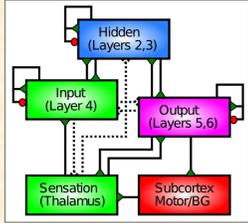


3. Neocortical Dynamics

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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

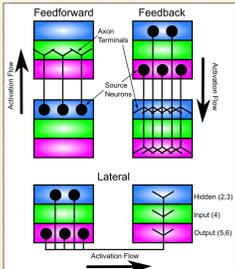


(fig. < O'Reilly, *Comp. Cog. Neurosci.*)

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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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Hierarchical Categorical Representations

- Successive layers of neural detectors
- Progressively more abstract

4/1/15 (fig. < O'Reilly, *Comp. Cog. Neurosci.*) 4

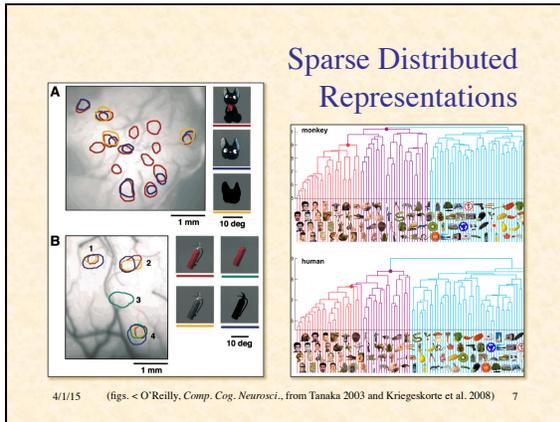
Cell Responses in V4

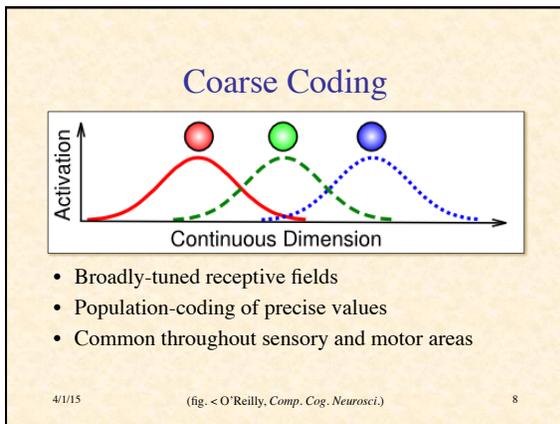
4/1/15 (fig. < Clark, *Being There*, 1997) 5

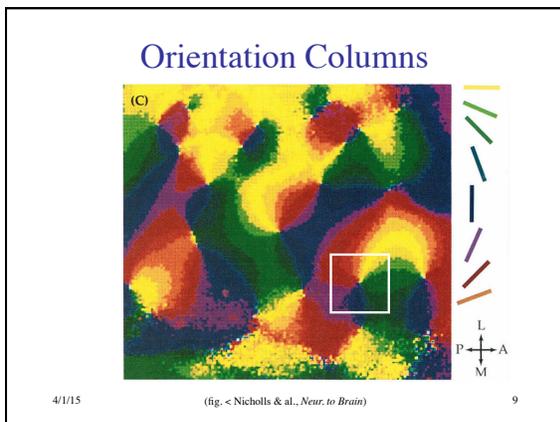
Sparse Distributed Representation

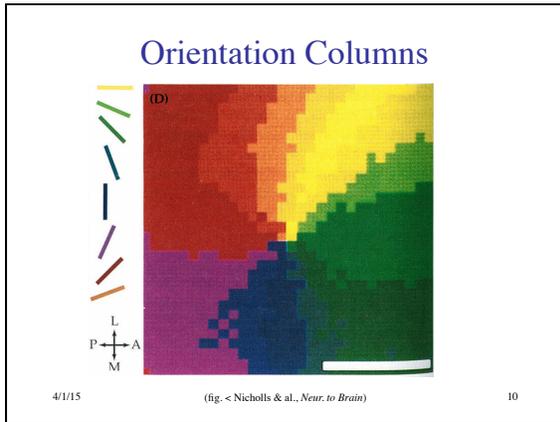
- Localist representation
 - “grandmother cells”
 - unlikely in brain
- K-out-of-N detectors
 - typically 15–25% of neurons active
- Approximate orthogonality

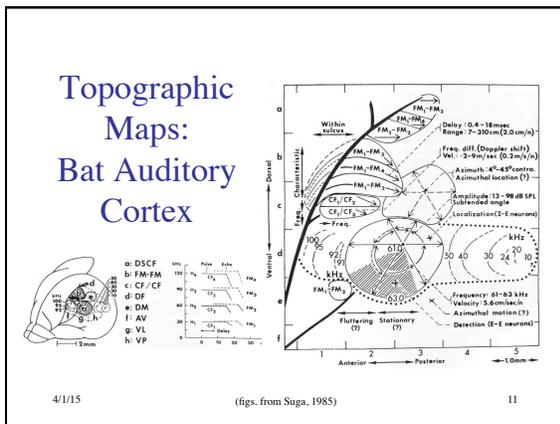
4/1/15 (fig. < O'Reilly, *Comp. Cog. Neurosci.*, from Tanaka, 2003) 6







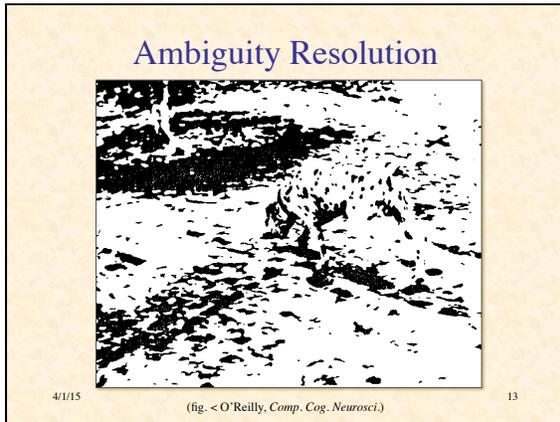




Bidirectional Excitation

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

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

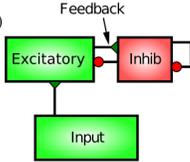


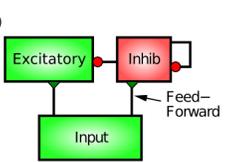
Inhibitory Competition and Activity Regulation

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

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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

4/1/15 (fig. < O'Reilly, *Comp. Cog. Neurosci.*) 15

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

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

LTP/LTD Approximation

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

The graph shows the change in weight dW as a function of the average synaptic activity $\langle xy \rangle_s$. The function is piecewise linear. For $\langle xy \rangle_s < \theta_p$, dW is negative (LTD), and for $\langle xy \rangle_s > \theta_p$, dW is positive (LTP). The threshold θ_p is shown as a vertical dashed line that can shift, representing a floating threshold. The slope of the LTP region is $1/\theta_d$.

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

4/1/15 (fig. < O'Reilly, *Comp. Cog. Neurosci.*) 19

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

4/1/15 (fig. < O'Reilly, *Comp. Cog. Neurosci.*) 20

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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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

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

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

$$\approx \eta (x_e y_e - x_m y_m)$$

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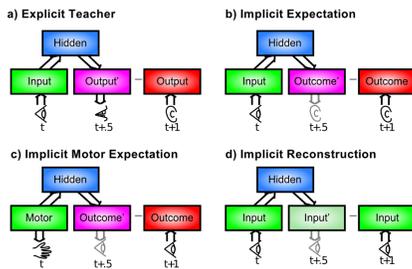
Learning Signals?

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

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Learning Situations



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

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