

# Learning

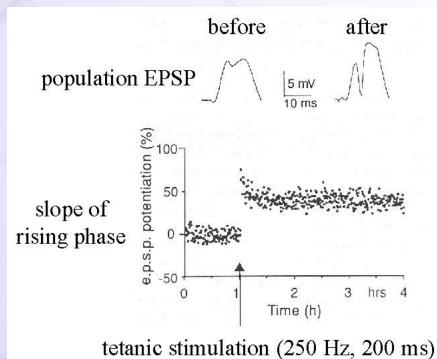
Computational Cognitive Neuroscience  
Randall O'Reilly

## Overview of Learning

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

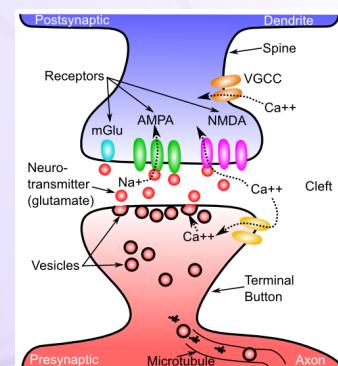
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### Synapses Change Strength (in response to patterns of activity)



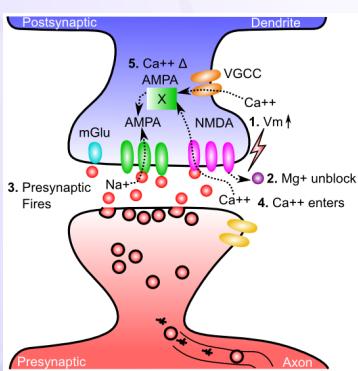
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### What Changes??



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### Gettin' AMPA'd



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### Hebbian Learning

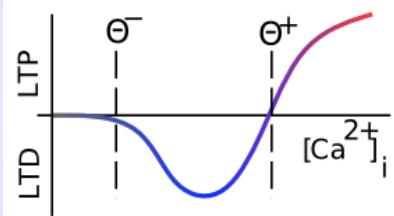
Neurons that **fire** together, **wire** together!

$$dW = f(x \ y)$$

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

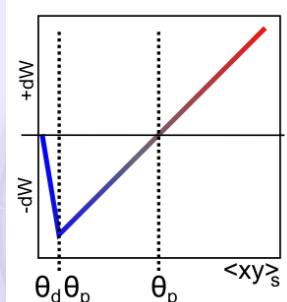
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## Which Way?

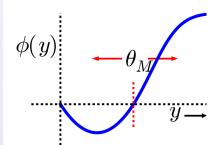


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## XCAL = Linearized BCM

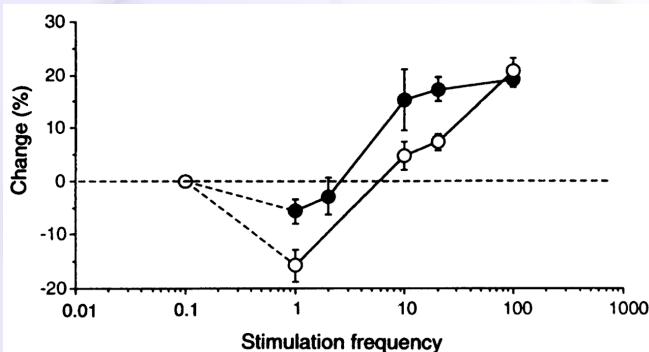


- Bienenstock, Cooper & Munro (1982) – BCM:
- adaptive threshold  $\Theta$** 
  - Lower when less active
  - Higher when more.. (homeostatic)



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## Threshold Does Adapt



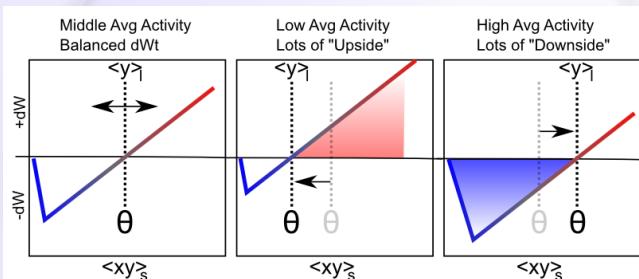
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## Computational: Self-Organizing and Error-Driven

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

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## Floating Threshold = Long Term Average Activity (Self Org)



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## 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!)

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## Limitations of Self-Organizing

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

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## Fix It!

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

Delta rule:

$$\text{Error} \quad dW = x(t - y) \quad \leftarrow t = \text{target}, y = \text{recv}, x = \text{send}$$

vs. Hebbian:

$$dW = xy$$

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## Two Phases

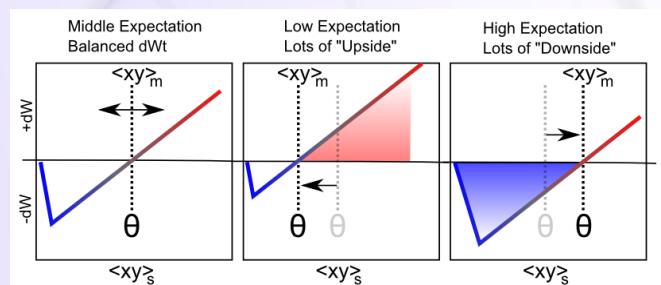
**Minus** phase: guess / prediction / expectation  
(what the network comes up with)

**Plus** phase: target / outcome / reality  
(what it *should* have come up with)

$$dW = x(y^+ - y^-)$$

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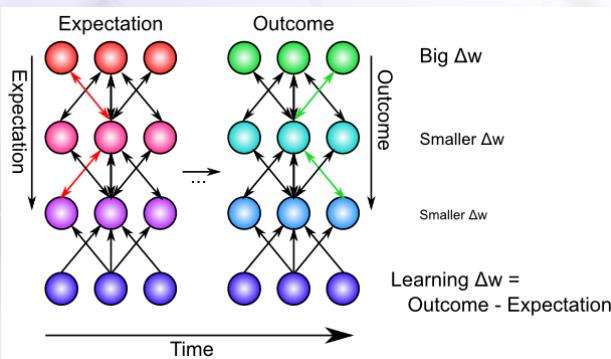
## Floating Threshold = Medium Term Synaptic Activity (Error-Driven)



$$dW = \text{Outcome} - \text{Expectation} = \langle xy \rangle_s - \langle xy \rangle_m$$

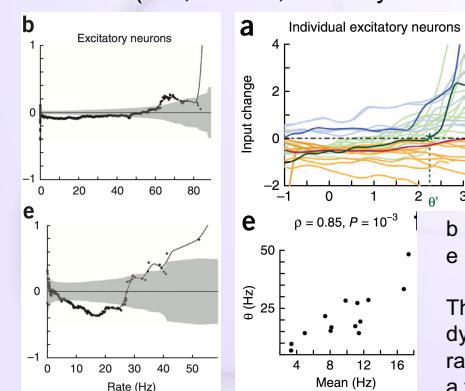
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## Backpropagation: Mathematics of Error-driven Learning



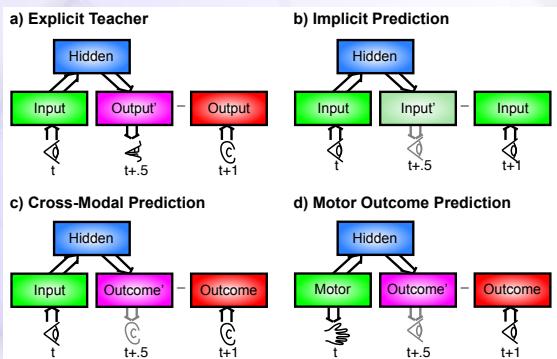
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## Evidence of Dynamic Thresholds (Lim, McKee, Woloszyn et al., 2015)

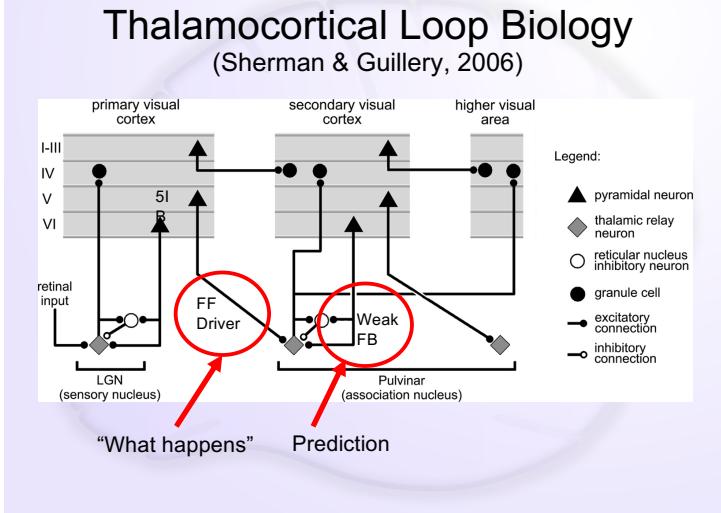


Threshold changes dynamically on a rapid time scale, as a function of short-term activity level!

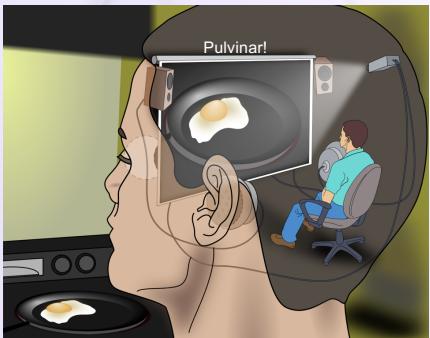
# Where Does Error Come From?



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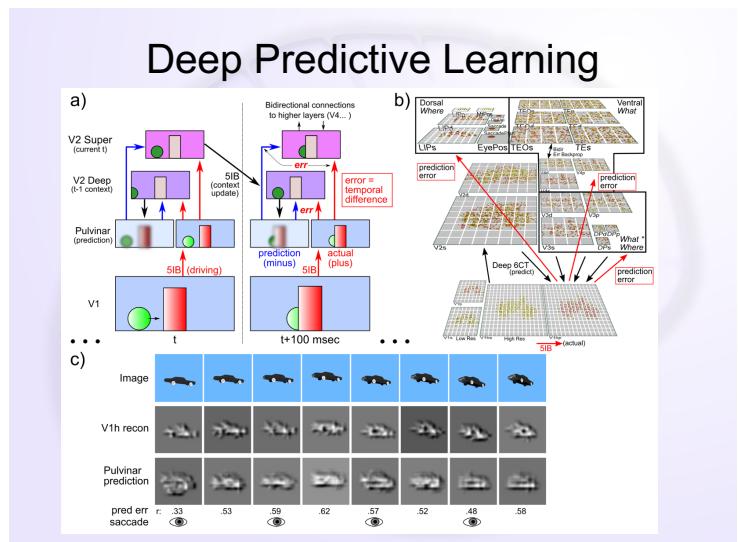
The Pulvinar = Projection Screen  
(c.f. Mumford, 1991 “blackboard”)



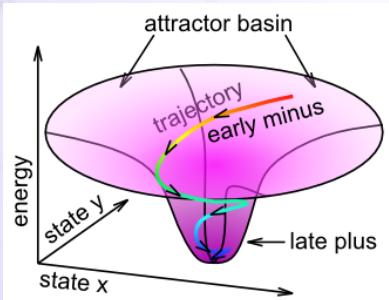
Pulvinar receives connections from all over visual cortex

and projects back out to these same areas

1. Few strong feedforward:  
“*what happens*”
  2. Many weaker feedback:  
*prediction*

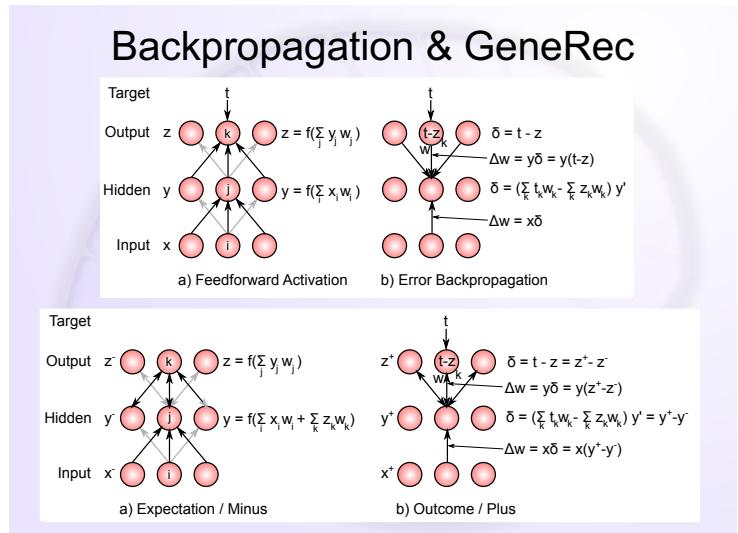


# Fast Threshold Adaptation: Late Trains Early

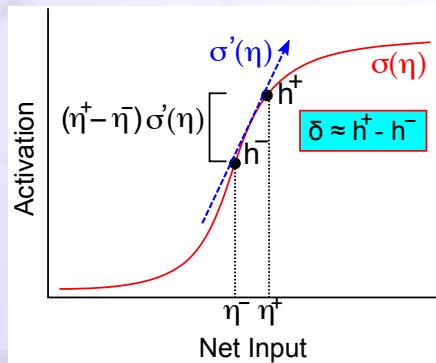


Essence of Err-Driven:  $dW = \text{outcome} - \text{expectation}$

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## GeneRec: Derivative Approximation



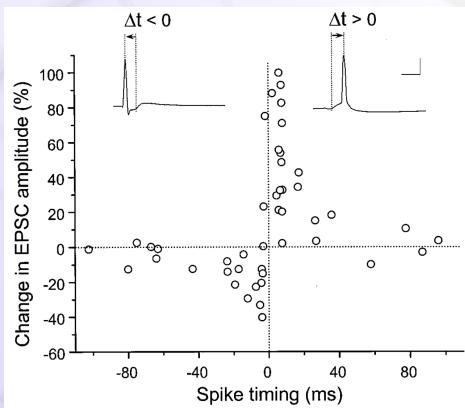
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## Biological Derivation of XCAL Curve

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

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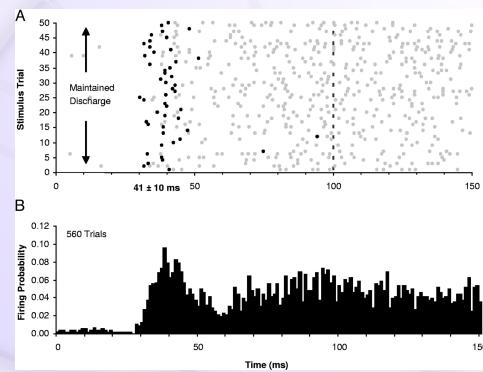
## Causal Learning?



STDP, Bi & Poo, 1998

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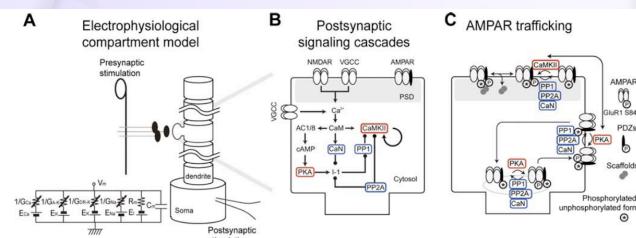
## Let's Get Real..



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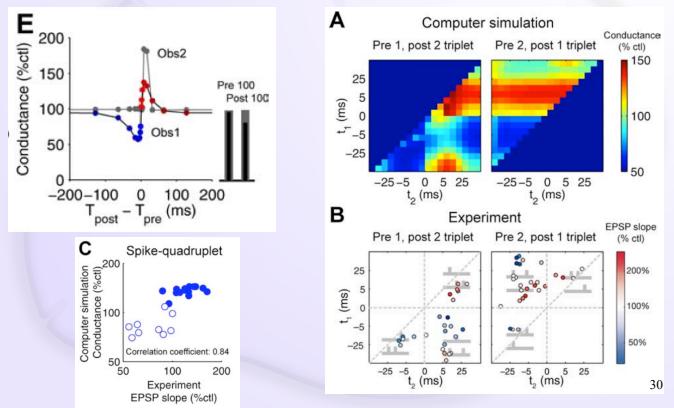
## Urakubo et al, 2008 Model

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

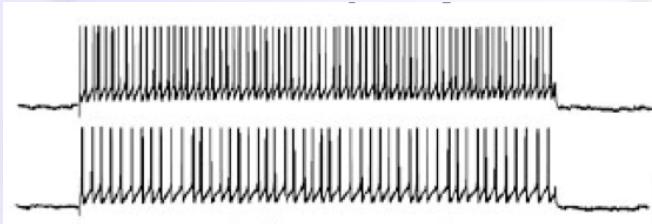


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## "Allosteric" NMDA Captures STDP (including higher-order and time integration effects)

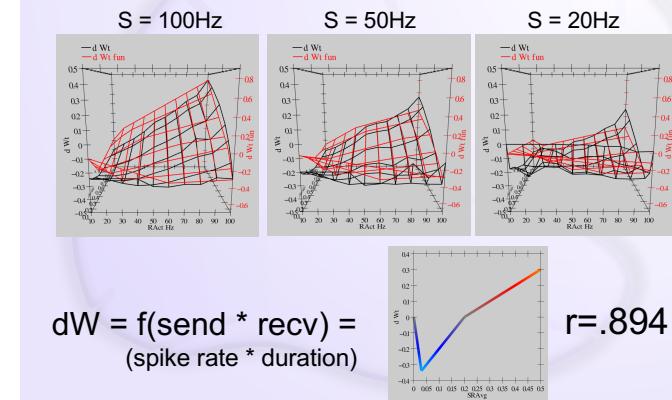


## What About Real Spike Trains?



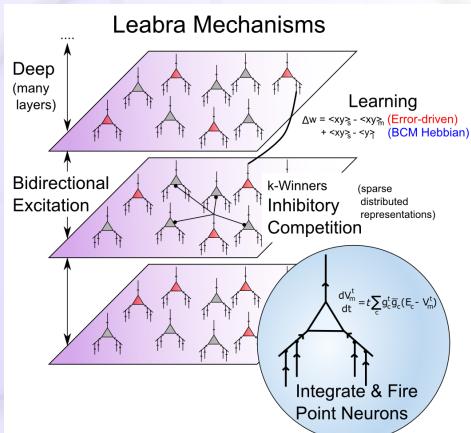
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## Extended Spike Trains = Emergent Simplicity



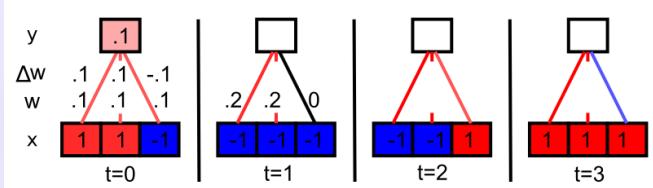
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## Leabra



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## Hebbian Learns Correlations



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