Lecture 13.3 Mechanistic Models

Reading Assignments

From the Textbook

Section 13.5

Suggestions for Further Reading

GCAL model: Bednar (2012), Stevens et al. (2013)

Q3: How do feature maps arise from neural mechanisms?

- SOM models are useful because they reproduce many of the different map patterns observed in the primary visual cortex using a simple approach.

- SOM is primarily a phenomenological or geometrical model—it focuses on the geometry and principles, not the neural mechanisms.

- Many of the mechanisms of the SOM have no counterpart in biological systems (e.g., initial full connectivity, initial long lateral interactions, and global selection of a single winning neuron); perhaps the chemoaffinity mechanisms provide a more practical solution to these issues.

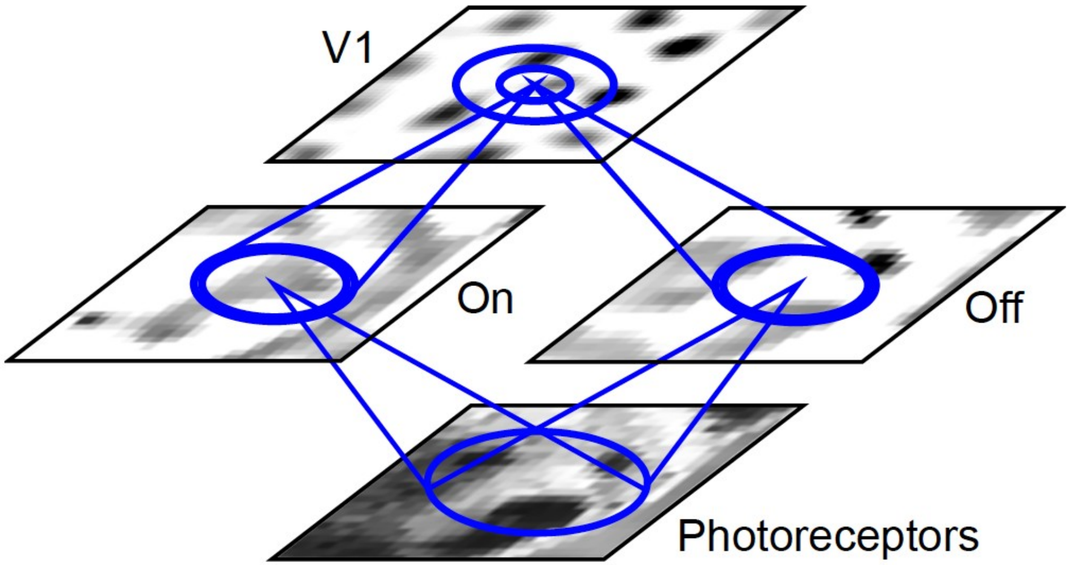
- We next consider a class of mechanistic map models that develop similar map patterns as SOM, using similar underlying principles.

- These models start from an initial state assumed to be determined through chemoaffinity, and then show how feature map patterns can develop using mechanisms like those found in biological neural maps.

Mechanistic feature map models

- Typically allow natural image inputs, so that the models can be tested with actual images and with patterns used in animal and human experiments.
- Start with topographic connectivity initially, both to model chemoaffinity mechanisms and to avoid having to have unrealistic full connectivity and shrinking lateral interactions.
- Use local neuron learning rules established from biological experiments.
- Use explicit connections, typically recurrent, instead of global supervisors “picking winners”.
- Allow multiple active areas in the cortex.
- Typically allow specific patterns of lateral connectivity between neurons, to match the observed patchy connectivity and feature-specific contextual modulation effects.
- Once the models reproduce the types of map patterns observed in abstract models like SOM and the Elastic Net, the models can be tested with realistic input patterns to see how they actually behave during visual tasks.

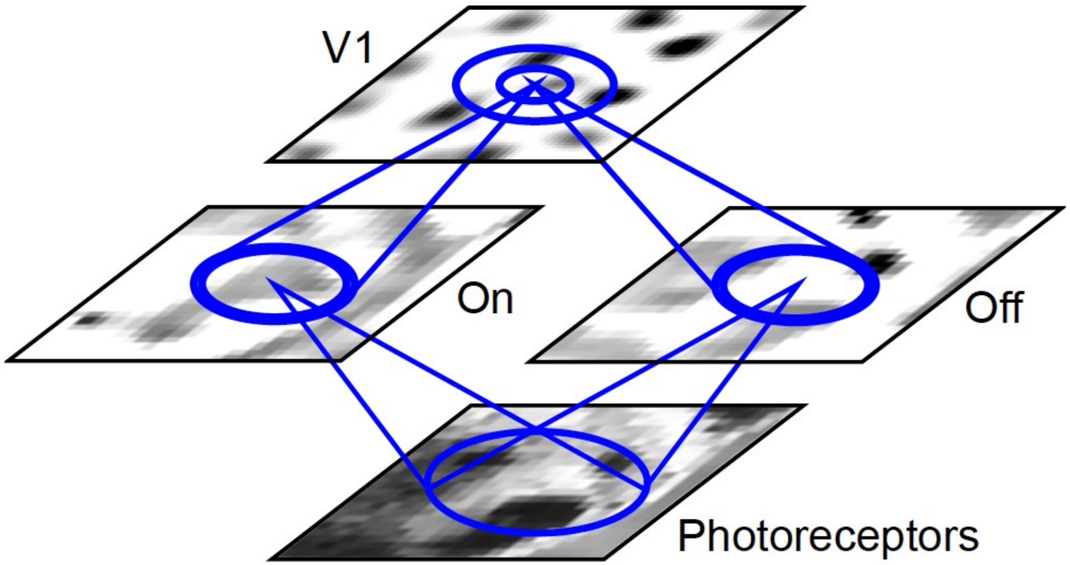
GCAL model of neural maps



- We next examine the GCAL mechanistic model of the type of map-formation processes modeled by SOM.
- Basic early vision model takes synthetic or natural image inputs and simulates subcortical and V1 processing.

- Subcortical pathway is hardwired and fixed throughout the simulation.
- All other connections to and within cortical areas:
    - are topographically localized (e.g., set up by chemoaffinity mechanisms),
    - are stored explicitly per neuron (not as a shared neighborhood function),
    - are initially isotropic or random, and
    - adapt by Hebbian learning (coactive units get stronger connections).

Basic GCAL model architecture

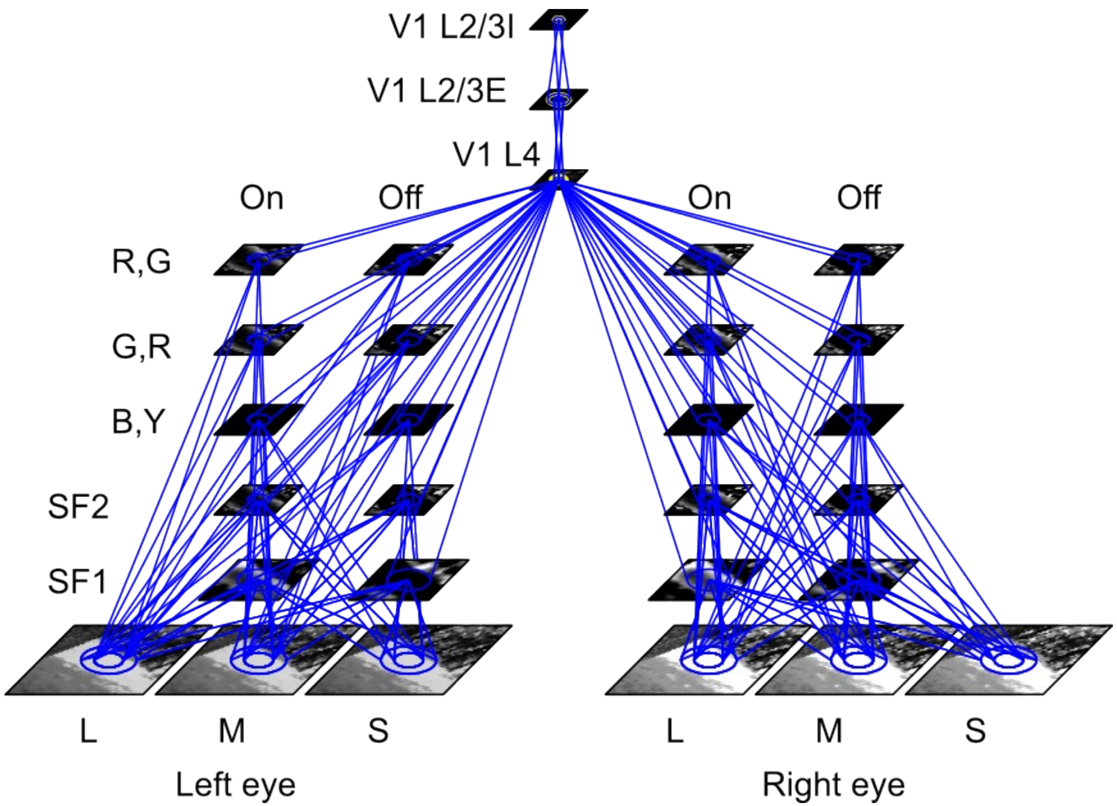


Model for retinotopy and orientation:

- Images are convolved with On and Off RGC/LGN difference-of-Gaussian RFs.
- On and Off channels have lateral inhibition for gain control (normalization).

- V1 has afferent, lateral inhibitory, and lateral excitatory connections.
- Initial V1 response to the On and Off input is a blurred image.
- Mexican-hat lateral interactions iteratively focus response into “bubbles”. (as in SOM’s neighborhood function, but not restricted to one “winner”).
- Connections, where present, are then strengthened between all active units.
- Eventually V1 neurons represent the input space, as in SOM.

Comprehensive GCAL model architecture

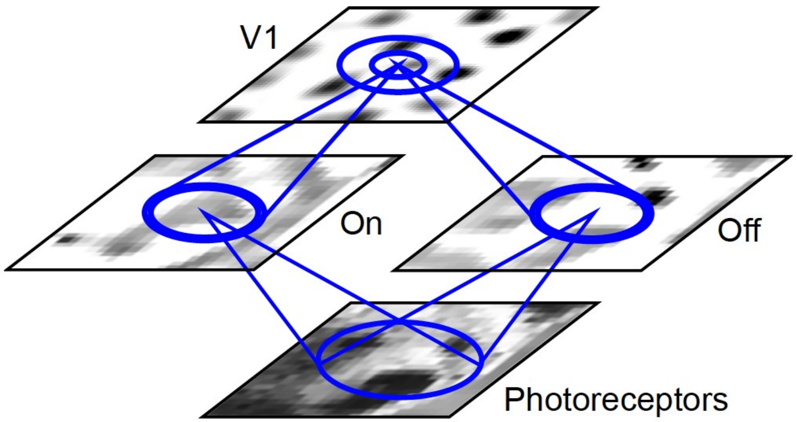


More complex GCAL variants follow same basic equations but can have multiple

- input sheets (here 2 eyes, 3 cone types)
- On and Off channels (2 sizes, 3 cone opponencies)
- V1 cell populations (2 layers, separate inhibitory/ excitatory cells)

- Can now develop preferences for retinotopic location, orientation, spatial frequency, color, motion direction, eye, and disparity.
- Final map preferentially weights inputs to each V1 L4 neuron from each subcortical pathway, which determines its preferred input patterns.

GCAL model activation

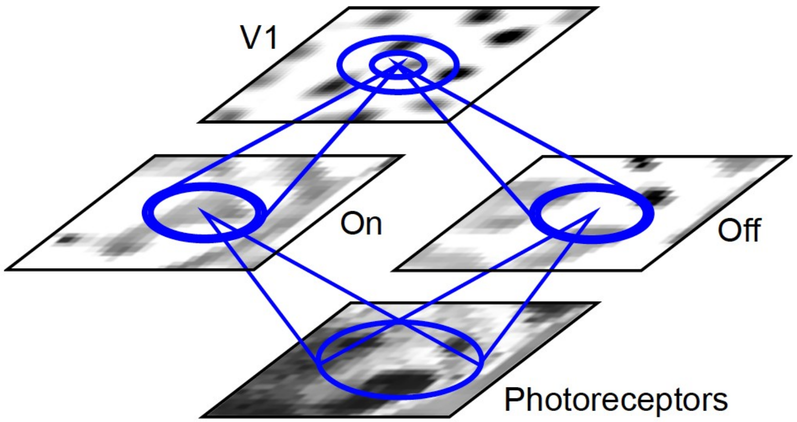


- For a given input pattern, the activation of the On and Off channels is computed as a convolution with a difference of Gaussians kernel, as in lecture 1, slide 8.
- The activation $v_{k\,l}$ of neuron (k, l) is computed from the incoming activity $\boldsymbol{x}_{pkl}$ multiplied by the weights $\boldsymbol{w}_{kl}$:

$$v_{kl} = \sigma\left(\sum_p \gamma_p \boldsymbol{x}_{pkl} \boldsymbol{w}_{pkl}\right)$$

- There are four sources of incoming activity: $p \in \{A_{on}, A_{off}, E, I\}$
- The relative strength of these sources is set using the γ parameters to balance afferent vs. lateral and excitatory vs. inhibitory inputs.
- The weighted sum of all inputs is then passed through a threshold nonlinearity σ, and the activity is recomputed until it settles; the local lateral excitation and longer-range inhibition results in focused bubbles.

GCAL model learning

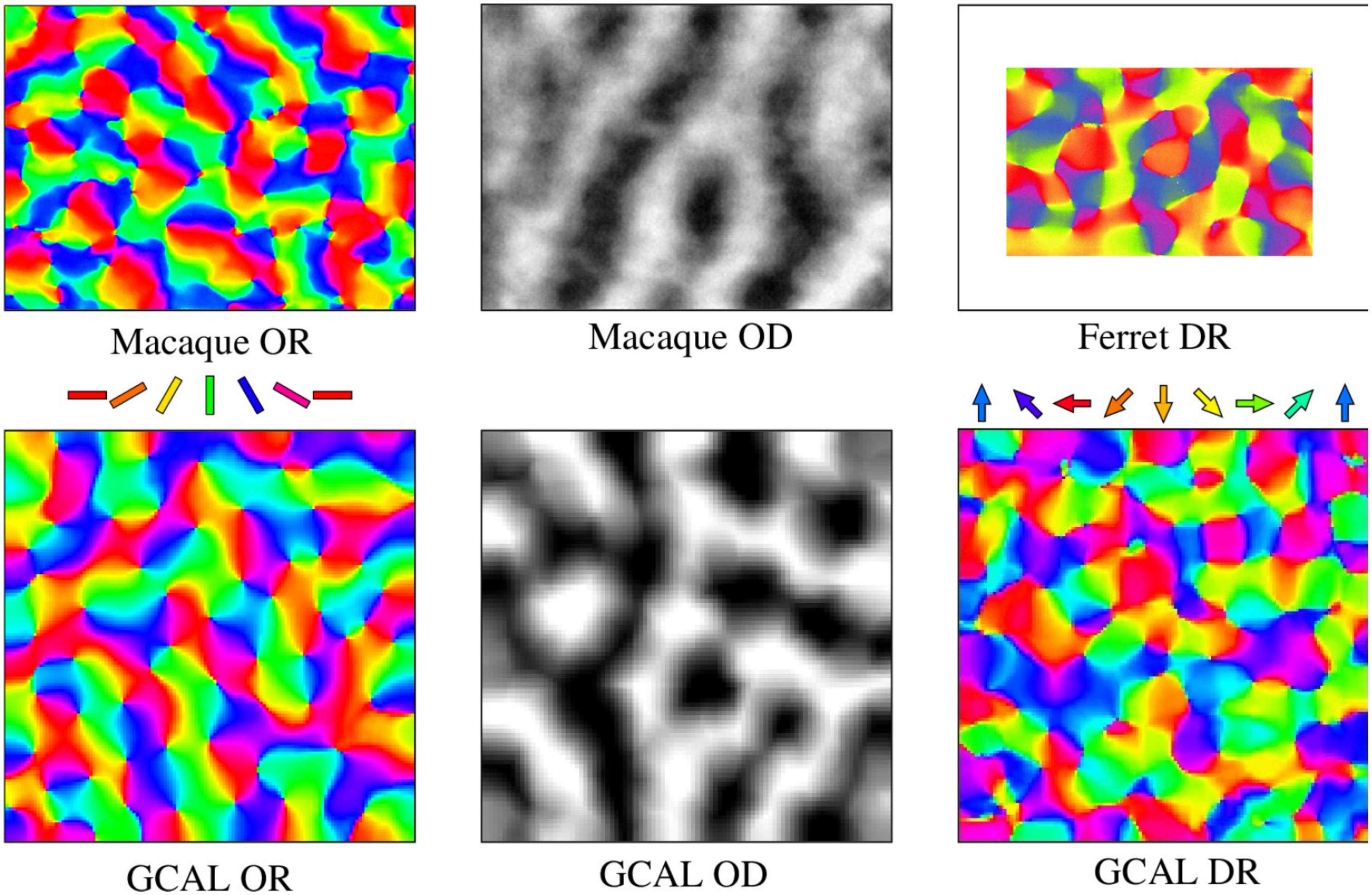


- Once activity settles, all V1 connections are adjusted by Hebbian learning:

$$\boldsymbol{w}'_{pkl} = \frac{\boldsymbol{w}_{pkl} + \alpha v_{kl} \boldsymbol{x}_{pkl}}{\|\boldsymbol{w}_{pkl} + \alpha v_{kl} \boldsymbol{x}_{pkl}\|_1}$$

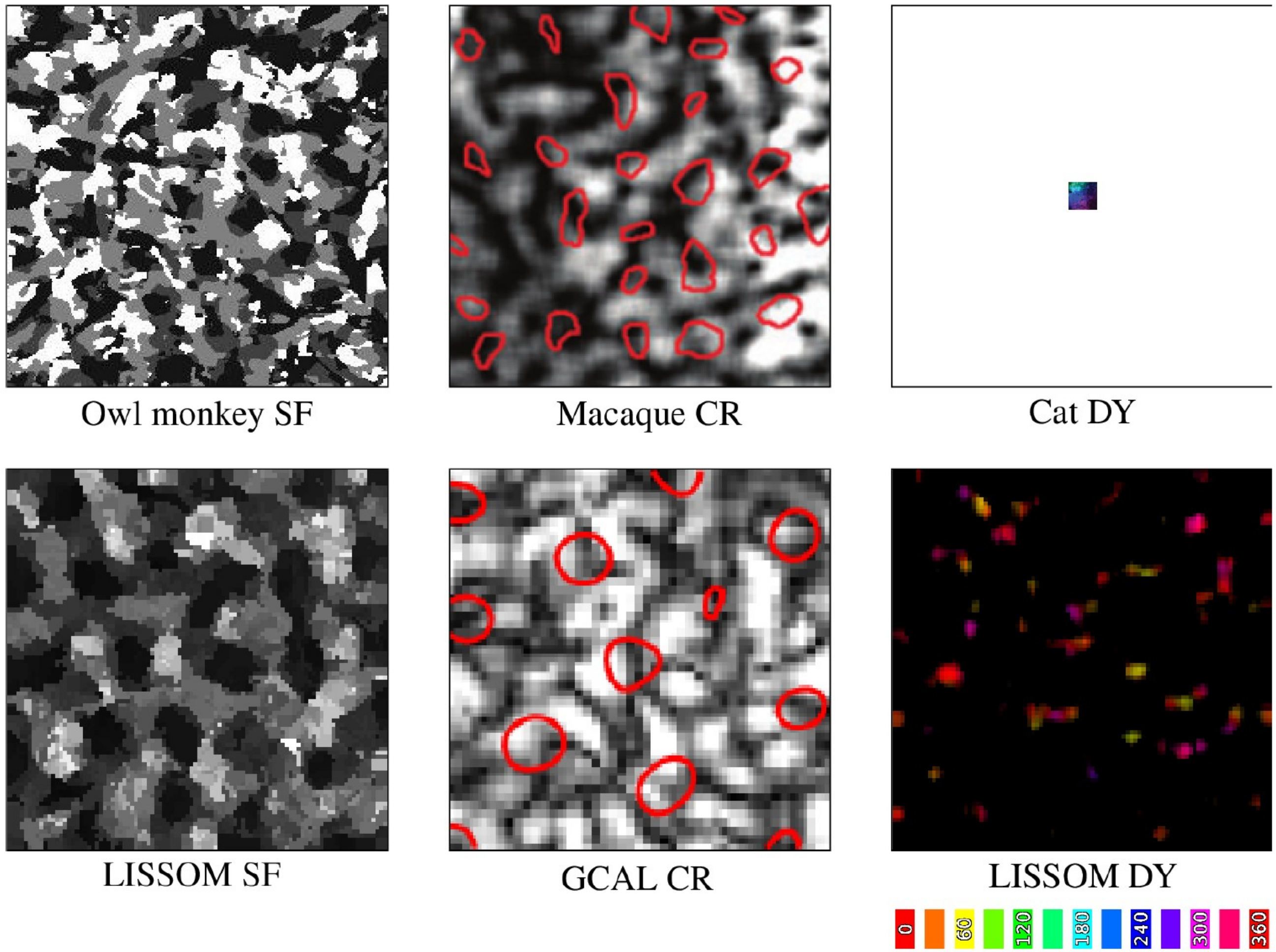
- Weights increase for connections with pre- and post-synaptic activity.
- The remaining weights then decrease, because all weights of a given type (afferent, lateral excitatory, or lateral inhibitory) are normalized to a constant sum.
- Afferent weights to neurons in active bubbles learn the pattern on the input within their connection field.
- Lateral weights store correlations between V1 neurons.

GCAL results: Animal and model V1 maps, I



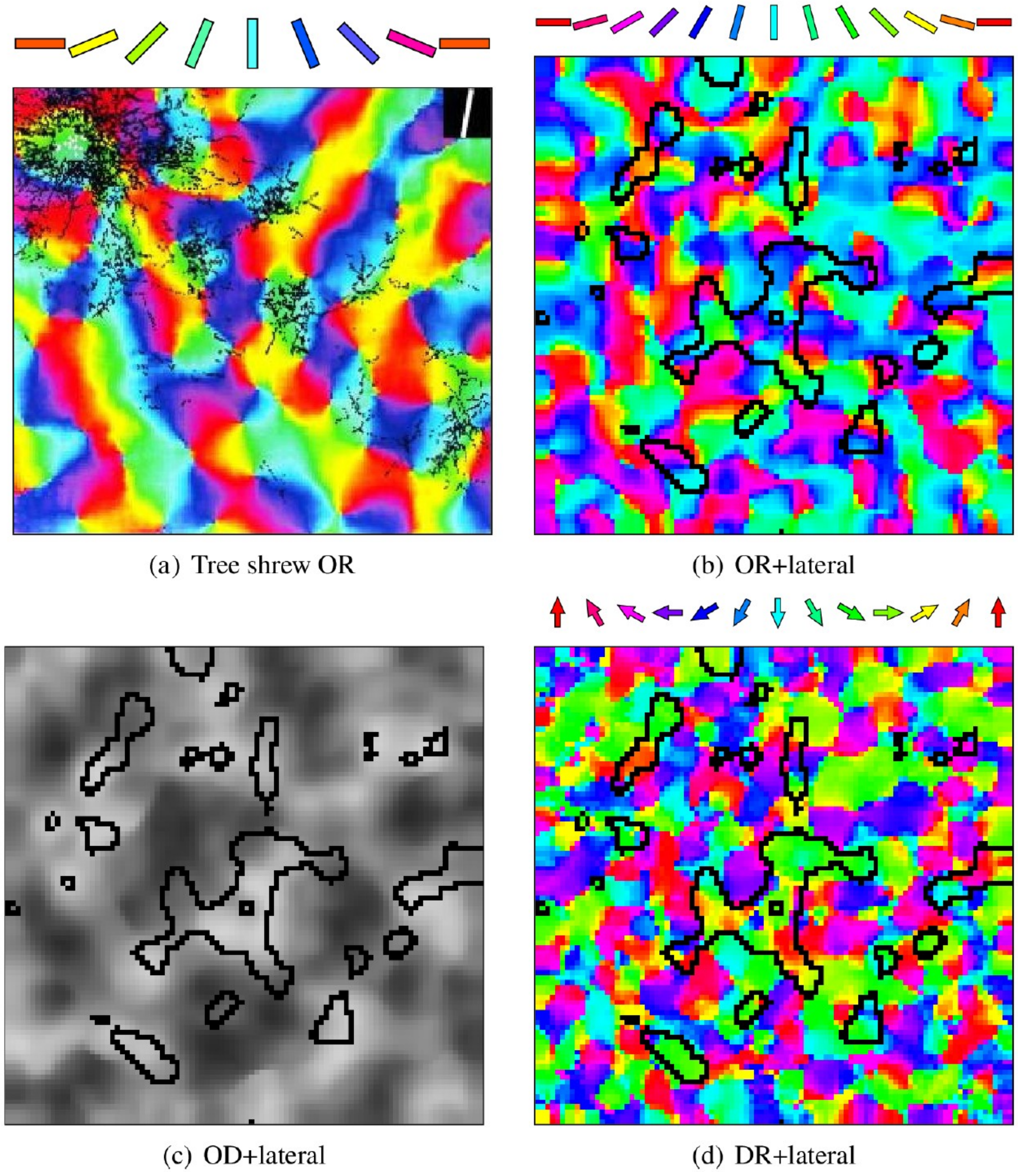
GCAL model orientation, ocular dominance, and direction maps closely resemble animal maps, achieving good coverage of the input dimensions.

GCAL results: Animal and model V1 maps, II



Properties of experimental maps for spatial frequency, color, and disparity are much less clear, but GCAL results seem comparable.

GCAL results: Lateral connections



(a) Lateral connections in animals follow the shape of the orientation map.

(b) Hebbian-learned-model lateral connections do as well.

(c–d) The same connections also respect all other maps, e.g., ocular dominance and motion direction.

The lateral connections link by similarity in the response properties, for the full multidimensional input space.

Functional phenomena in mechanistic models

- Once the maps have formed, neurons in GCAL have receptive fields determining their response to isolated input patterns, and lateral connectivity determining how active neurons will interact.

- The behavior of these mechanisms can then be tested by running simulated psychophysical or physiological experiments.

- For instance, the patchy lateral connectivity leads to surround modulation effects, where neighboring visual elements interact via cortical circuitry to affect how they are perceived.

- Similarly, changes in these connections during visual experience leads to realistic visual aftereffects, such as the tilt aftereffect and the McCollough effect.

- The model would need to be extended to account for feedback effects from higher cortical levels.