Neurons and Neural Computation

- I. Importance of Neural Computation
  - Neuroscience: What brain tissue does.
  - Computational theory of mind: Implementing elementary information processes.

The Resting Potential
9.00 Introduction to Psychology  
Prof. S. Pinker  
Week 4, Lecture 2: Neural Computation

**The Action Potential**
- Repolarization phase of action potential
- Depolarization phase of action potential

**Synaptic Transmission**

**Excitatory and Inhibitory Synapses**
- The terminals of this axon have excitatory effects.
- The terminals of this axon have inhibitory effects.
Feature Detectors

Neural Computation

- Computing logical functions with neurons.
  Kosher =
  \{ [Chews its cud] AND [Has cloven hooves]} OR \\
  \{ [Has fins] AND [Has scales]} \\

Neural Computation

- Multiply each input signal by the "weight" (strength) of the synapse.
- Sum the weighted signals.
- If they exceed the cell's threshold, fire.

Building Logic Gates out of Neurons
Local vs. Distributed Representations

- Local representation: “grandmother cell,” “yellow Volkswagen detector”
- Distributed representation; “auto-associator”:

Pattern completion by auto-associators:

Learning in Neural Networks

- **Neural Computation:**
  - Multiply each input signal by the "weight" (strength) of the synapse.
  - Sum the weighted signals.
  - If they exceed the cell's threshold, fire.
- **Neural Learning:**
  - Change the weights of synapses.
  - Change the thresholds of cells.
Learning in Neural Networks, continued

- Real but simple example of learning in a neural network: Aplysia (sea snail). See textbook.
- More complex but still hypothetical form of neural learning:

Perceptron Learning Procedure

- Compare current output to correct output (from "teacher").
- If too low, increase weights for active inputs, and decrease threshold.
- If too high, decrease weights for active inputs, and increase threshold.

How a two-layer network can learn "OR" with the perceptron learning procedure.

Input: 1 0
Correct Output: 1
Actual Output: (1 X 0) + (0 X 0) = 0. 0 < 1.0. Therefore 0.
Too small.
Increase first weight by .1.
Leave second weight alone.
Decrease threshold by .1.
A 3-layer network that *can* compute XOR:

But: A three-layer network needs a fancier learning procedure: “Error back-propagation.”

Relating Neural Networks to Psychology

- Lateral inhibition: Turn on your own output; turn down your neighbor's output.
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Lateral inhibition as an explanation for:
- Mach bands
- The Hering grid
- Simultaneous contrast
Each step in the photograph has a uniform intensity, but the perceived intensity of each step is not uniform. The output pattern (solid line) produced for the defined input intensity distribution. From: Cowan and Dror (2007).

FIGURE 2-10: The Helson grid. Gray spots appear at each intersection, except the one you are looking at.
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Relating Neural Networks to Psychology, continued

• **Opponent process circuits:**
  – Two inputs to one cell, from opposite kinds of stimuli (red/green, dark/light, move up/down, etc.
  – A signal for one perceptual quality excites an output; a signal for the complementary quality inhibits the output.
  – The level of activity of the output (excited or inhibited relative to resting level) determines the perceived quality.

Lateral Inhibition + Opponent-Process =

• Simultaneous *color* contrast (similar to simultaneous lightness contrast, but with color, not lightness, affected by neighboring patch)
• **Habituation:** Neurons that fire a lot over a long period of time "get tired."

• Opponent-process circuitry plus habituation:
  - Show stimulus A for a long time → A cells habituate
  - Show neutral stimulus → A cells habituated (below resting rate), B cells fresh (at resting rate)
  - B > A, so perceive neutral stimulus as B

• Explains:
  - Color aftereffects
  - Motion aftereffects