able to take back into account part of its complexity. One consequence is that a Poisson spiking neuron is modeled by the probability distribution $P_{M_k|I}$ (instead of $P_{M_k|S}$, see Figure 2) which depends on the image $i$. Instead of being parametrized by the neuron's tuning curve, the Poisson law is parametrized by the neuron's receptive field[1]. The goal of Task 1 is to refine the results of Ganguli [4] in a more general context where the concept of "tuning curve density" is replaced by an equivalent concept of "receptive field density". In parallel, such models allow to run simulations that are essential to evaluate their strengths and weaknesses. The outcomes are twofold: a theory and an associated code enabling numerical simulations.

**Task 2: A Bridge Between Electrophysiology and Psychophysics** Using this framework to explain effects observed in psychophysics (*eg* the effect of spatial frequency/contrast over speed perception) provides hypothesis about the "receptive fields density" of the neural population observable using electrophysiology. In the same way, electrophysiology enables a characterization of the neural population by its "receptive fields density". Therefore, it provides hypothesis about potential effects that could be observed in psychophysics. Finally, electrophysiology and psychophysics become unified in a common framework. The goal of Task 2 is to run experiments both in psychophysics and electrophysiology using similar stimuli generated from a common generative model. Such stimuli has shown useful both in electrophysiology and psychophysics [5, 13]. The collected data will enable the comparison between a theoretical "receptive fields density" that explains the psychophysical effect and the empirical "receptive field density" measured using electrophysiology.

**Task 3: Can We Fool the Brain Through Adaptation Mechanisms ?** In the model developed above, neurons are rigid units that combine each other to compute a likelihood that is biased by a "receptive field density". However, neurons are known to adapt their receptive field to the statistics of sensory inputs [2]. In this context, the "receptive field density" is not fixed anymore and thus is the Bayesian prior. Therefore, by forcing short-term adaptation mechanisms one can modify the internal prior of an observer that can be measured subsequently using psychophysics or electrophysiology. Inspired by [10], the goal of Task 3 is to run experiments both in psychophysics and electrophysiology. The protocols must involve stimulation known to provoke visual illusions (*eg* motion after effect) followed by a classical stimulation. Such a protocol allows to study the effects of induced adaptation on the classical stimulus perception and whether or not it affects the observer prior.

**Skills for the Project** I have a Master's degree in applied mathematics and I have passes the highest competitive exam for academic teaching in mathematics (French agrégation). My PhD has led me to work both in mathematics and neurosciences. I have acquired data analysis and signal processing skills

[1]For a neuron: the region of the visual field in which a stimulus modifies its firing rate.

in particular on psychophysical data, extracellular recording and optical imaging. I have also learned how to run psychophysical experiments properly and I have been closely involved in electrophysiological experiments.

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