

## 3. Neocortical Dynamics

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## Functions of Layers

- Input
  - layer 4
  - from sensation or other areas
- Hidden
  - layers 2 & 3
- Output
  - layers 5 & 6
  - to motor systems or other areas

(fig. -< O'Reilly, Comp. Cog. Neurosci.)

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## Connection Directions

- Feedforward
  - from Hidden in lower to Input in higher
- Feedback
  - from Hidden & Output in higher to Hidden & Output in lower
- Lateral
  - from Hidden and Output to all three layers in same area
- Bidirectionality
  - pervasive

(fig. -< O'Reilly, Comp. Cog. Neurosci.)

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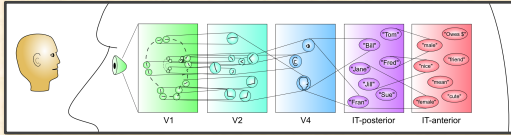
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### Hierarchical Categorical Representations



- Successive layers of neural detectors
- Progressively more abstract

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(fig. < O'Reilly, *Comp. Cog. Neurosci.*)

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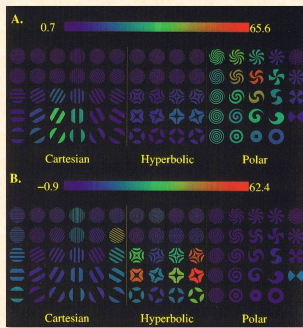
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### Cell Responses in V4



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(fig. < Clark, *Being There*, 1997)

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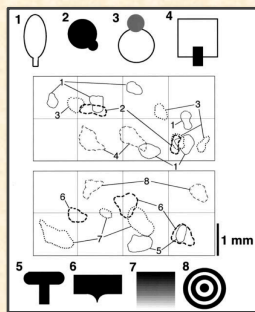
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### Sparse Distributed Representation

- Localist representation
  - "grandmother cells"
  - unlikely in brain
- K-out-of-N detectors
  - typically 15-25% of neurons active
- Approximate orthogonality



(monkey IT cortex)

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(fig. < O'Reilly, *Comp. Cog. Neurosci.*, from Tanaka, 2003)

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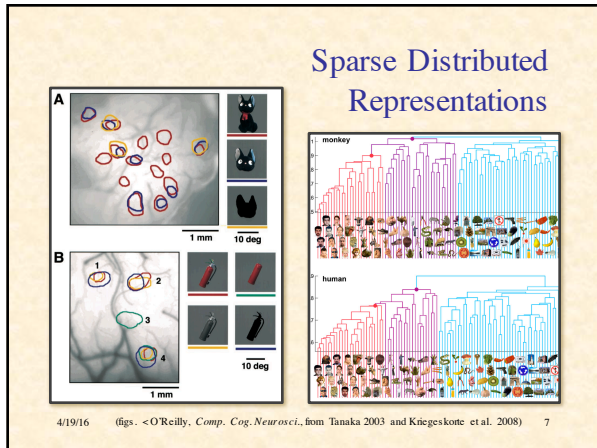
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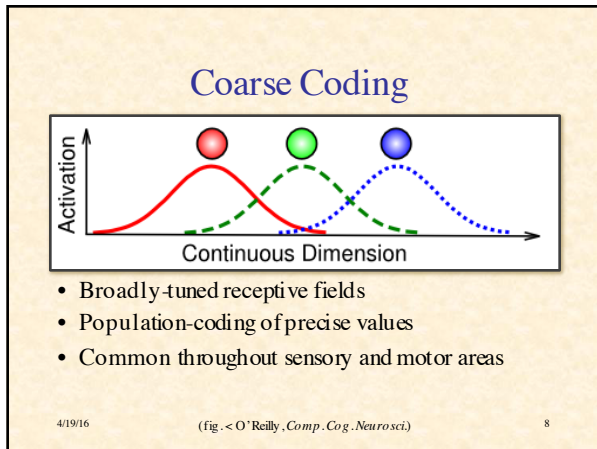
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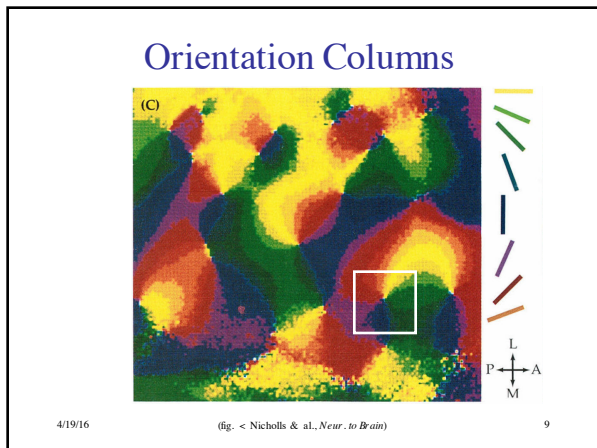
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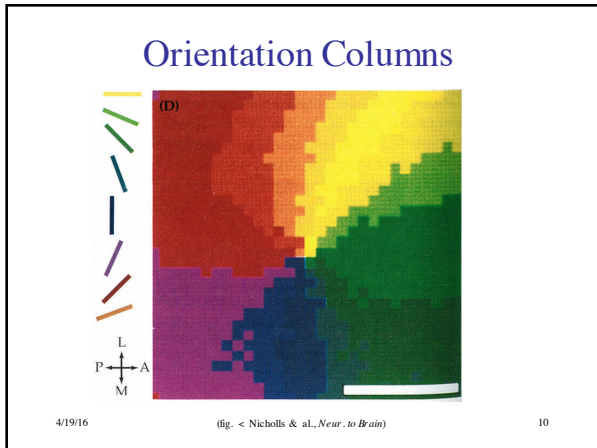
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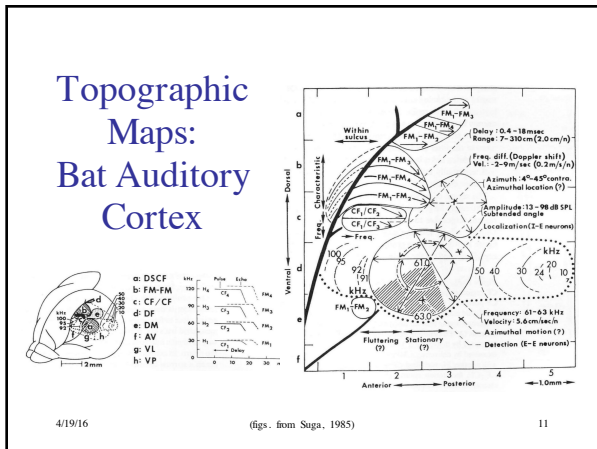
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### Bidirectional Excitation

- Functions
  - recognition
  - top-down imagery
  - ambiguity resolution
  - pattern completion
- Attractor dynamics
  - convergence on good representation
  - energy vs. harmony

(fig. < O'Reilly, *Comp. Cog. Neurosci.*)

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### Ambiguity Resolution



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### Inhibitory Competition and Activity Regulation

- Activity regulation
- Selective attention
- Competition
  - K winners take all
  - can be implemented algorithmically
- Sparse distributed representation

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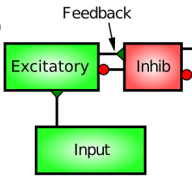
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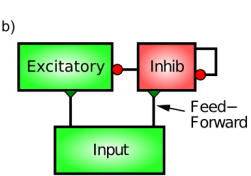
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### Activity Regulation

a)



b)



- Feedback: reactive, reflects actual level of activity, robust, responsive, may be unstable
- Feedforward: anticipatory, limits feedback oscillation, slow, brittle
- Work well together

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## 4. Learning Mechanisms

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### Spike Timing Dependent Plasticity (STDP)

1.  $V_m$  elevated by backpropagating action potential
2. Repels  $Mg^{2+}$  opening NMDA channels
3. Presynaptic neuron fires, releasing glutamate
4. Glutamate binds unblocked NMDA channels, allowing  $Ca^{2+}$  influx
5.  $Ca^{2+}$  increases number & efficacy of AMPA receptors

(fig. < O'Reilly, Comp. Cog. Neurosci. > 17)

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### Long-term Potentiation (LTP) vs. Long-term Depression (LTD)

- LTP vs. LTD depends on  $Ca^{2+}$  concentration over several 100 msec
- Records possible causal connection
- Actual situation is more complicated with multiple APs

(figs. < O'Reilly, Comp. Cog. Neurosci. > 18)

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### LTP/LTD Approximation

- Piecewise linear approximation to LTP/LTD
- Typical  $\theta_d = 0.1$
- Floating threshold
- $\Delta W = \eta f_{XCAL}(\langle xy \rangle_s, x \langle y \rangle_l)$

$$f_{XCAL}(c, \theta_p) = \begin{cases} c - \theta_p & \text{if } c > \theta_p \\ -c(1 - \theta_p) / \theta_d & \text{otherwise} \end{cases}$$

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### Homeostatic Behavior

Middle Avg Activity  
Balanced dWt

Low Avg Activity  
Lots of "Upside"

High Avg Activity  
Lots of "Downside"

- Floating threshold adapts to long-term postsynaptic activity
- Tends to equalize activity among neurons

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### Competitive Learning

- Competitive learning network
  - two layers, randomly initialized weights
  - second is self-reinforcing, mutually inhibitory
  - “winner takes all” dynamics
- Learning
  - winner moves toward last
  - weight vectors move to centers of clusters

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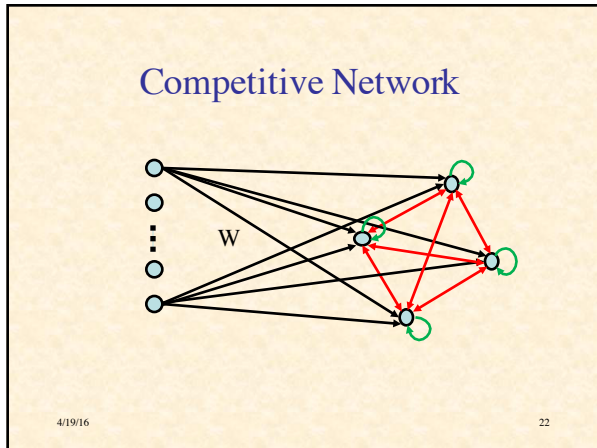
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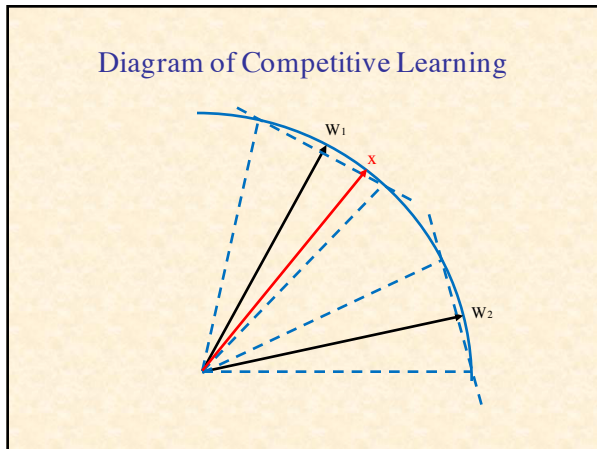
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- ### Self-Organizing Learning
- Inhibitory competition
    - ensures sparse representation
  - Hebbian "rich get richer"
    - adjustment toward last pattern matched
  - Slow threshold adaptation
    - adjusts receptive fields
    - equalizes cluster probabilities
  - Homeostasis
    - distributes activity among neurons
    - more common patterns are more precisely represented
  - Gradually develops statistical model of environment
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### Error-Driven Learning

- For achieving intended outcomes
- Fast threshold adaptation
- Short-term outcome – medium-term expectation
  - ✓ “plus phase” – “minus phase”
- Depends on bidirectional connections
  - ✓ communicates error signals back to earlier layers
- Contrastive Attractor Learning (CAL)
  - ✓ approximately equivalent to BP when combined with bidirectional connections

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### Contrastive Attractor Learning

- Network learns contrast between:
  - early phase/expectation (minus)
  - late phase/outcome (plus)
- Gets more quickly to late phase, which has integrated more constraints

$$f_{\text{XCAL}}(c, \theta_p) = \begin{cases} c - \theta_p & \text{if } c > \theta_p \theta_d \\ -c(1 - \theta_p) / \theta_d & \text{otherwise} \end{cases}$$

$$\Delta W = \eta f_{\text{XCAL}}(\langle x \rangle_s, \langle y \rangle_m)$$

$$\approx \eta (x_s y_s - x_m y_m)$$

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### Learning Signals?

- What constitutes an “outcome”?
- Dopamine bursts arise from unexpected rewards or punishments (reinforcers)
  - violation of expectation
  - needs correction
- Dopamine modulates synaptic plasticity
  - controls  $\lambda$ :  $\Delta W = \eta f_{\text{XCAL}}(x_s y_s, x_m (\lambda y_1 + (1 - \lambda) y_m))$
- Probably not the whole story

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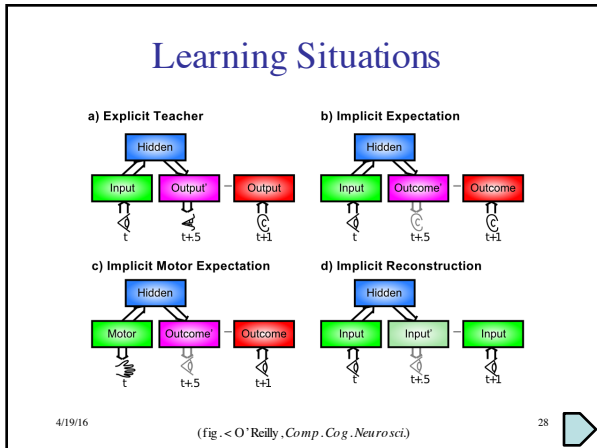
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