



Role of feature selectivity in visual perturbation responses

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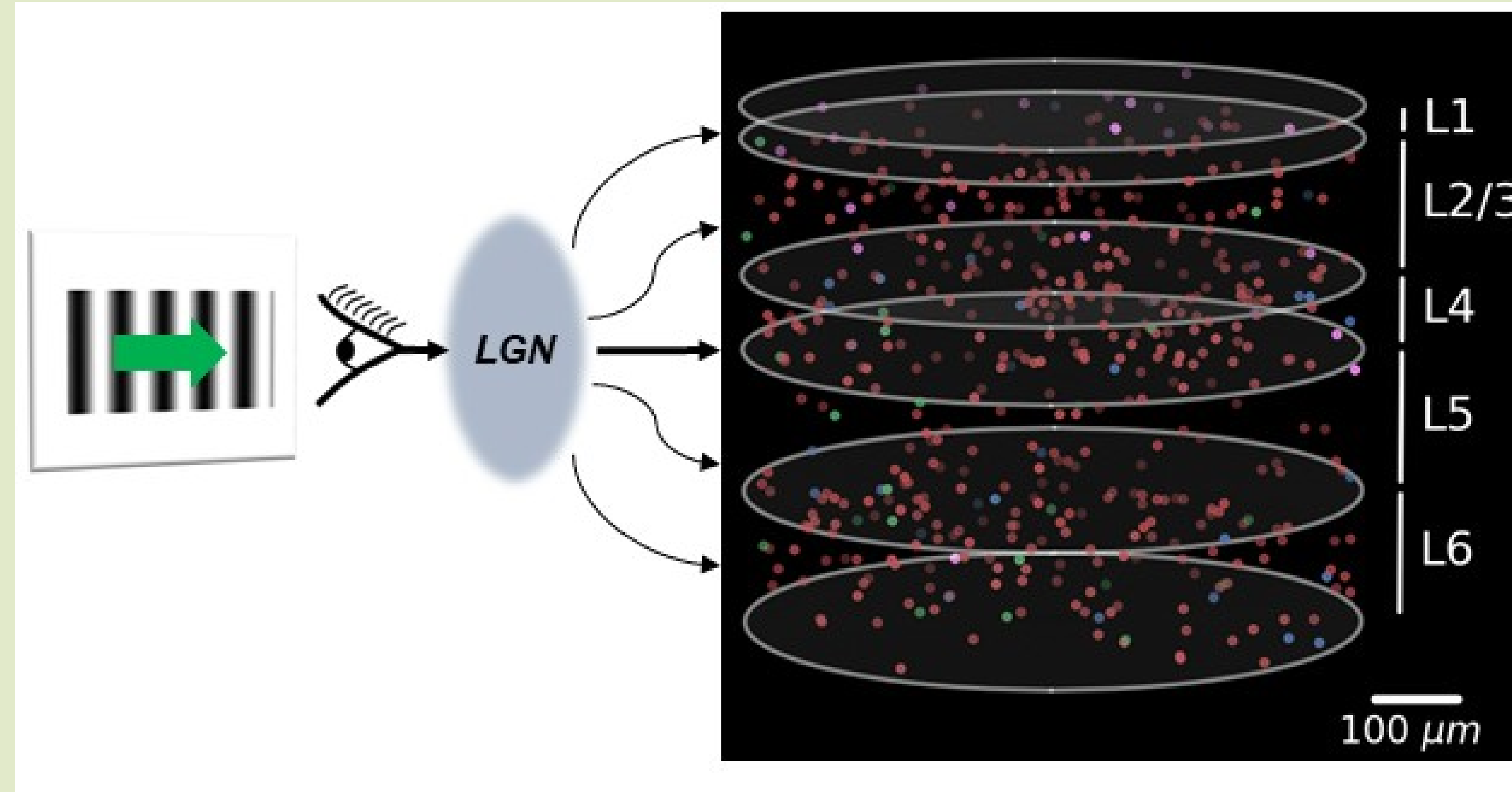
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INTRODUCTION

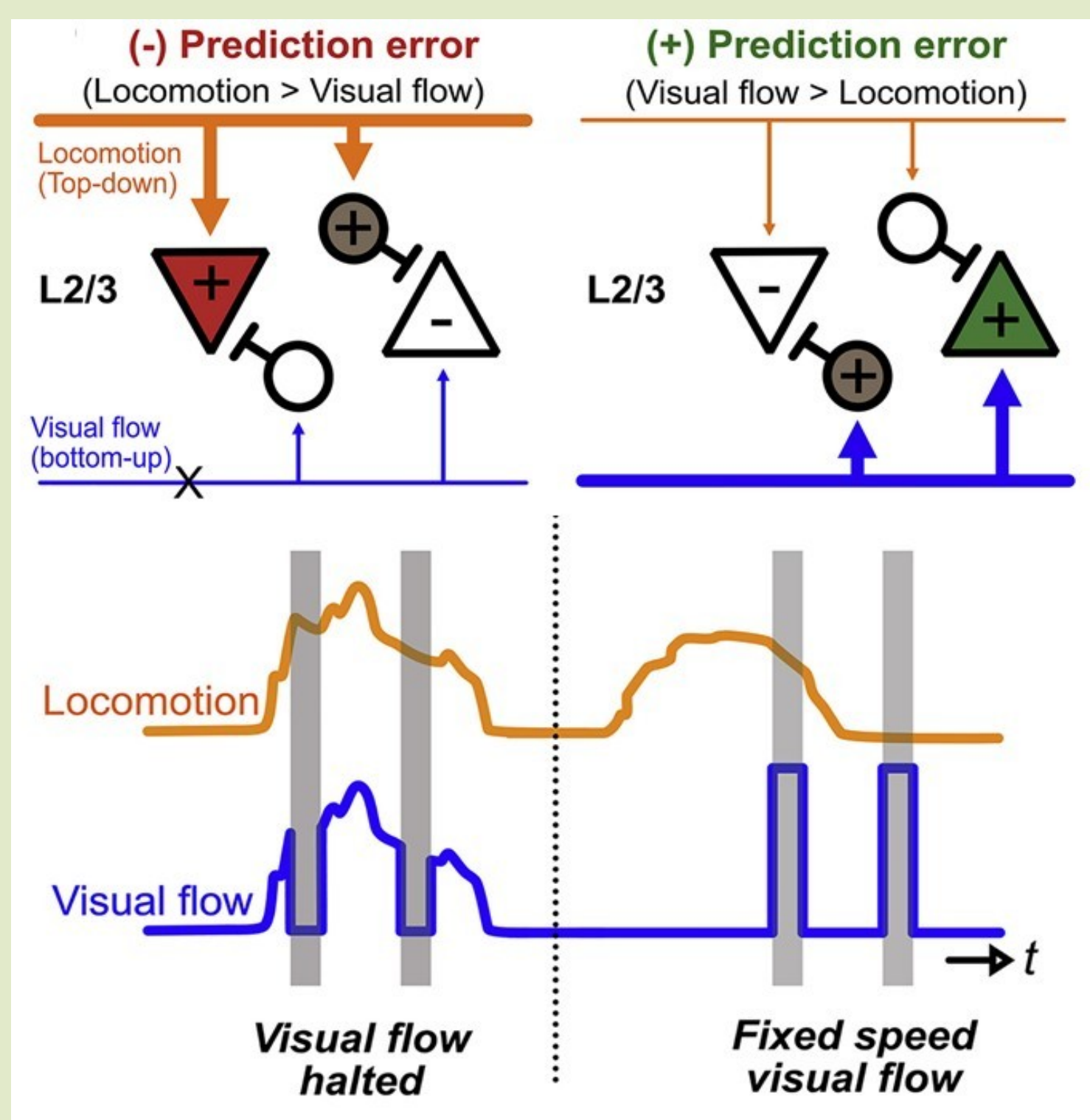
Since we started to interact with the outside world, we have learned to distinguish whether the movement is coming from our own actions or from the movement of external objects. To distinguish between these experiences, it is necessary to factor out the sensory consequences of our actions from incoming sensory information. The main framework accounting for this sensorimotor integration is the **predictive coding**, which suggests that an internal representation of the world lies in the neocortex circuitry. This representation, which is used to make predictions about incoming sensory input, is being continuously updated using the sensed information from the surroundings.



Therefore, understanding how the encoded structure of canonical microcircuits in the neocortex implements brain computation is an important open research question. The implementation and analysis of computational models of canonical microcircuits can help addressing this question. In this sense, the Allen Institute has developed a model for a microcircuit of the primary visual cortex in mouse that builds on a huge body of experimental work.

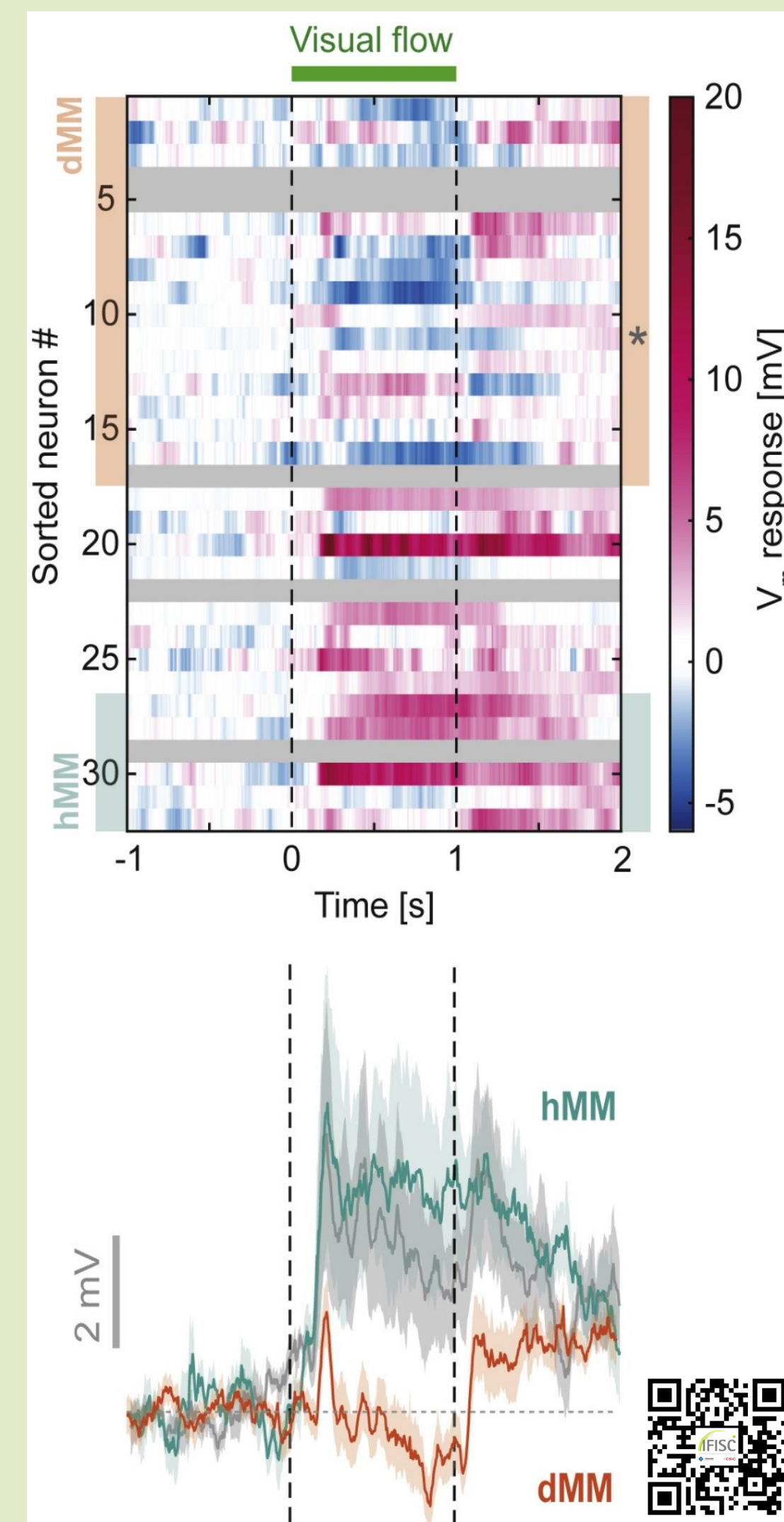
In this work we perform extensive numerical simulations of the model introduced by the Allen Institute to analyse the effect that different visual stimuli have on layer 2/3 (L2/3) excitatory neurons, which are the main candidates to behave as **prediction error (PE) neurons**.

STATE OF ART



Predictive coding proposes that L2/3 neurons compute a difference between visual and locomotion-related input to convey visuomotor prediction errors. This computation comes in two flavours: positive PE neurons that subtract a **top-down prediction** from the bottom-up sensory input and negative PE neurons that subtract sensory input from the top-down prediction.

The experimental evidence shows that a subset of L2/3 neurons strongly respond to a sudden mismatch between visual flow feedback and locomotion speed.



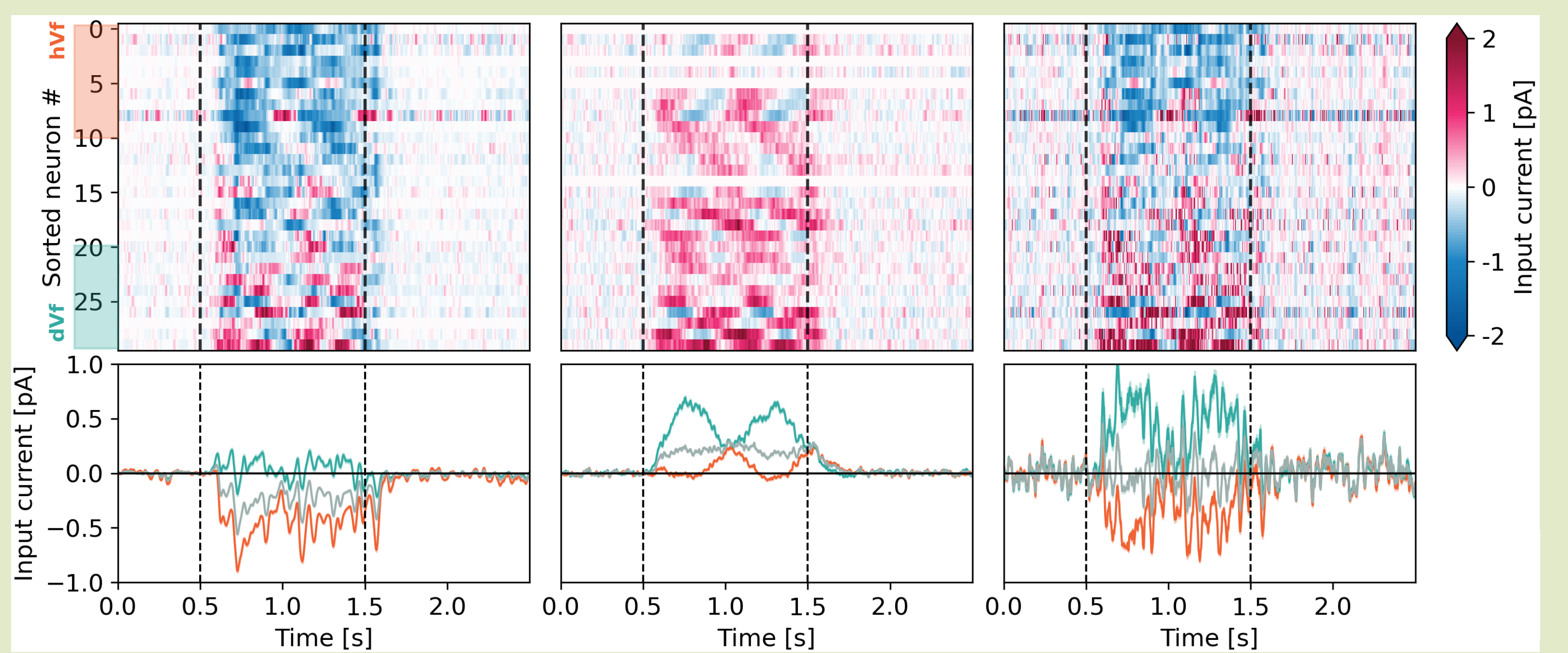
Experimental results. **Top:** Heatmap of the average membrane voltage response to visual flow of experimentally measured L2/3 excitatory neurons. **Bottom:** Average response across the different types of L2/3 excitatory neurons: hyperpolarizing (blue) and depolarizing (red) neurons.

RESULTS

In the V1 model proposed by the Allen Institute we can measure the input currents received by each neuron. This provides an interesting way of classifying L2/3 excitatory neurons depending on their input currents variations:

- Depolarized with visual flow (**dVf**) neurons, which depolarize when the visual flow turns ON.
- Hyperpolarized with visual flow (**hVf**) neurons, which hyperpolarize when the visual flow turns ON.

The analysis of the model shows that dVf neurons depolarization is carried out mainly by the bottom-up input. On the contrary, hVf neurons hyperpolarization seem to be driven by a reduction on the recurrent current, mainly driven by inhibitory interneurons of layers 2/3 and 4.



Computational results. Heatmap of the average recurrent (left), bottom-up (mid) and total (right) input current response to visual flow onset across L2/3 excitatory neurons. Particularly, neurons that hyperpolarize (orange) and depolarize (turquoise) due to the input are observed. Check the QR code to see the presented visual input.

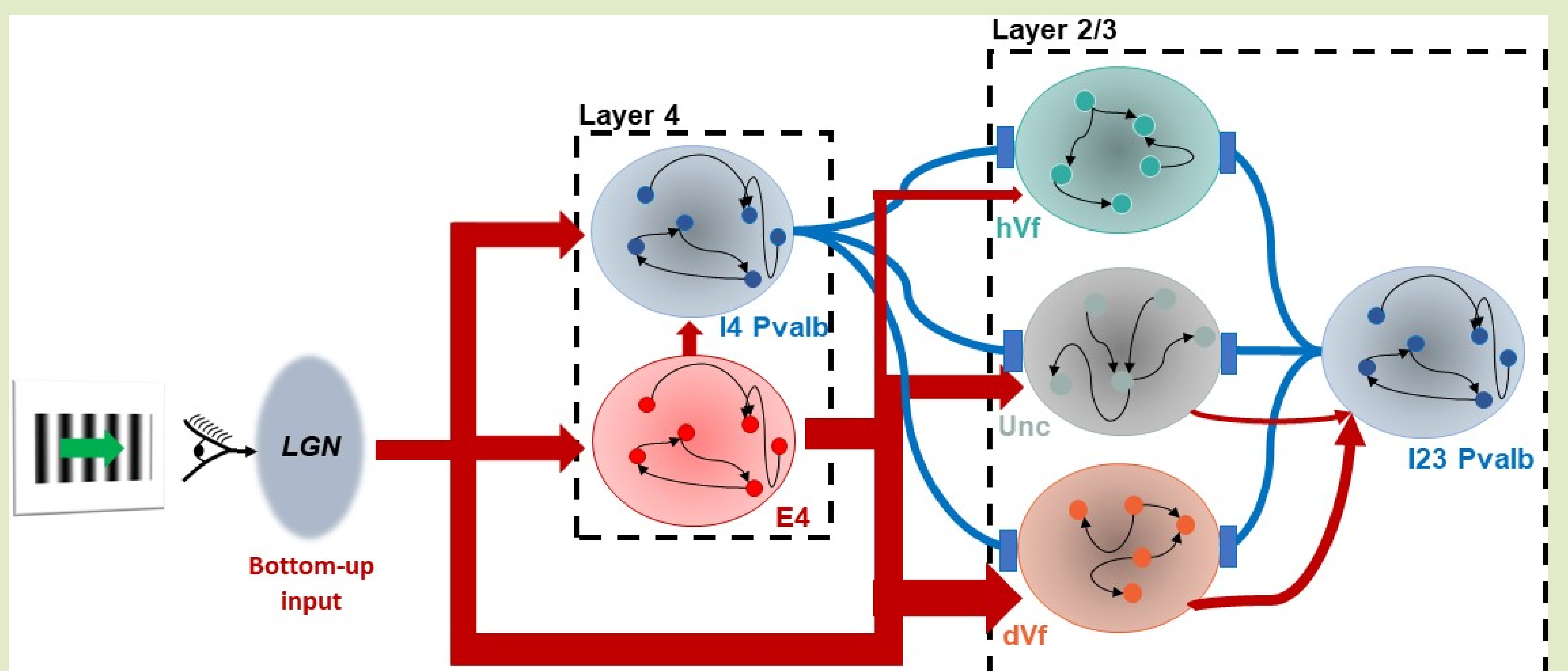
DISCUSSION

➤ The neurons that depolarize (dVf) have a preferred orientation close to that of the drifting gratings. This translates into an increase of the excitatory current they receive both directly from the LGN and using layer 4 excitatory neurons as a magnifier of the signal. Moreover, they depolarize Parvalbumin interneurons from layer 2/3.

➤ The neurons that hyperpolarize (hVf) do not have a clear orientation preference and a large subset of them do not have a direct connection with thalamic units, which translates into a null bottom-up input. However, the increase of inhibition triggered by dVf neurons directly affects them, resulting into a recurrent inhibition that drives them.

Altogether, the mechanism that triggers this behavioural separation may be understood as a *winner-take-all* architecture between dVf and hVf neurons mediated by Parvalbumin interneurons, a population of inhibitory neurons in layer 2/3.

Subsequent work aims at integrating top-down input that represents the prediction received at lower cortical areas such as the primary visual cortex.



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