Learning dynamics in a neural network model of the primary visual cortex

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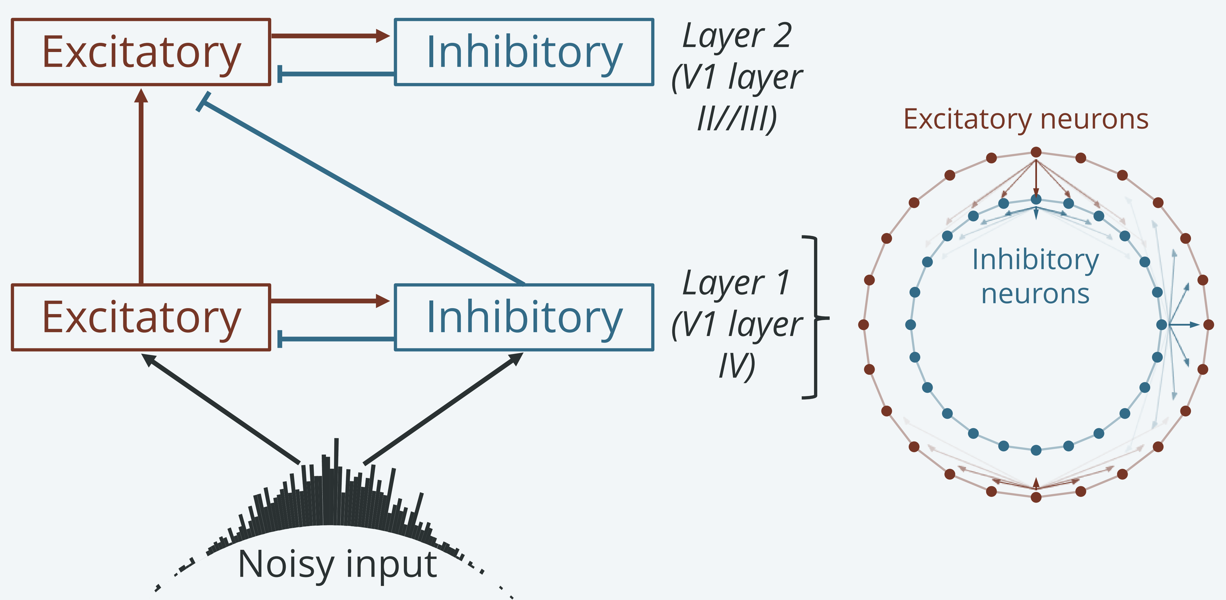
Abstract

We present a **spiking neural network** capable of self-organizing its synaptic weights to process noisy images streams. Our model **matches V1 biological properties** and makes predictions on the distinct role of cortical layers IV and II/III in visual processes.

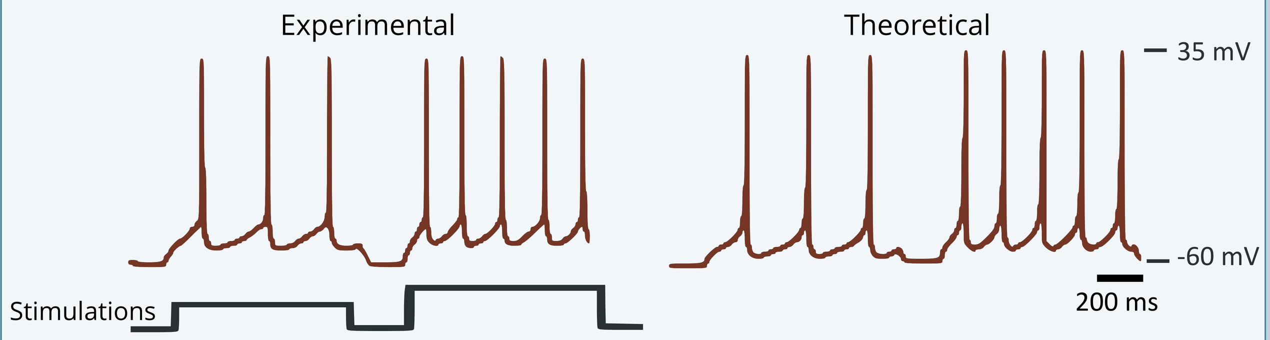
Introduction

- The primary visual cortex (*V1*) is the entry point of the cortical processing of images from the retina. V1-inspired neural networks have achieved humanlike visual accuracy, but rely on **Deep Learning** algorithms which **are biologically implausible**.
- Bridging the gap between natural and artificial networks, we built a model with an emphasis on bio-realism and learning capacity. Our neural network uses **Spike Timing Dependent Plasticity** (*STDP*) and is structured in a **cortical-like topology**.
- This network processes visual inputs coming from a **simplified model of the retina and LGN**.

Methods

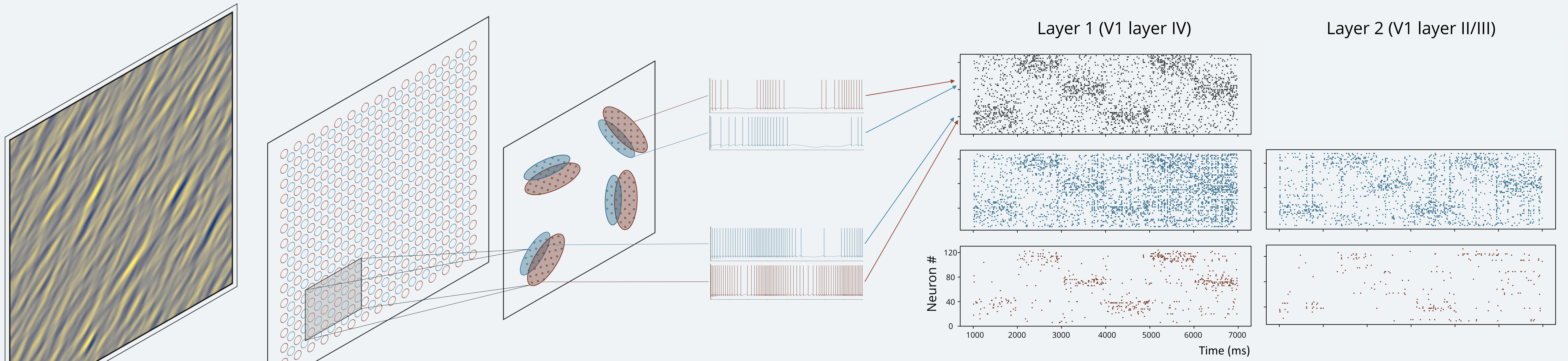


The cortical part of the model processes input with **two recurrent layers** of inhibitory and excitatory neurons, where populations make synapses preferentially with close neighbors.



We used **leaky integrate-and-fire neuron** models, which closely reproduce neocortical neurons' activity *.

Results : Topology and Plasticity drive V1 activity



Rasterplot of the layer 1 (left) and layer 2 (right) activity. For the sake of clarity, populations were only recorded for 6000 ms and single-neuron spikes were plotted from a reduced-size model, made of 240 neurons. Activity produced by the pre-cortical neurons is shown on top of layer 1 activity.

We tested the model with **Motion Clouds**, which are oriented gratings with natural texture properties.

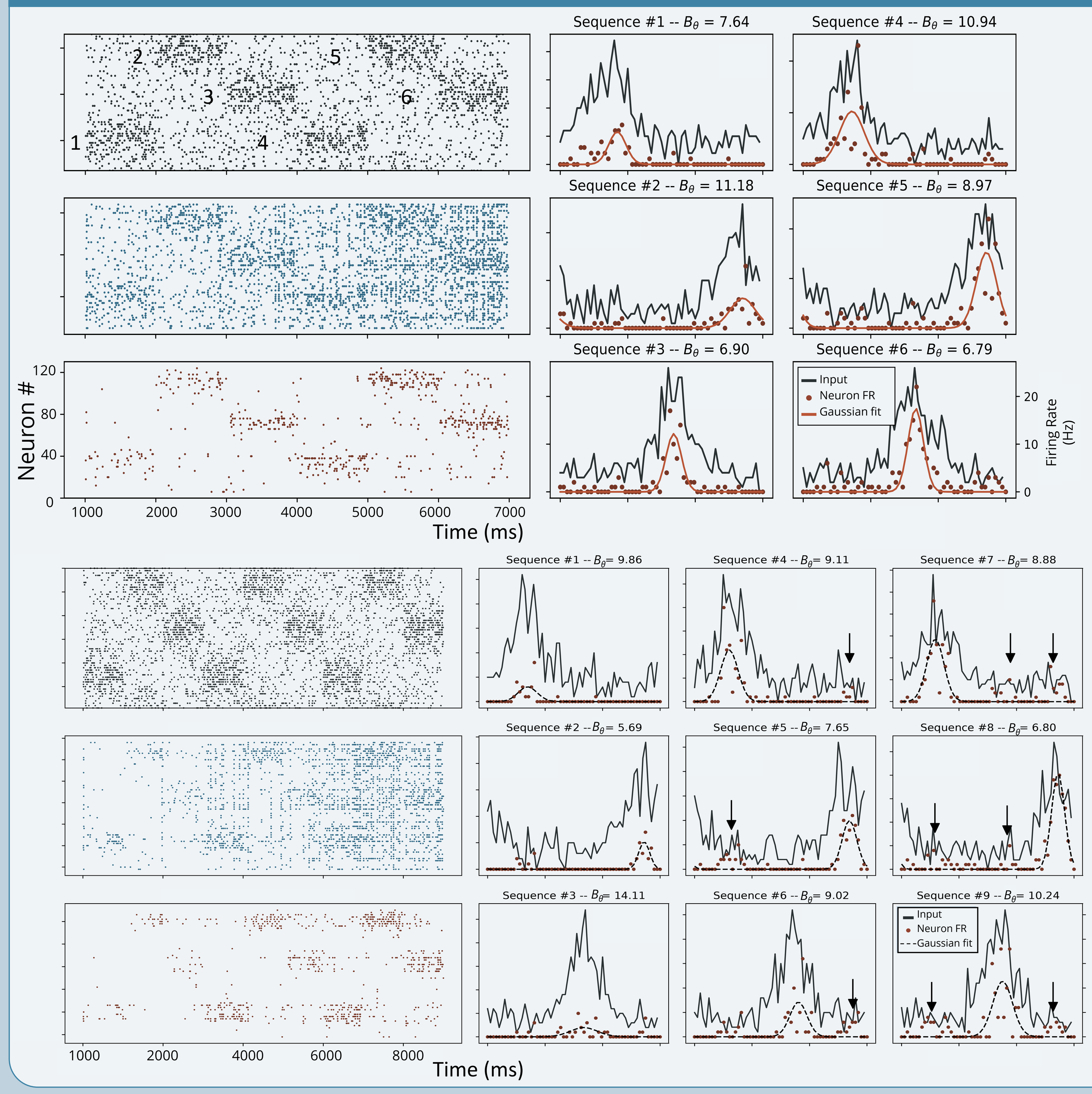
A grid of ON/OFF receptive fields extracts local contrast information in real-time, like the **retina and LGN.**

Grouping multiple receptive fields afferences onto a single spiking neuron produces orientation-sensitive spiking patterns as observed in **V1.**

Simple recurrence and STDP are sufficient to reproduce cortical-like spiking patterns, notably :

- Noise reduction even at the first level of the network
- Sparsification of spiking activity in higher level layers
- Self-reinforcing activity as a function of stimuli presentation

Results : Self-Organizing learning in V1



Activity from rasterplots was plotted in chunks of 1000 ms (right panels), which is the duration of a single stimulus.

Population firing rates were fitted with a circular gaussian curve and orientation tuning selectivity was evaluated using the bandwidth as a precision metric.

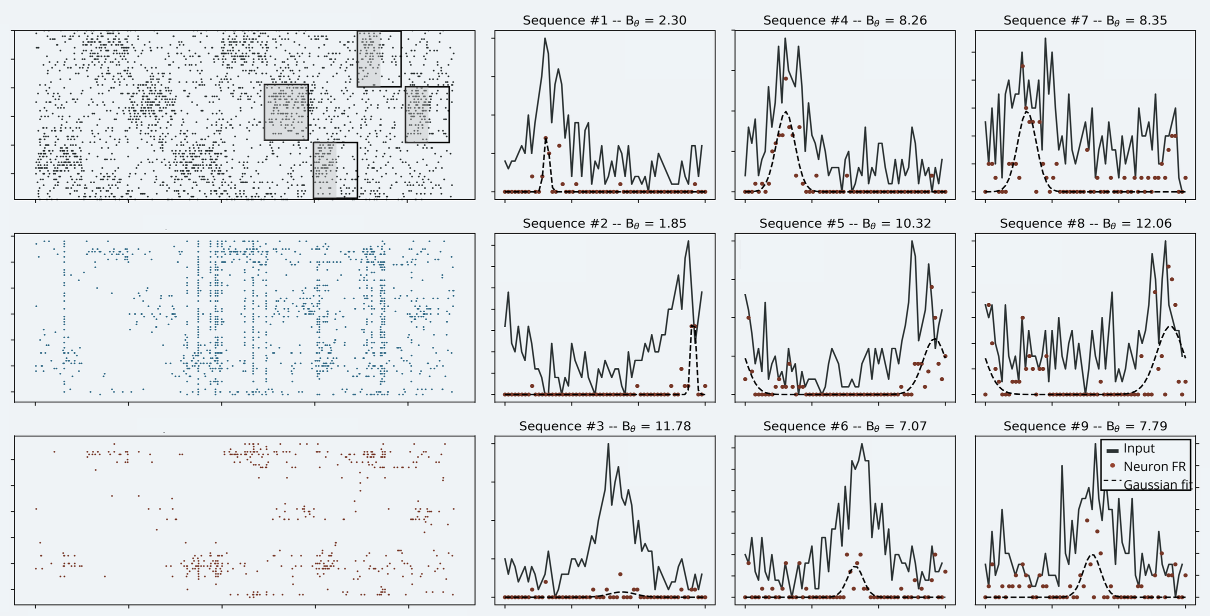
For the second layer, these simulations were lengthened by an additional 3000 ms, during which three additional stimuli are presented.

The **first layer** quickly exhibits a narrow, orientation-selective spiking activity.

With only two seconds of stimulus presentation, the network's tuning curve bandwidth, $\mathbf{B_\theta}$, becomes sharper than the input's (15°),

The **second layer** is more sparse and learns a higher level of representation.

The spiking patterns is not only based on the current input, but also on all possible types of inputs already learned by the first layer (black arrows).



After 6 stimulations, the last of which is in the leftmost black box in the top-left rasterplot, stimulation duration was halved for the last 3 stimuli.

The pattern learned spatial but also temporal, in the sense that once the cortical network learned from second-long stimulations, it produces second-long firing patterns even when stimulation duration is actually halved.

Acknowledgements

Complete bibliography, animated figures and open-access code (with helpful guidelines) are available either at https://github.com/hugoladret/InternshipM2 or by e-mail if requested.

* We are grateful to Pr. Eugene M. Izhikevich for free reproduction permissions to his spiking neuron figures, available at www.izhikevich.com