3. Neocortical Dynamics

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

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
Hierarchical Categorical Representations

- Successive layers of neural detectors
- Progressively more abstract

Cell Responses in V4

Sparse Distributed Representation

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

Coarse Coding
- Broadly-tuned receptive fields
- Population-coding of precise values
- Common throughout sensory and motor areas

Orientation Columns

Orientation Columns

Topographic Maps: Bat Auditory Cortex

Bidirectional Excitation

- Functions
  - recognition
  - top-down imagery
  - ambiguity resolution
  - pattern completion
- Attractor dynamics
  - convergence on good representation
  - energy vs. harmony
Part 4B: Real Neurons

Ambiguity Resolution

Inhibitory Competition and Activity Regulation

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

Activity Regulation

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

Spike Timing Dependent Plasticity (STDP)

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

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

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

- Piecewise linear approximation to LTP/LTD
- Typical $\theta_d = 0.1$
- Floating threshold

$LTP/LTD$ approximated by

$$\Delta W = \eta f_{\text{SCAL}} \left( \langle xy \rangle, x \langle y \rangle \right)$$

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

Homeostatic Behavior

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

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
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

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

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

\[
f_{SCAL}(c, \theta) = \begin{cases} 
  c - \theta & \text{if } c > \theta \\
  -\epsilon(1 - \theta) / \theta & \text{otherwise}
\end{cases}
\]

\[
\Delta W = \eta f_{SCAL}(x, y) x
\]

\[
= \eta (x, y) - x y)
\]
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 $\lambda$: $\Delta W = \eta f_{\text{SCM}}(r_y, r_u, (\lambda Y + (1-\lambda) Y_u))$
- Probably not the whole story

Learning Situations

(a) Explicit Teacher

(b) Implicit Expectation

(c) Implicit Motor Expectation

(d) Implicit Reconstruction

(Reprinted from O’Reilly, Comp. Cog. Neurosci.)