Learning

Computational Cognitive Neuroscience

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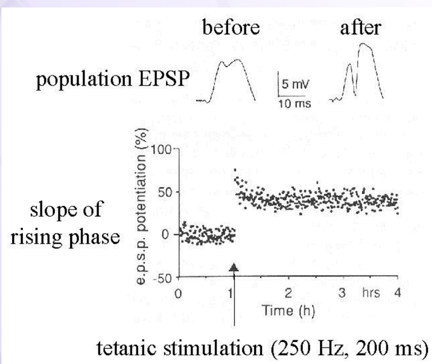
Overview of Learning

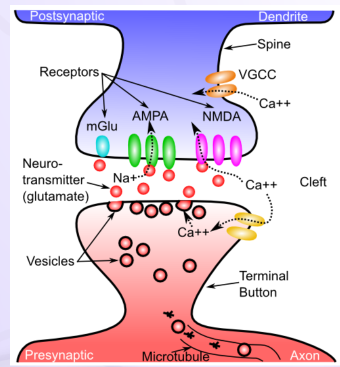
- Biology: synaptic plasticity
- Computation:
  - Self organizing – soaking up statistics
  - Error-driven – getting the right answers

Synapses Change Strength

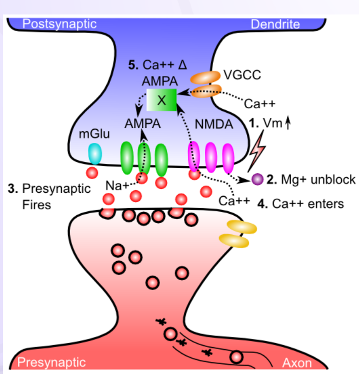
(in response to patterns of activity)



What Changes??



Gettin' AMPA'd



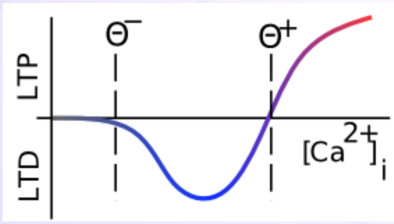
Hebbian Learning

Neurons that ***fire*** together, ***wire*** together!

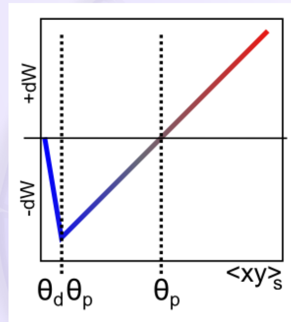
dW = f(x y)

Change in synaptic weight is a function of both sending (x) and receiving (y) activity!

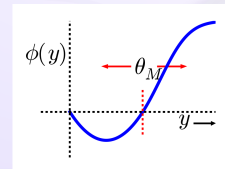
Which Way?



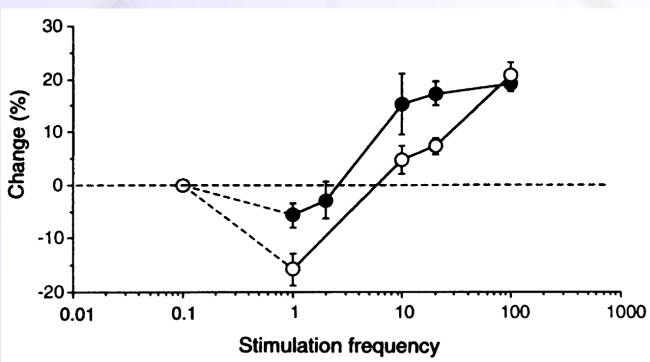
XCAL = Linearized BCM



- Bienenstock, Cooper & Munro (1982) – BCM:
- **adaptive threshold Θ**
  - Lower when less active
  - Higher when more.. (homeostatic)



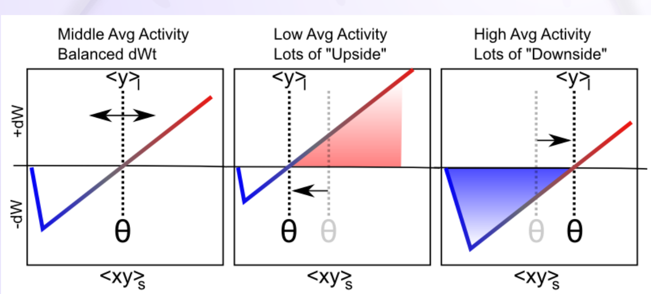
Threshold Does Adapt



Computational: Self-Organizing and Error-Driven

- Self-organizing = learn general statistics of the world.
- Error-driven = learn from difference between expectation and outcome.
- Both can be achieved through XCAL.

Floating Threshold = Long Term Average Activity (Self Org)



Self Organizing Learning

- Inhibitory Competition: only some get to learn
- Rich get richer: winners detect even better
  - But also get more selective (hopefully)
- Homeostasis: keeping things more evenly distributed (higher taxes for the rich!)

Limitations of Self-Organizing

Can't learn to solve challenging problems – driven by statistics, not error..

Fix It!

Error-driven learning drives weight changes as a function of ***errors***: directly tries to fix the problem!

Delta rule:

Error

dW = x (t – y)   <- t = target, y = recv, x = send

vs. Hebbian:

dW = x y

Two Phases

Minus phase: guess / prediction / expectation

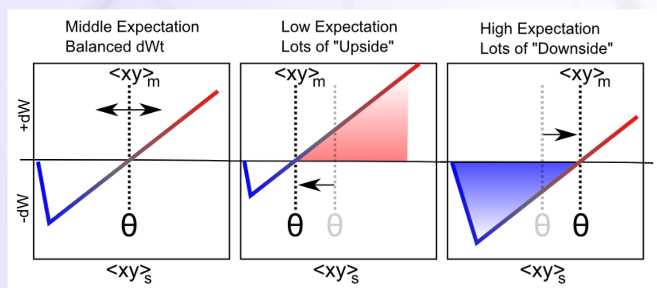
(what the network comes up with)

Plus phase: target / outcome / reality

(what it *should* have come up with)

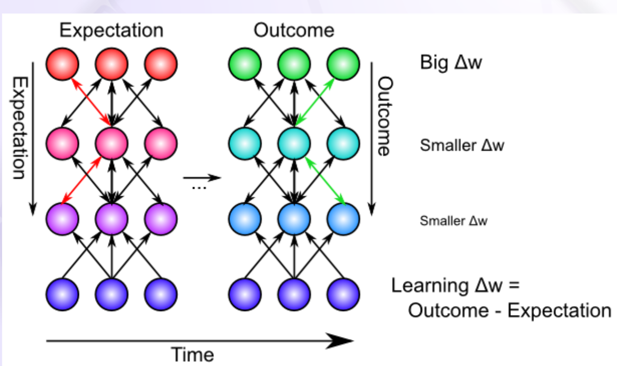
dW = x (y^+ – y^-)

Floating Threshold = Medium Term Synaptic Activity (Error-Driven)



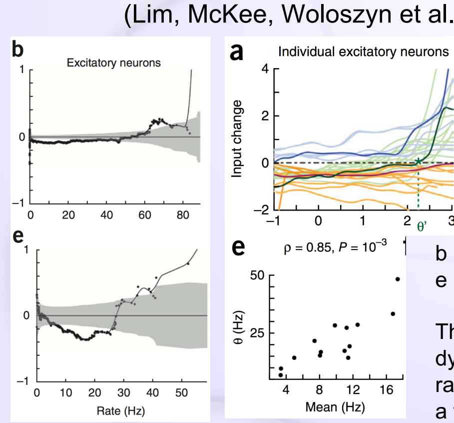
dW = Outcome – Expectation = $<xy>_s$ - $<xy>_m$

Backpropagation: Mathematics of Error-driven Learning



Evidence of Dynamic Thresholds

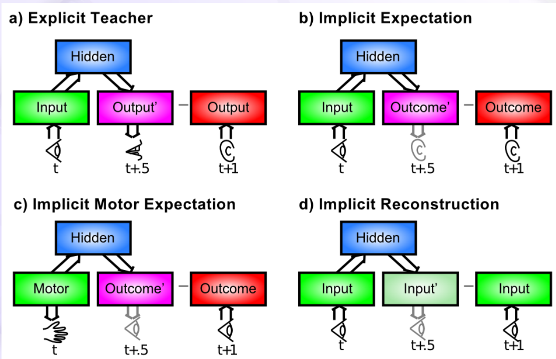
(Lim, McKee, Woloszyn et al., 2015)



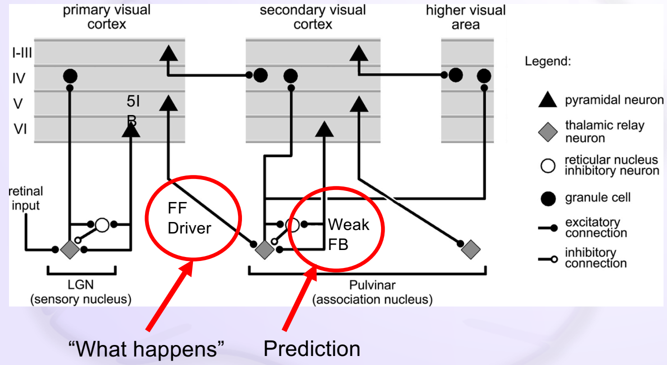
b = passive viewing
e = active task

Threshold changes dynamically on a rapid time scale, as a function of short-term activity level!

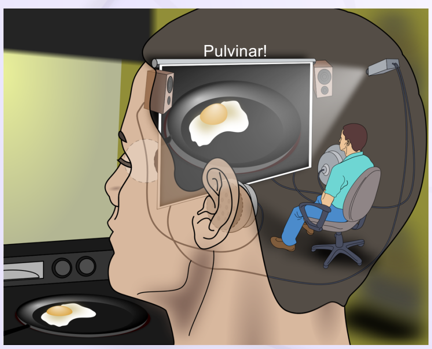
Where Does Error Come From?



Thalamocortical Loop Biology
(Sherman & Guillery, 2006)



The Pulvinar = Projection Screen
(c.f. Mumford, 1991 "blackboard")



Pulvinar receives connections from all over visual cortex

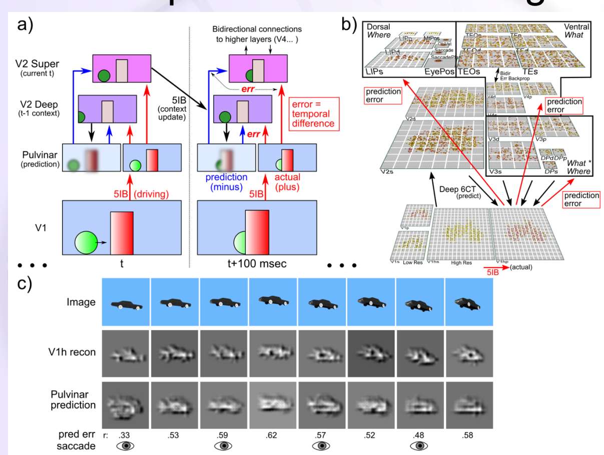
and projects back out to these same areas

Two inputs:

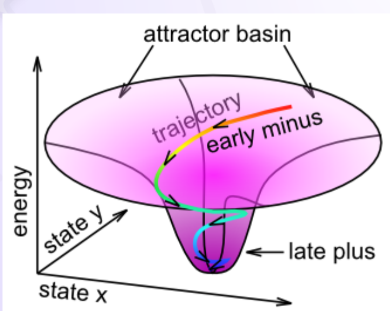
1. Few strong feedforward: *"what happens"*

2. Many weaker feedback: *prediction*

Deep Predictive Learning

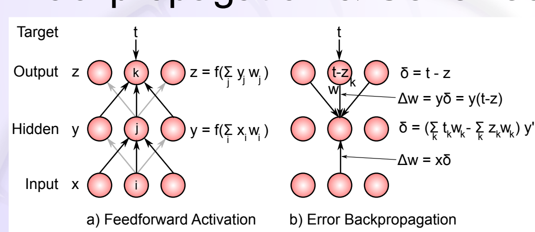


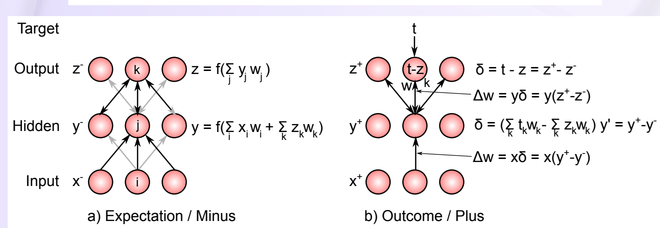
Fast Threshold Adaptation: Late Trains Early



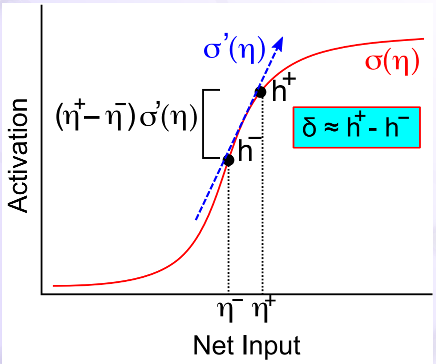
Essence of Err-Driven: dW = outcome - expectation

Backpropagation & GeneRec





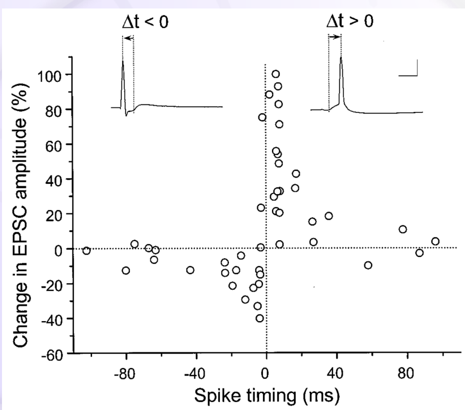
GeneRec: Derivative Approximation



Biological Derivation of XCAL Curve

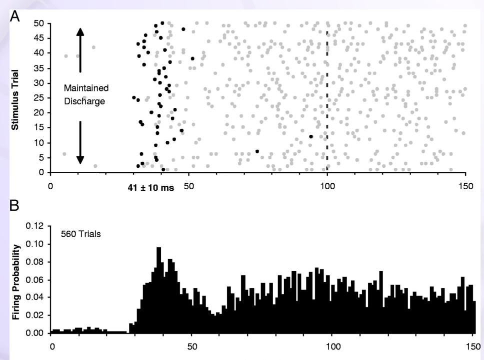
- Can use a detailed model of Spike Timing Dependent Plasticity (STDP) to derive the XCAL learning curve
- Provides a different perspective on STDP..

Causal Learning?



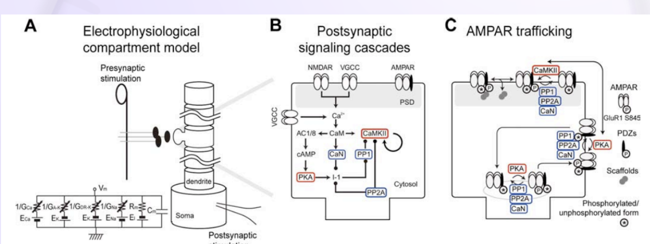
STDP, Bi & Poo, 1998

Let's Get Real..



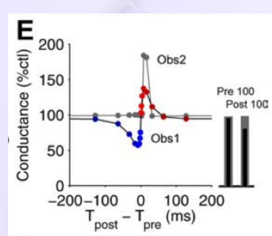
Urakubo et al, 2008 Model

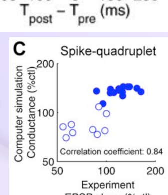
- Highly detailed combination of 3 existing strongly-validated models:

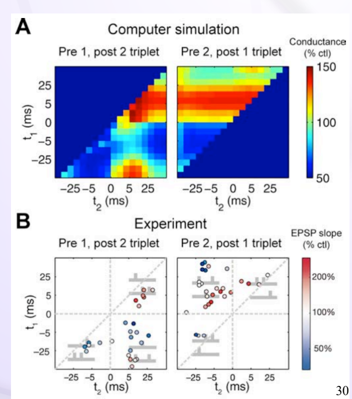


"Allosteric" NMDA Captures STDP

(including higher-order and time integration effects)





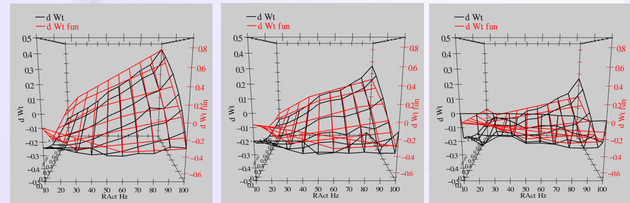


What About Real Spike Trains?

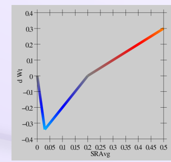
31

Extended Spike Trains = Emergent Simplicity

S = 100Hz S = 50Hz S = 20Hz



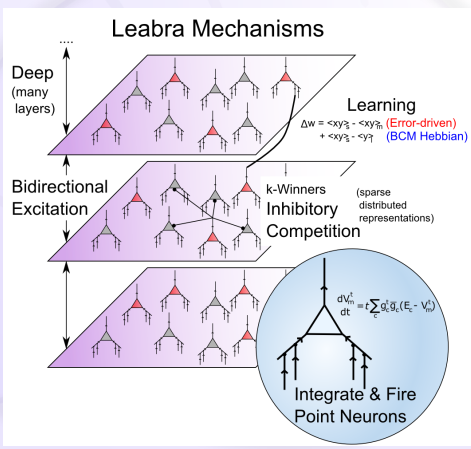
dW = f(send * recv) =
(spike rate * duration)



r=.894

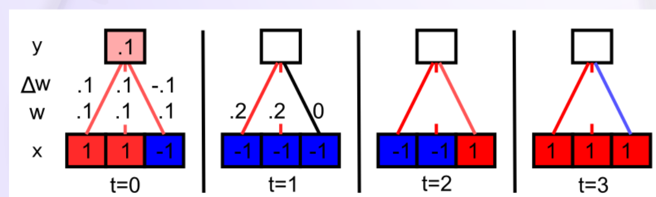
32

Leabra



33

Hebbian Learns Correlations



34