Emergent Intelligence via Synaptic Tuning

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**Hebb Rule: Fire Together, Wire Together**

When an axon of cell A is near enough to excite a cell B and repeatedly or persistently takes part in firing it, some growth process or metabolic change takes place in one or both cells, such that A’s efficiency as one of the cells firing B, is increased.

\[ \Delta w_{i,j} = \lambda u_i v \]
Hebbian Learning Rules

**General Hebbian:**
\[ \Delta w_i = \lambda u_i v \]

**Basic Homosynaptic**
\[ \Delta w_i = \lambda (v - \theta_v) u_i \]

**Basic Heterosynaptic BCM**
\[ \Delta w_i = \lambda v (u_i - \theta_i) \]

**BCM**
\[ \Delta w_i = \lambda u_i v (v - \theta_v) \]

**Homosynaptic**
All active synapses are modified the same way, depending only on the strength of the postsynaptic activity.

**Heterosynaptic**
Active synapses can be modified differently, depending upon the strength of their presynaptic activity.
Positive Feedback $\Rightarrow$ Weight Explosions

High post-synaptic firing $\Rightarrow w_{ij} \uparrow \Rightarrow$ Higher firing $\Rightarrow w_{ij} \uparrow \ldots$

- All activation-function outputs in $[0, 1]$ $\Rightarrow$ Major trouble!
- Outputs in $[-1, 1]$ $\Rightarrow$ Still trouble!
- Thresholding (e.g. in homosynaptic, heterosynaptic and BCM rules) $\Rightarrow$ Still trouble!

Solutions

- BCM + dynamic $\theta_v$: effective, but expensive.
- Weight normalization: effective, but expensive.
- Oja rule: $\Delta w_i = \lambda v (u_i - v \mid w_i \mid) = u_i v - v^2 \mid w_i \mid$
  - *Forgetting* term implicitly controls weight explosion
  - *Emergent weight normalization!*
  - Achieves Principle Component Analysis (PCA)
Hebbian Learning with Spiking Neurons

Now learning depends upon the **individual spike times** of neurons, not their average rate of spike production.

![Diagram of spiking neurons](image)

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Change in synaptic strength ($\Delta s$) as function of $\Delta t = t_{\text{pre}} - t_{\text{post}}$, the times of the most recent pre- and post-synaptic spikes. The maximum magnitude of change is roughly 0.4% of the maximum possible synaptic strength/conductance.
Pairing spikes for STDP calculations is not so easy.
A common solution: consider all pairs.
Is there a simpler mechanism?
Song and Abbott, 2000

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\[
\begin{align*}
  w_a &\leq w_a - kM \\
  w_b &\leq w_b - kM \\
  w_a &\leq w_a + kP_a \\
  w_b &\leq w_b + kP_b \\
  m_+ &\rightarrow m_- > m_+
\end{align*}
\]
Emergence in the Song-Abbott Model

- \( m_- > m_+ \) insures that random activity produces overall LTD, not LTP.
- No need to compare spikes across time or space. Memory variables accumulate the key information.
- Weight normalization - total weight doesn’t get too high or low.
- Cooperation and Competition: presynaptic neurons that happen to spike simultaneously (cooperate) can out-compete others for control of the post-synaptic neuron.
Small group (C,D) drives neuron X. But A,B,E and F fire close enough to X to get LTP.
After LTP, the large group can fire X on its own. So X fires earlier, and it fires before C and D, so their efferents have LTD. Now the larger group controls X.
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Predictions (i.e. high activity of predictive neuron) that coincide with sensory input $\rightarrow$ LTP.

Predictions unmatched by N activity $\rightarrow$ LTD. Many spikes from predictive neuron go unanswered in N $\rightarrow$ depression in Song-Abbott model also.

After LTP, predictions alone can activate N.

(Right) Results from Artola et. al. (1990)
Downing(2009).
Based on networks in thalamus, cortex and hippocampus.
Prediction: Place cell fires **before** arriving at the location that it represents. Burgess(2003).
Emerging Phase Precession via LTP and LTD

Learning a Sequence

STDP Window

CA3 Place Cells
- Random recurrence (2-5%)
- No topology

STDP can produce these connections

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Clusters and Concepts

Gamma waves and LTP compress sequences into clusters $\approx$ concepts.
Contexts B and D both predict the same concept, but via different neurons: C₁ and C₂.

Assume context D occurs much less than B, then many of the D → C₂ links can weaken.

When D does fire, it’s shared context with B (pentagons) can lead C₁ to fire, but not C₂. So D → C₁ links strengthen.

Eventually, both B and D trigger C₁.

C₂ has been remapped to C₁.
After arena exploration and re-mapping, Neuron C may or may not be neuron C₁ or C₂.