The Law-Gold model

CS786

30th September 2024

Assignment 3

- Due on 22nd Oct 11:59 pm
- You'll be teaching CNNs Gestalt principles
- Following the paper I mentioned in the Gestalt class
- Will post details and the assignment link later this week in HelloIITK
- No class tomorrow
  - We meet after the midsem break

How *intelligent* are convolutional neural networks?

Zhennan Yan
Xiang Sean Zhou
Siemens Medical Solutions USA, Inc.
65 Valley Stream Parkway, Malvern, PA 19355, USA
xiang.zhou@siemens-healthineers.com

Hypotheses

- Attentional weighting
  - Observers learn to attend to discriminative features of stimuli
- Stimulus imprinting
  - Detectors developed that are specialized for stimuli
- Differentiation
  - Perceptual adaptation by the development of increasingly differentiated object representations
- Unitization
  - Development of sensory units that are triggered when a complex configuration occurs

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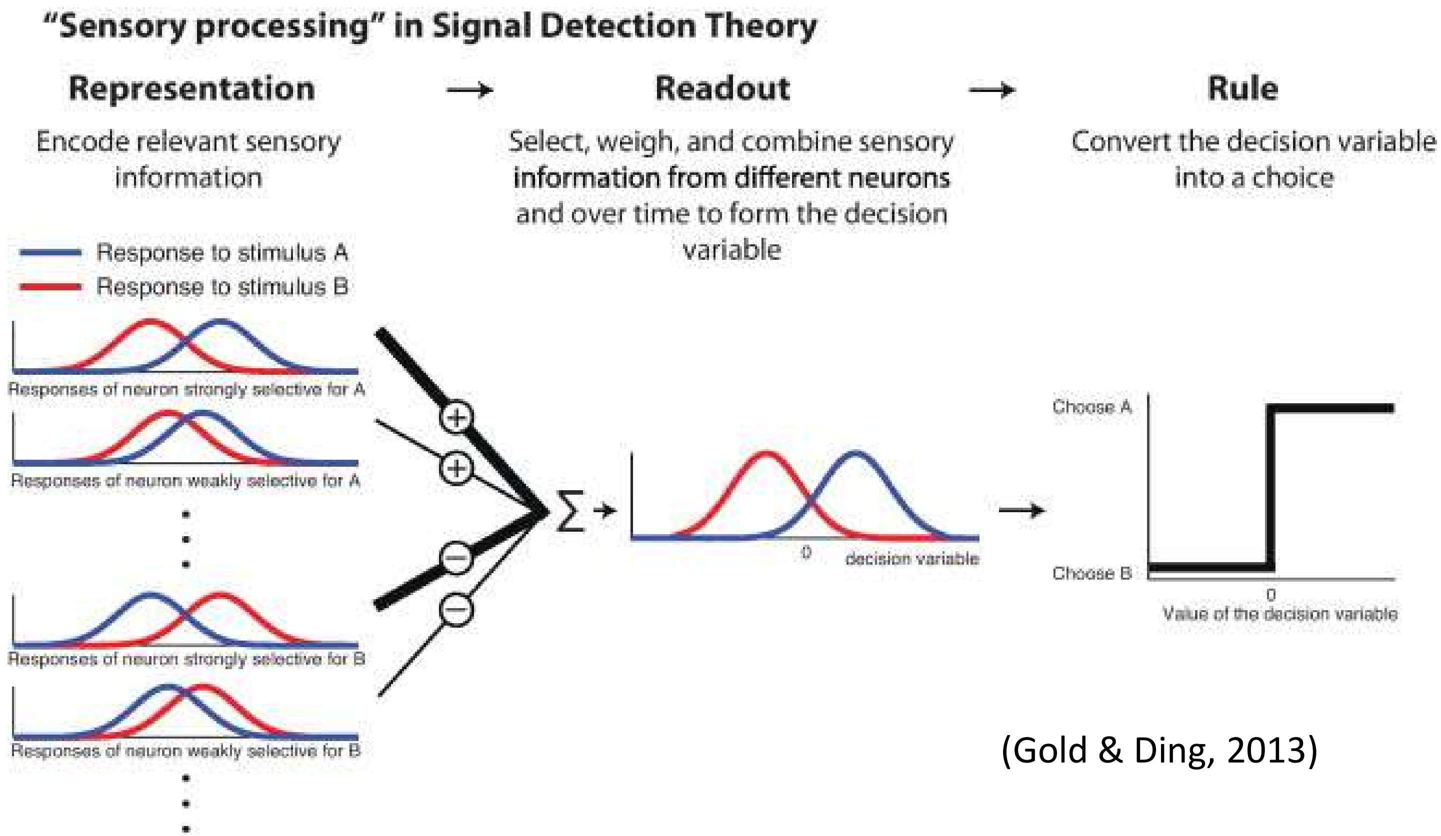
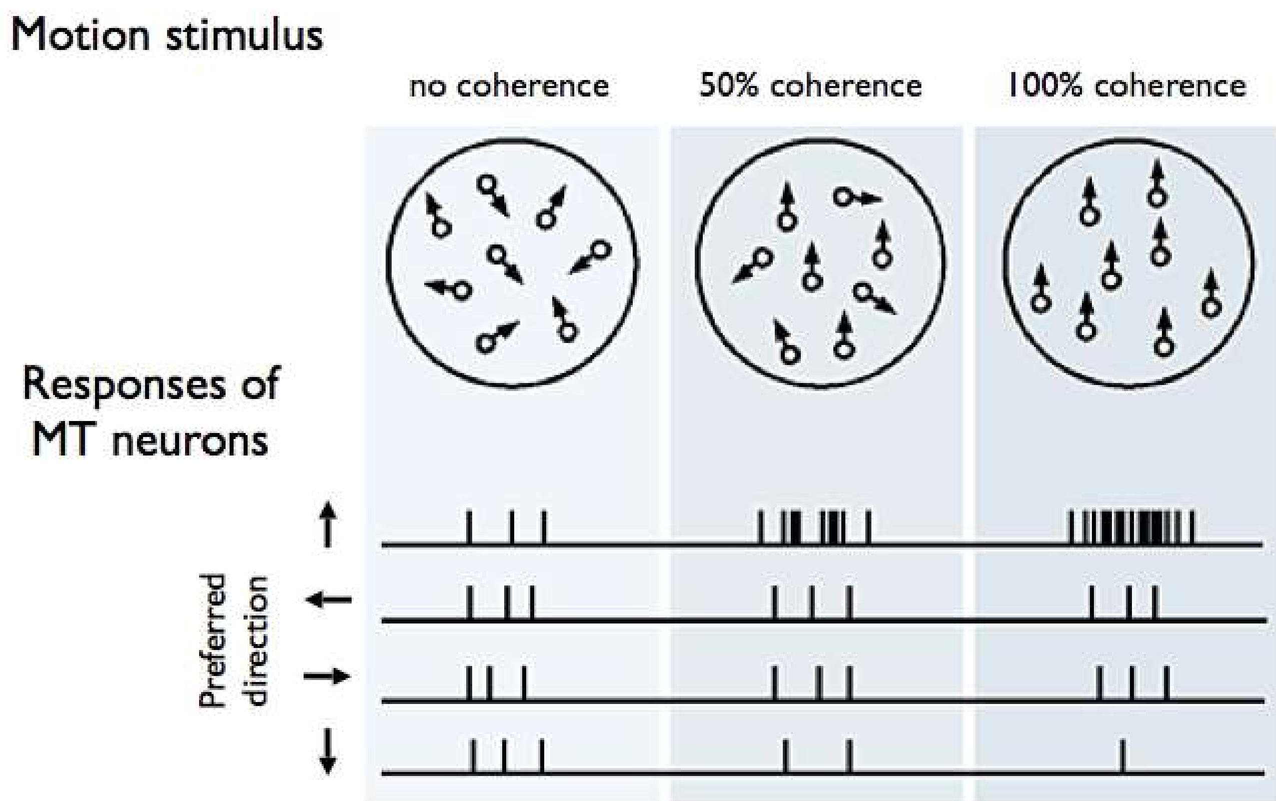
Perceptual learning as improved decision-making



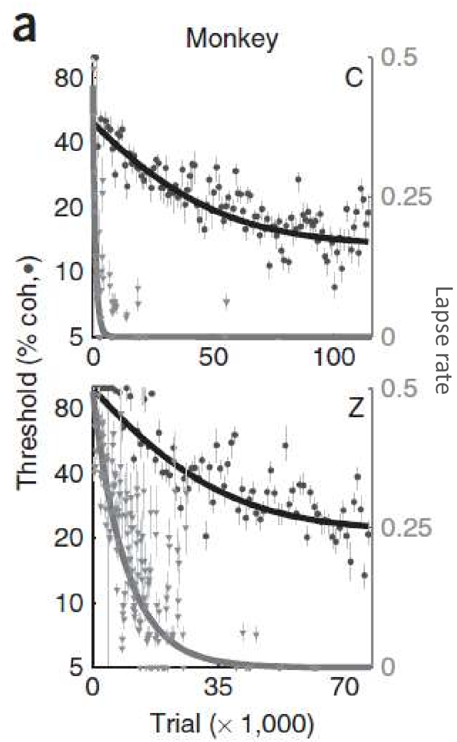
(Gold & Ding, 2013)

Motion coherence and MT neurons

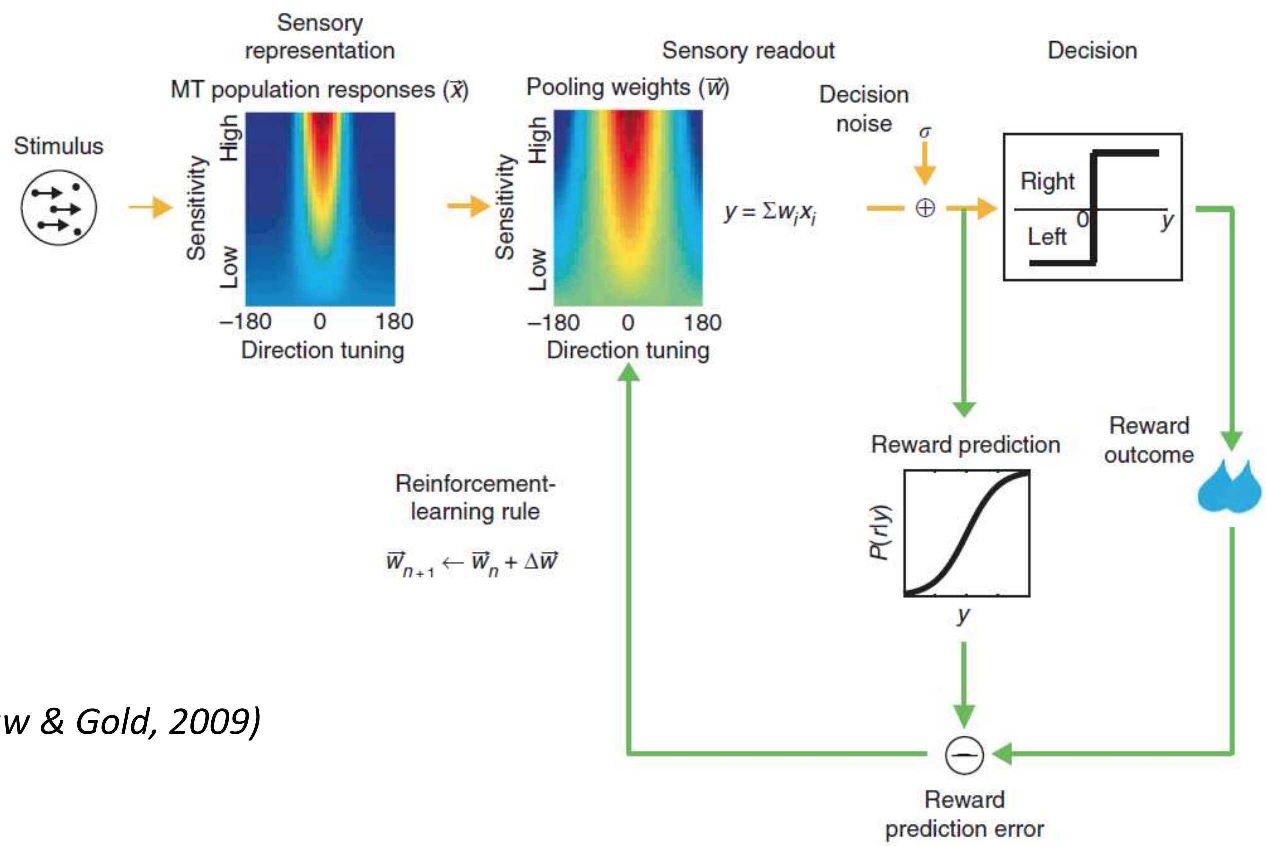


The dataset

- Recorded spiking response of neurons in monkey LIP cortex
- Neurons responsive to different motion directions
- Measured behavioral and neural data across multiple sessions (e.g. 165 sessions over 645 days for monkey C)



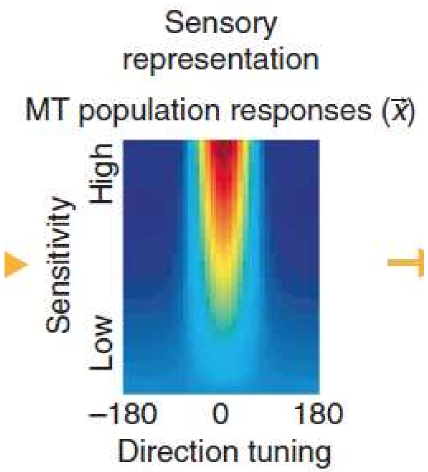
The model



(Law & Gold, 2009)

Sensory representation

- MT modeled as a population of 7200 neurons
  - 200 for each of 36 evenly spaced directions in the 2D plane
  - Trial-by-trial stimulus responses fixed using neuronal data



Individual neuron model

- Each neuron's response to a given stimulus modeled as Gaussian with mean *m*

$$m = T\{k_0 + COH[k_n + (k_p - k_n)f(\theta|\Theta)]\}$$

$$f(\theta|\Theta) = e^{\frac{-(\theta-\Theta)^2}{2\sigma_\theta^2}}$$

  - k_0 is spiking response at 0% coherence
  - k_n is spiking response at 100% coherence in null direction
  - k_p is spiking response at 100% coherence in preferred direction
  - COH is coherence as a fraction
  -
  - Θ is the neuron's preferred direction

Interneuron correlations

- Neurons with shared direction tuning should fire frequently together
- Equally excitable neurons should fire frequently together
- So neuron spiking rates should be correlated, based on similarity in
  - directional tuning
  - motion sensitivity

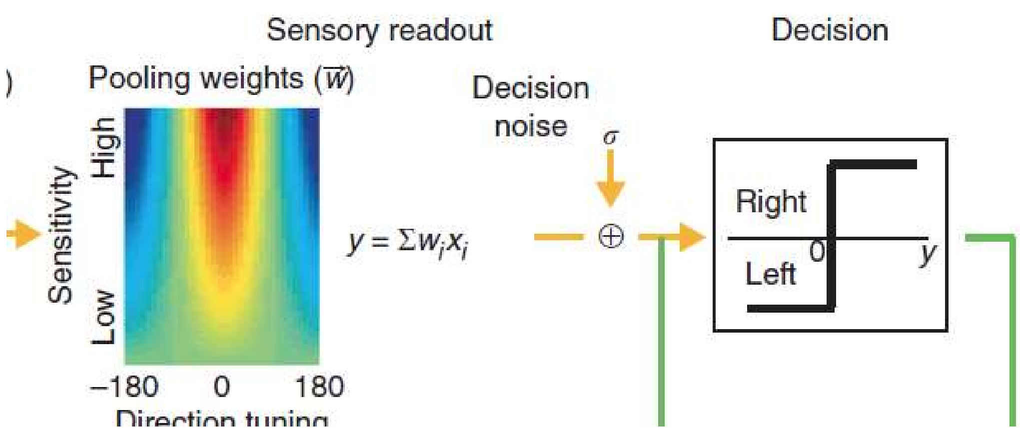
$$g_{sen} = \begin{cases} \rho_{\max} - \frac{|sen_i - sen_j|}{b_{sen}} & \text{if} \rho_{\max} > \frac{|sen_i - sen_j|}{b_{sen}} \\ 0 & \text{otherwise} \end{cases}$$

$$\rho_{ij} = \begin{cases} g_{sen} \times g_{dir} & \text{if i} \neq \text{j} \\ 1 & \text{otherwise} \end{cases}$$

$$g_{dir} = e^{\frac{|\Theta_i - \Theta_j|}{b_{dir}}}$$

Decision variable construction

- Variable constructed by pooling neuronal responses



Pooled neuronal responses

- Construct a 7200 bit vector **x**

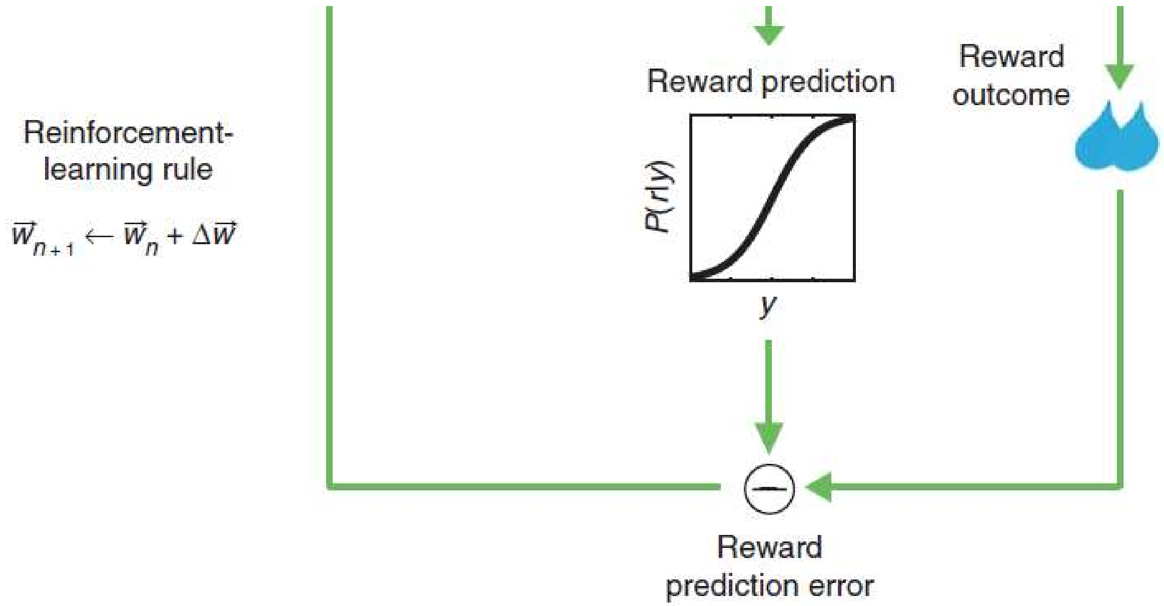
$$x_i = m_i + \sqrt{v_i r_i}$$

- Here, **r** = U**z**, **z** ~ N(0,1) and U is the square root of the correlation matrix
- All neuron responses pooled to yield decision variable corrupted by decision noise

$$y = \sum_{i}^{\text{neurons}} w_i x_i + \mathcal{N}(0, 25) + \mathcal{N}(0, 2y)$$

The magic sauce: weight learning

- Using reinforcement learning



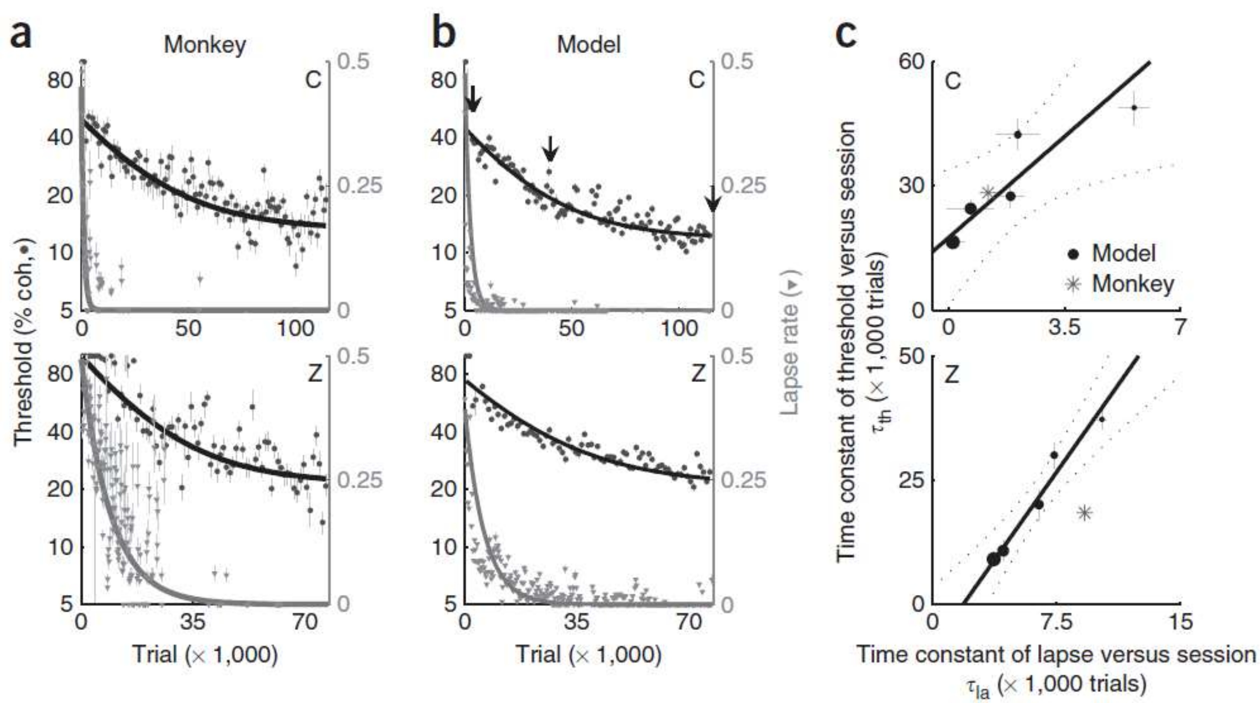
Reinforcement learning in neurons

- Prediction error

$$\Delta \mathbf{w} = \alpha C(r - mE[r])(\mathbf{x} - nE[\mathbf{x}])$$

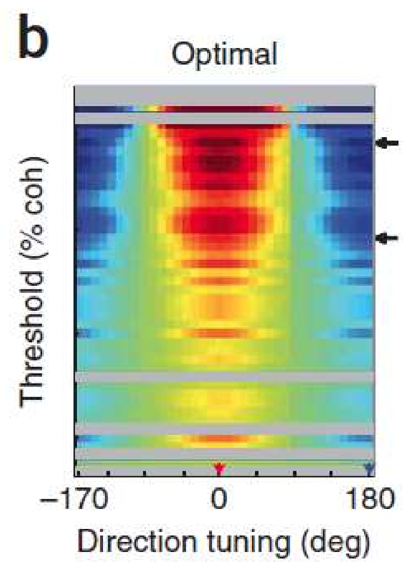
- C is -1 for left, +1 for right
- r is whether there was success or not on the trial
- E[r] is the predicted probability of responding correctly given the pooled MT responses y
- **x** is the vector of MT responses
- E[x] is the vector of baseline MT responses
- M = 1, n = 0 for the most successful rule

Good fit for the behavioral data

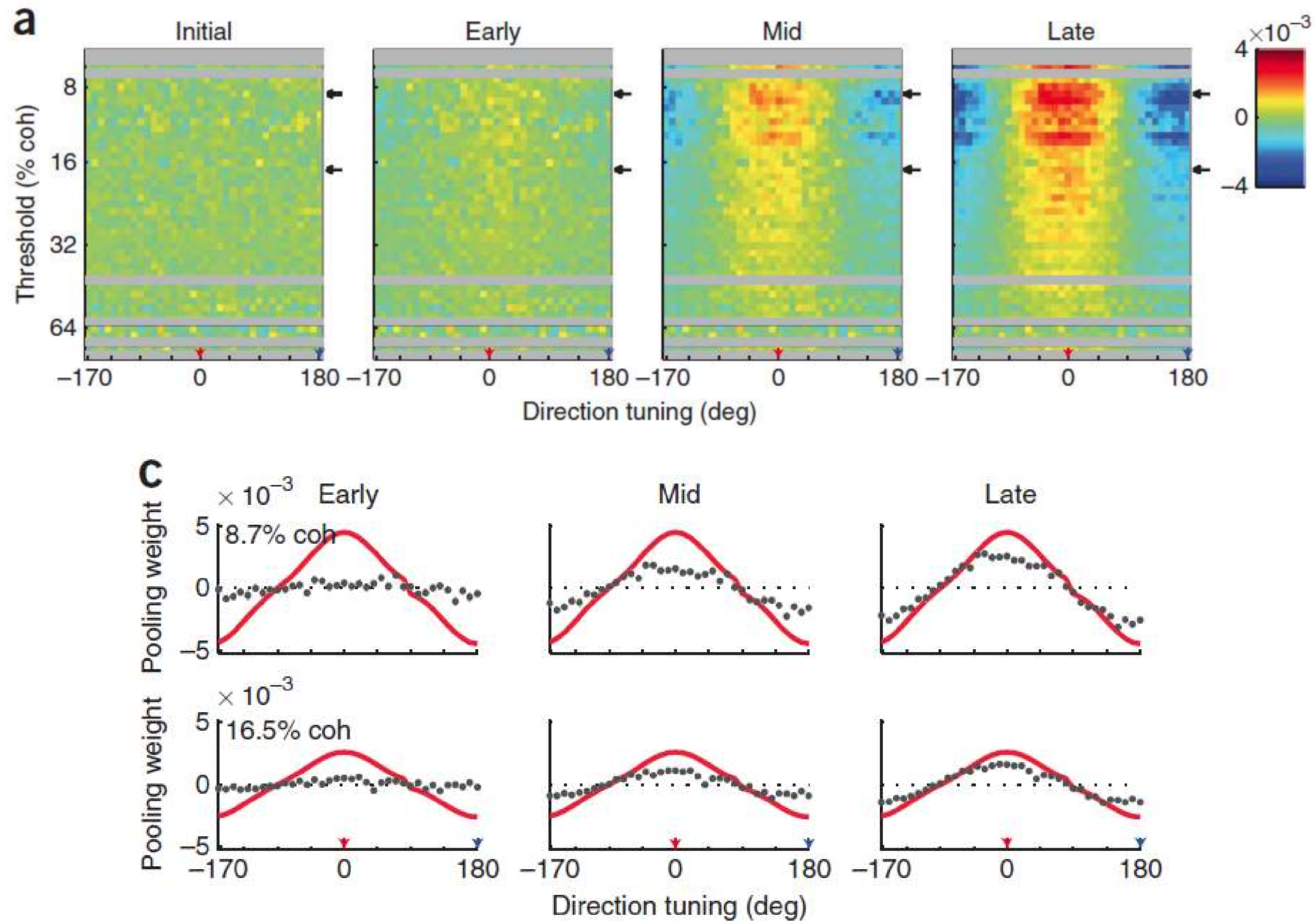


How did the tuning weights vary?

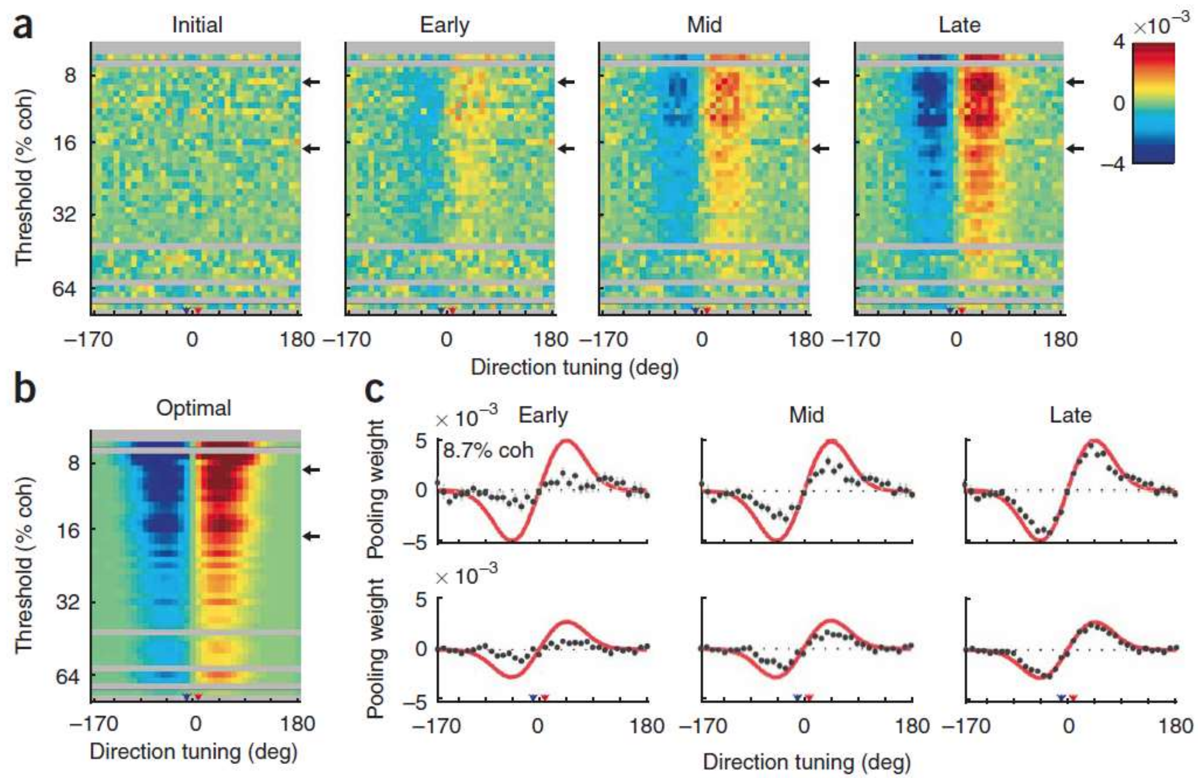
- Graph plots neuron weights on y-axis and directional tuning on x-axis
- This plot shows the optimal weights to discriminate motion directions 180 degrees apart
- Some neurons (not all) learn that direction 0 should get high positive weights and direction 180 should get high negative weights



Model LIP headed the right way

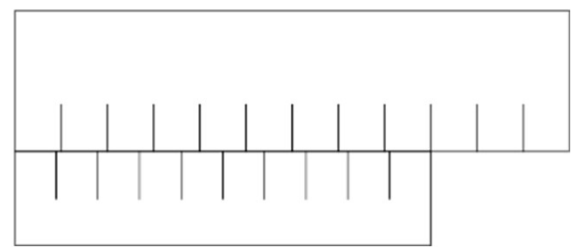


Fine discrimination task



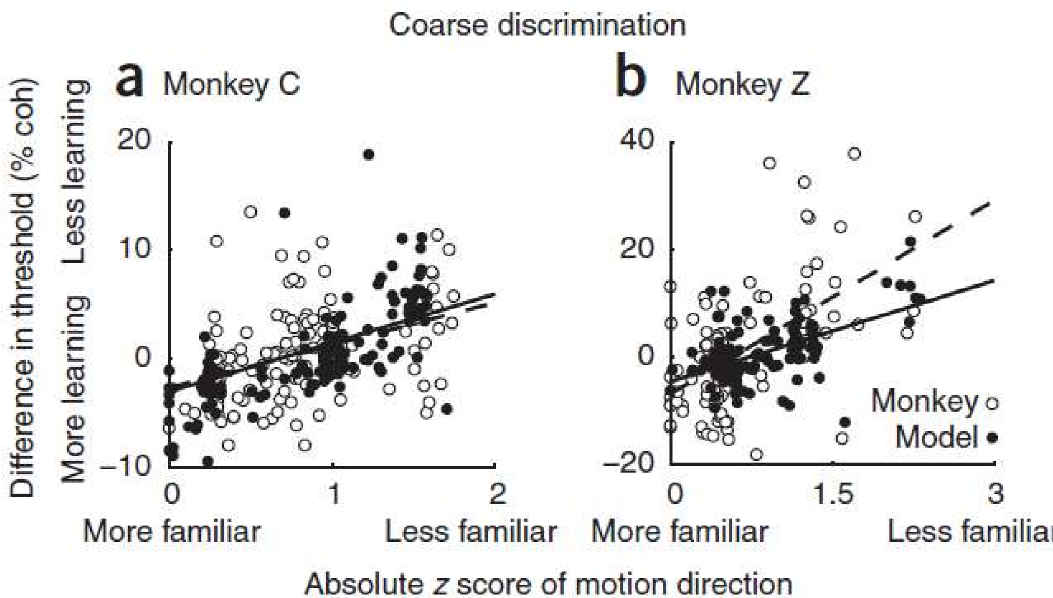
Perceptual learning is hyper-specific

- Training with horizontal Vernier scales can improve discrimination threshold 6-fold
- But horizontal training does not translate to vertical direction



Training specificity predictions

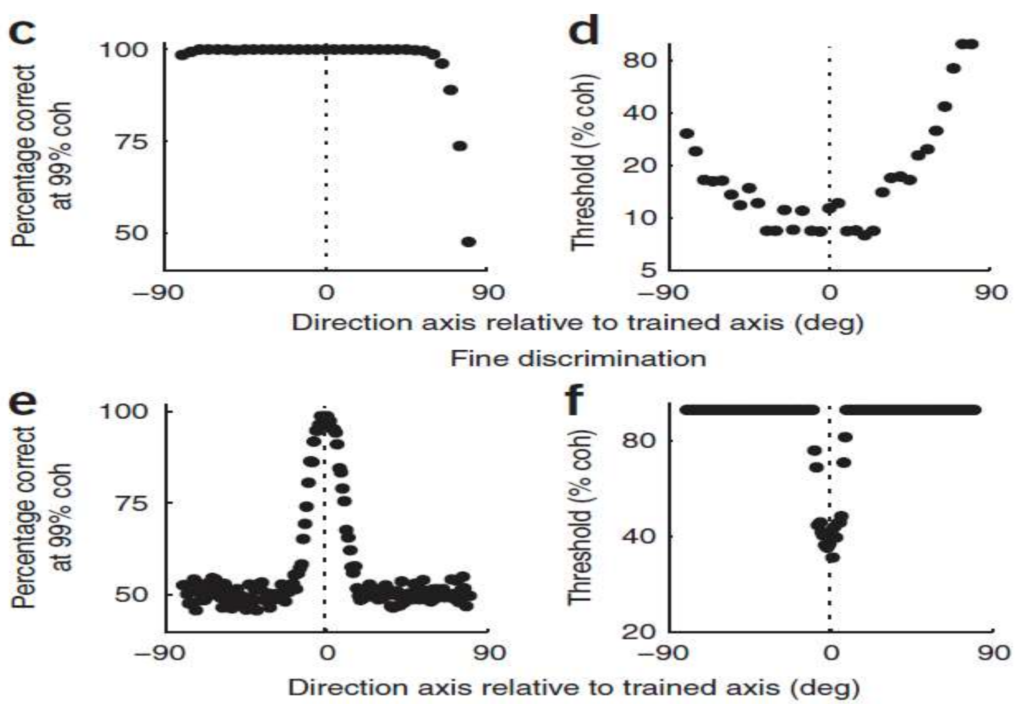
- Infrequently seen directions show less learning



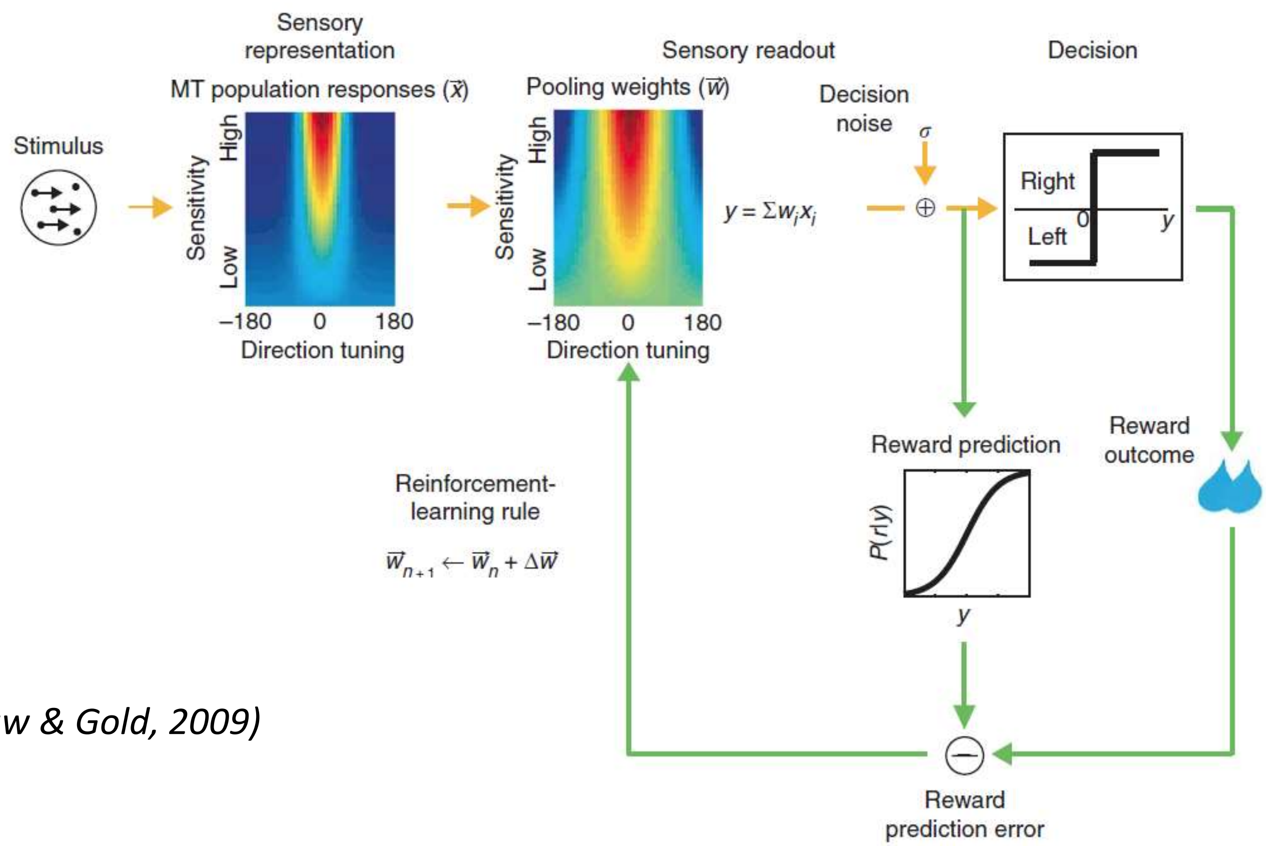
Model predicts differential sensitization

Sensory-motor association

Perceptual sensitivity



The model



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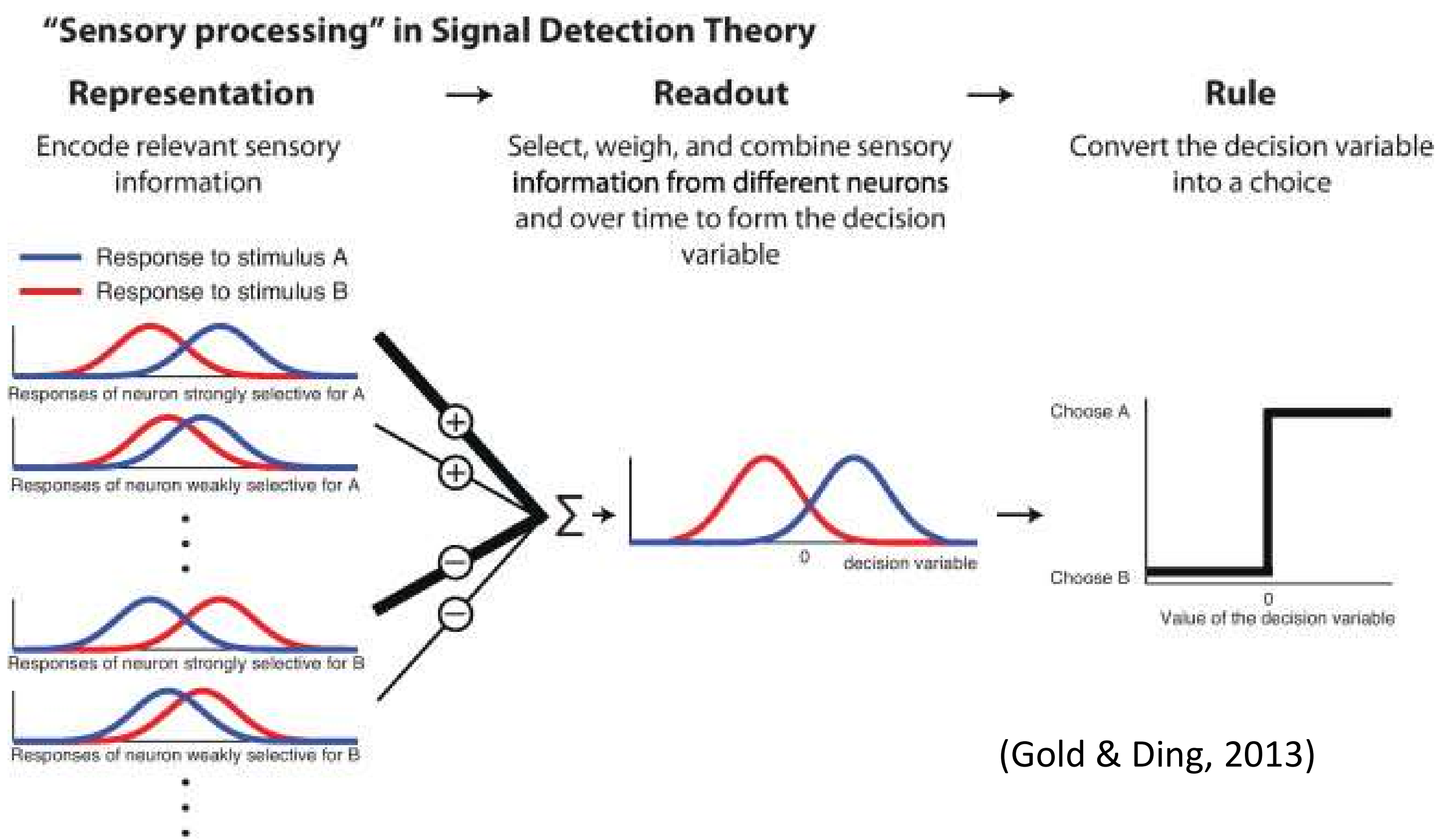
Perceptual learning as decision-making



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