Learning Rules Across the Brain

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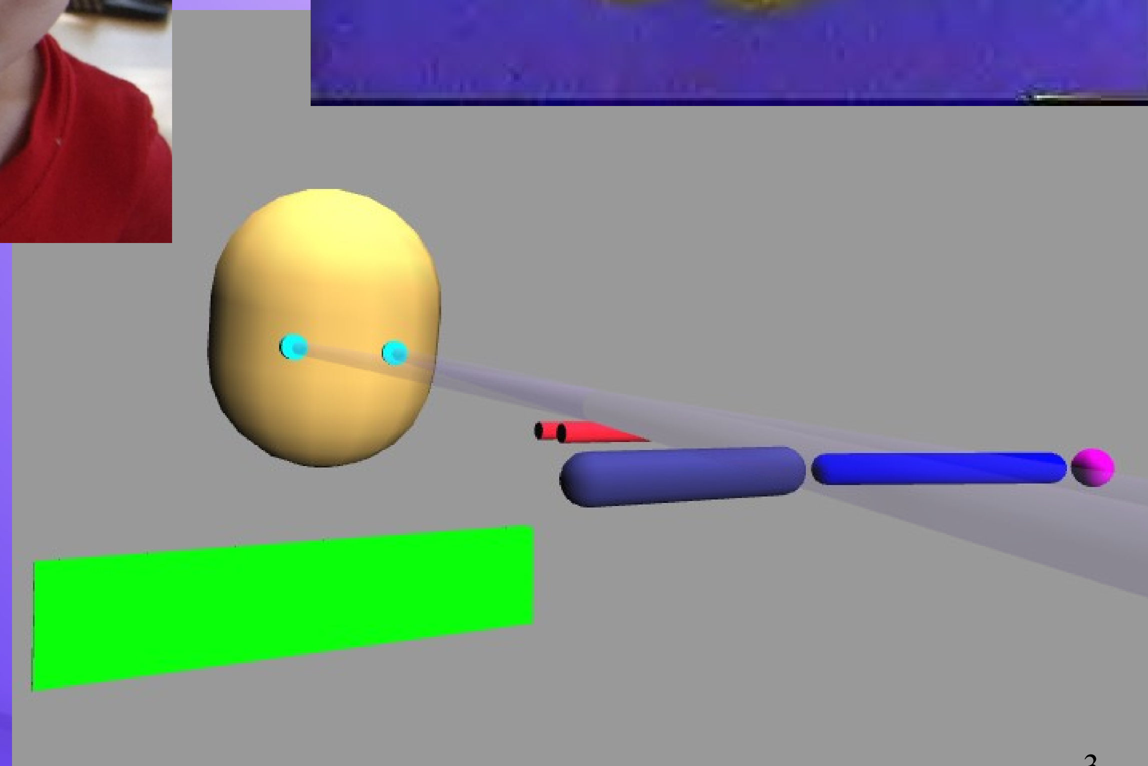
Ultimate Goal:
Build a Brain that Builds Itself..

- Start with basic neural infrastructure…
- Add a lot of real world experience…
- Presto: instant human intelligence!

- How does human brain pull off this magic trick?



Kai (15mo)

Max (3.5yr)

Emer (?)

Learning Rules Across the Brain

	Learning Signal			*Dynamics*		
Area	**Reward**	**Error**	**Self Org**	**Separator**	**Integrator**	**Attractor**
Primitive						
Basal Ganglia	+++	- - -	- - -	++	-	- - -
Cerebellum	- - -	+++	- - -	+++	- - -	- - -
Advanced						
Hippocampus	+	+	+++	+++	- - -	+++
Neocortex	++	+++	++	- - -	+++	+++

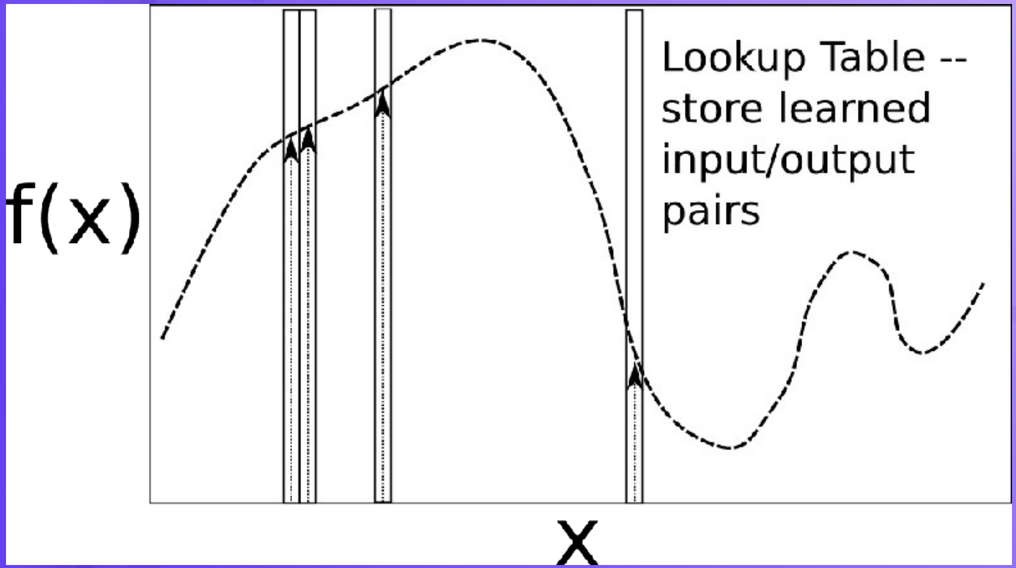
+ = has to some extent … +++ = defining characteristic – definitely has
\- = not likely to have … - - - = definitely does not have

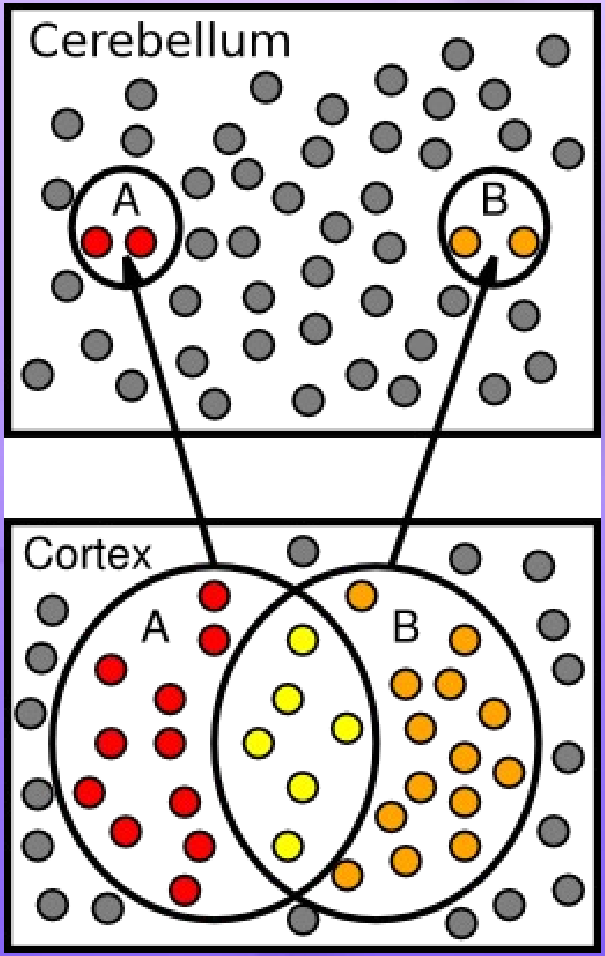
Primitive, Basic Learning..

Area	Learning Signal			Dynamics		
	Reward	Error	Self Org	Separator	Integrator	Attractor
Primitive Basal Ganglia	+++	- - -	- - -	++	-	- - -
Cerebellum	- - -	+++	- - -	+++	- - -	- - -

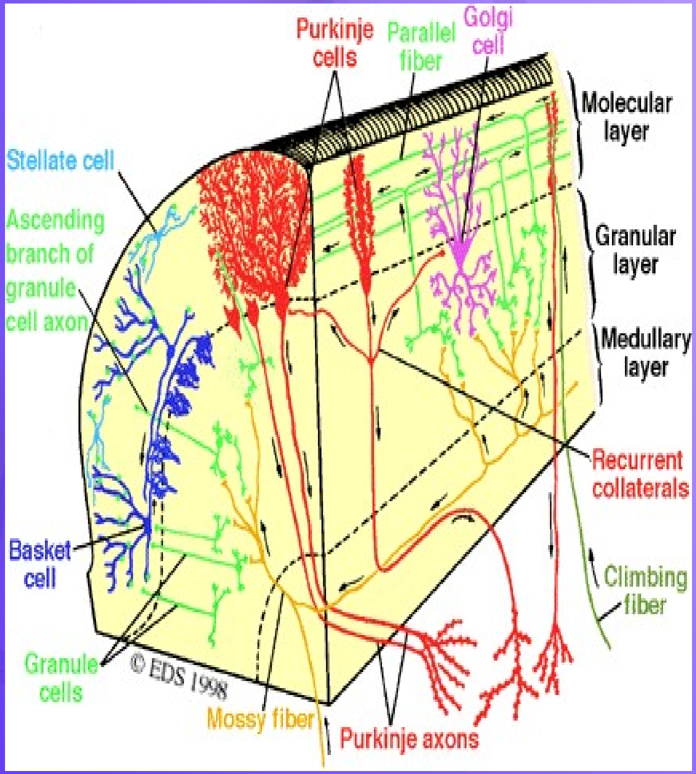
- Reward & Error = most basic learning signals (self organized learning is a luxury..)
- Simplest general solution to any learning problem is a *lookup table* = separator

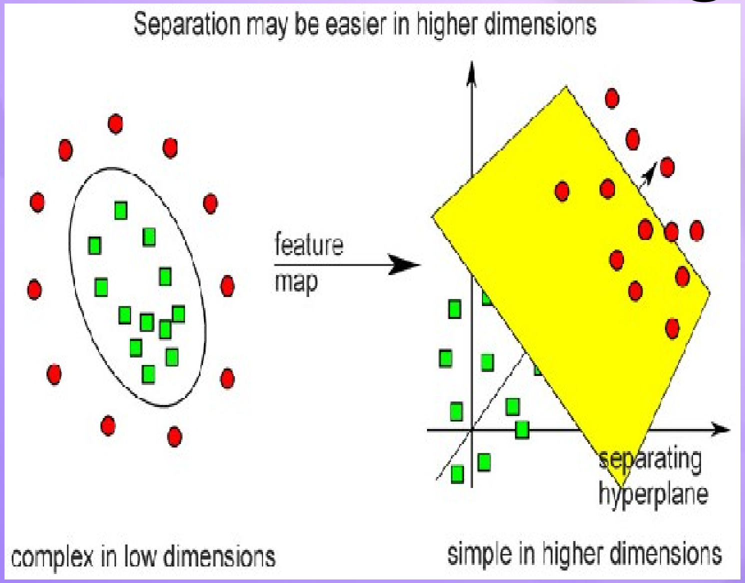
Lookup Table & Pattern Separation





Cerebellar Error-driven Learning





Cerebellum =
Support Vector Machine

- Granule cells = high-dimensional encoding (separation)
- Purkinje/Olive = delta-rule error-driven learning
- Classic ideas from Marr (1969) & Albus (1971)

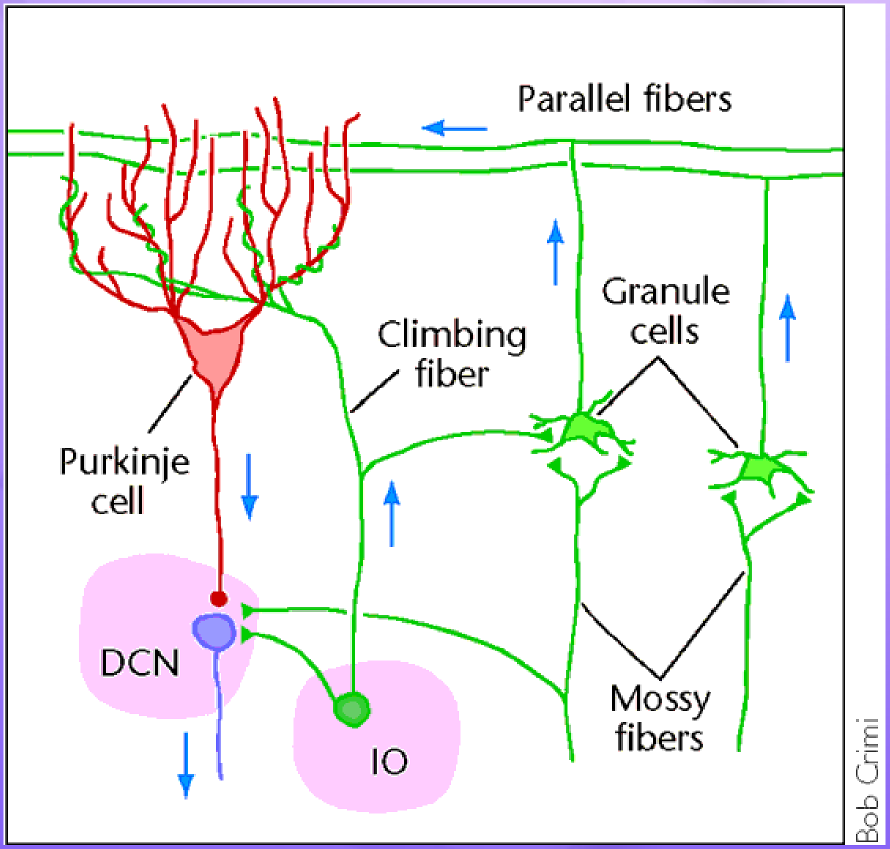
Cerebellum is Feed Forward

Feedforward circuit:

- Input (PN) -> granules -> Purkinje -> Output (DCN)
- Inhibitory interactions – no attractor dynamics
- Key idea: does delta-rule learning bridging small temporal gap:

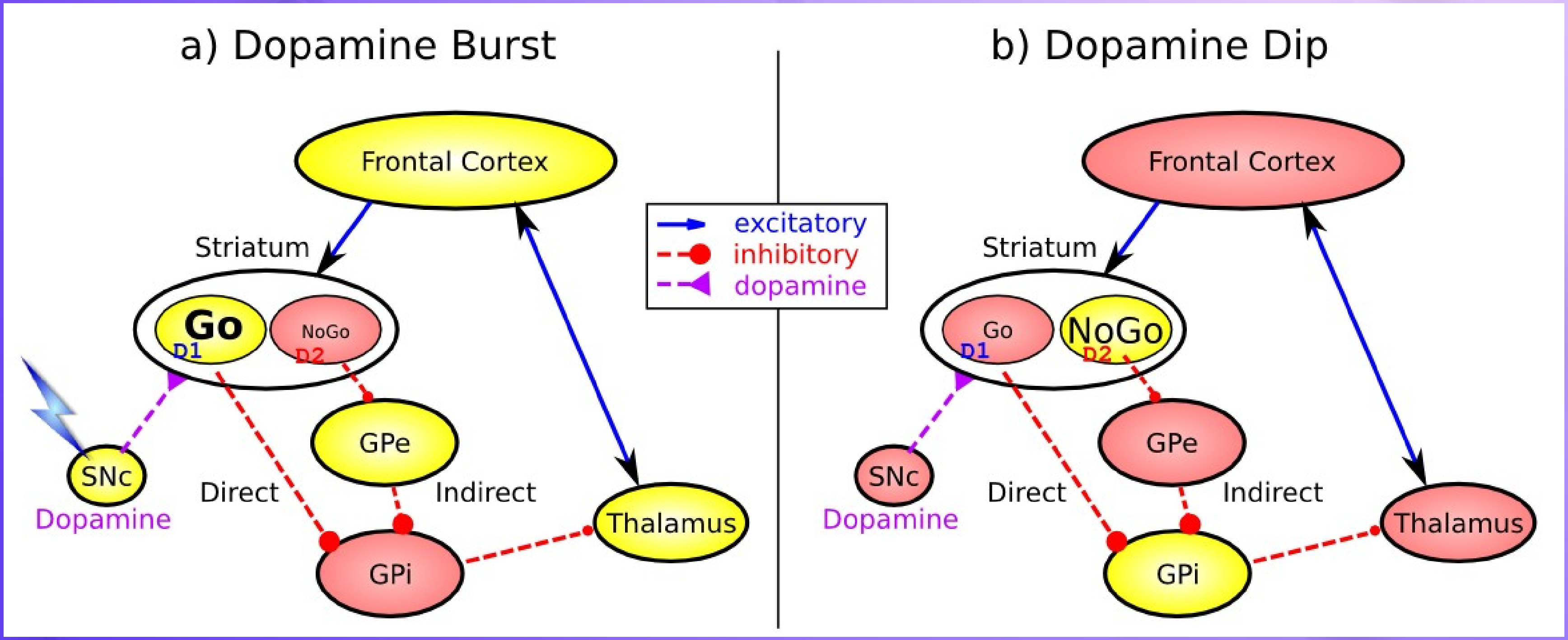
  S(t-100) -> R(t)

  ^ Error(t+100)



Basal Ganglia Reward Learning

(Frank, 2005…; O'Reilly & Frank 2006)



- Feedforward, modulatory (disinhibition) on cortex/motor (same as cerebellum)
- Co-opted for higher level cognitive control -> PFC

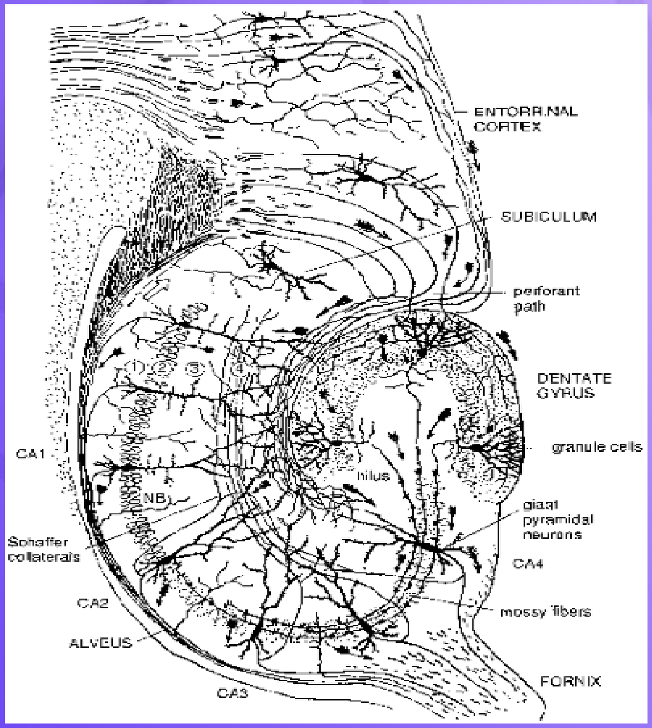
BG + Cerebellum Capacities

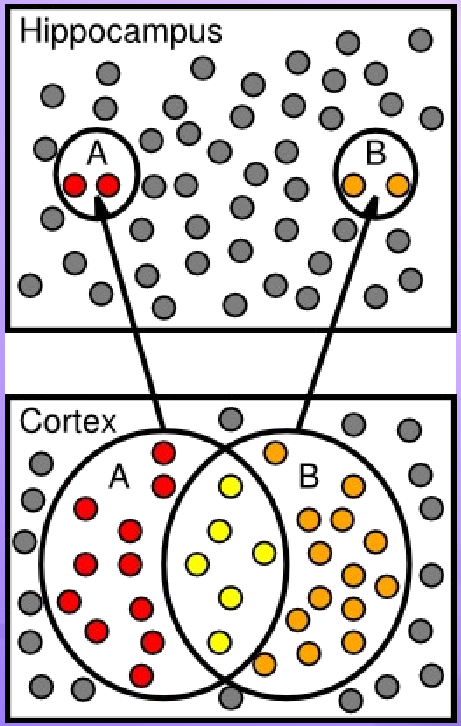
- Learn what satisfies basic needs, and what to avoid (BG reward learning)
  - And what information to maintain in working memory (PFC) to support successful behavior
- Learn basic Sensory -> Motor mappings accurately (Cerebellum error-driven learning)
  - Sensory -> Sensory mappings? (what is going to happen next..)

BG + Cerebellum Incapacities

- Generalize knowledge to novel situations
  - Lookup tables don’t generalize well..
- Learn abstract semantics
  - Statistical regularities, higher-order categories, etc
- Encode episodic memories (specific events)
  - Useful for instance-based reasoning
- Plan, anticipate, simulate, etc..
  - Requires robust working memory

Hippocampal Episodic Memory



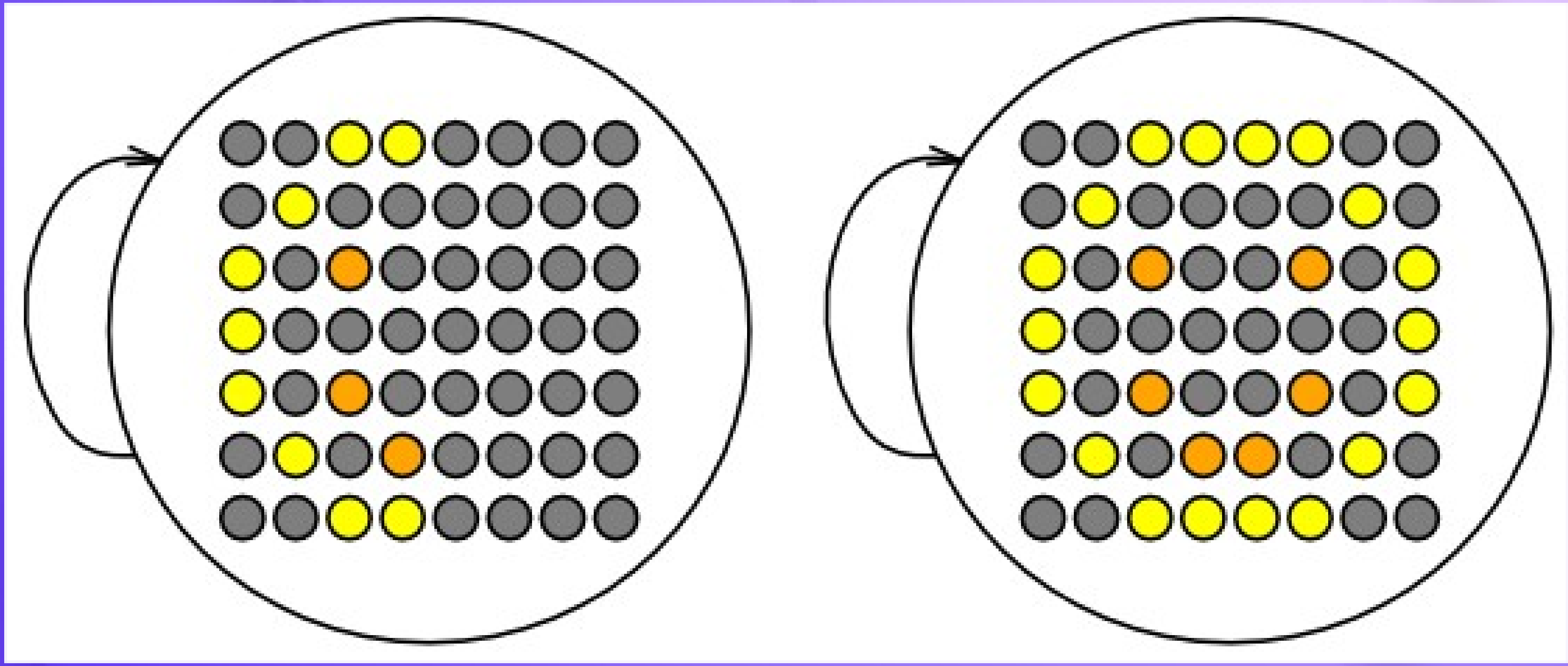


Area	Reward	Error	Self Org	Separator	Integrator	Attractor
Primitive Basal Ganglia	+++	- - -	- - -	++	-	- - -
Cerebellum	- - -	+++	- - -	+++	- - -	- - -
Advanced Hippocampus	+	+	+++	+++	- - -	+++

Hebbian Learning = Automatic
(O'Reilly & Rudy, 2001)

- Hippocampus is a constant "tape recorder" of your life
- You never know when something interesting might have happened 5 minutes ago..

Recall = Attractor
(content addressable memory..)



Recurrent connectivity is powerful but dangerous – hippocampus is major source of epilepsy..

Neocortex!

Area	*Learning Signal* Reward	Error	Self Org	Separator	*Dynamics* Integrator	Attractor
Primitive Basal Ganglia	+++	- - -	- - -	++	-	- - -
Cerebellum	- - -	+++	- - -	+++	- - -	- - -
Advanced Hippocampus	+	+	+++	+++	- - -	+++
Neocortex	++	+++	++	- - -	+++	+++

- Integrates many different experiences to generate synthetic semantic knowledge (i.e., *common sense*), serves as the basis for generalization
- Integrative learning is necessarily slow! (long life, neotonism) (McClelland, McNaughton & O'Reilly,1995)

Slow Integrative Learning

- Average: each term weighted by 1/N
- Running average: $x(t) = x(t-1) + 1/\tau(s(t) - x(t))$

  As $1/\tau$ gets smaller, window of integration gets larger

- Can't average over everything!!
  - Just gives you a big gamoosh blob!
- ***Integrative learning requires error-driven learning!***

Spike Based Error-Driven Learning

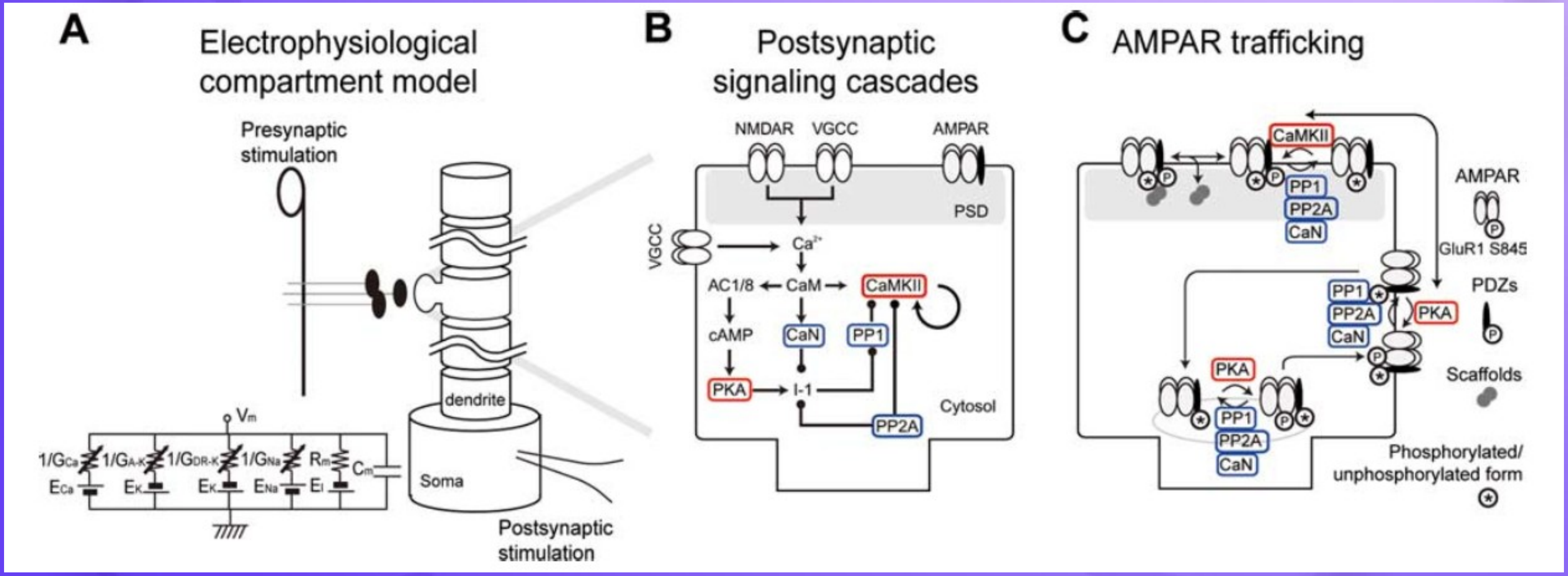
For 25 years:

- Biology (Hebbian) < - > Cognition* (Backprop)
  - * e.g., recognizing 100's of objects, learning to read..

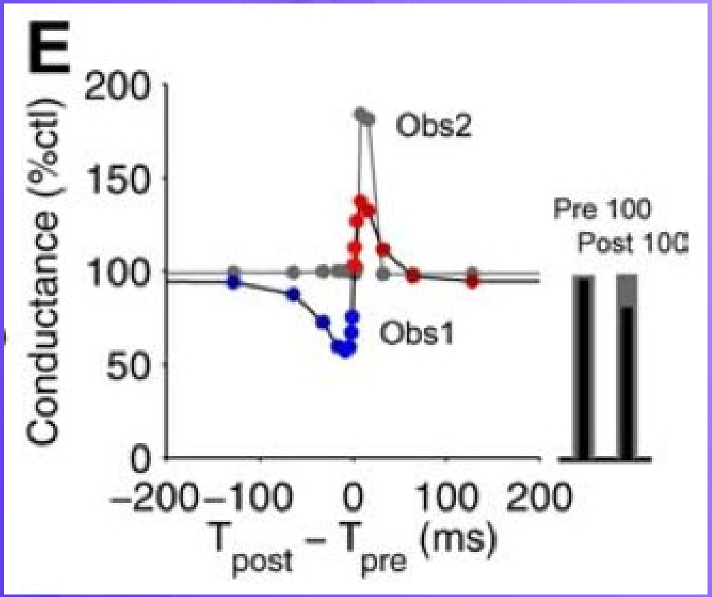
- Biology has advanced:
  - Spike Timing Dependent Plasticity (STDP)
  - Urakubo et al (2008) model: bottom-up brawn
- Cognition too:
  - Backprop -> Contrastive Hebbian Learning (CHL), Deterministic / Restricted Boltzmann Machine, GeneRec, Xie & Seung…
- **Can we unify them once and for all??**

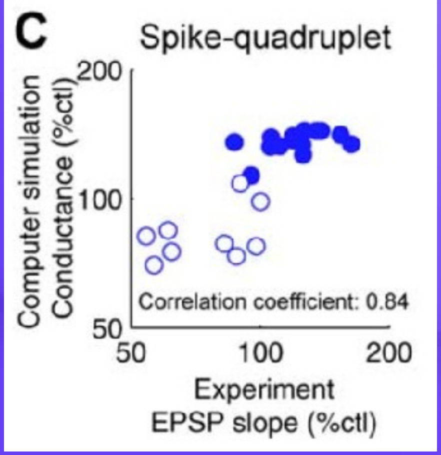
Urakubo et al, 2008 Model

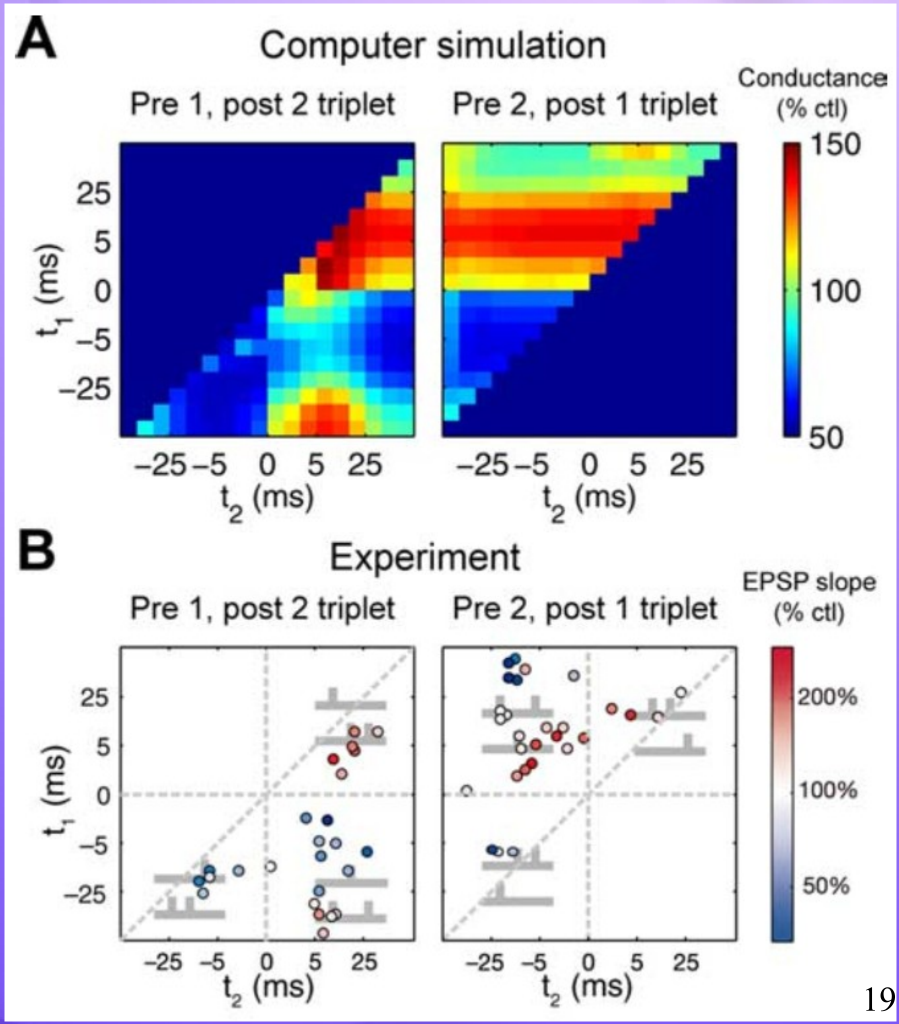
- Highly detailed combination of 3 existing strongly-validated models:



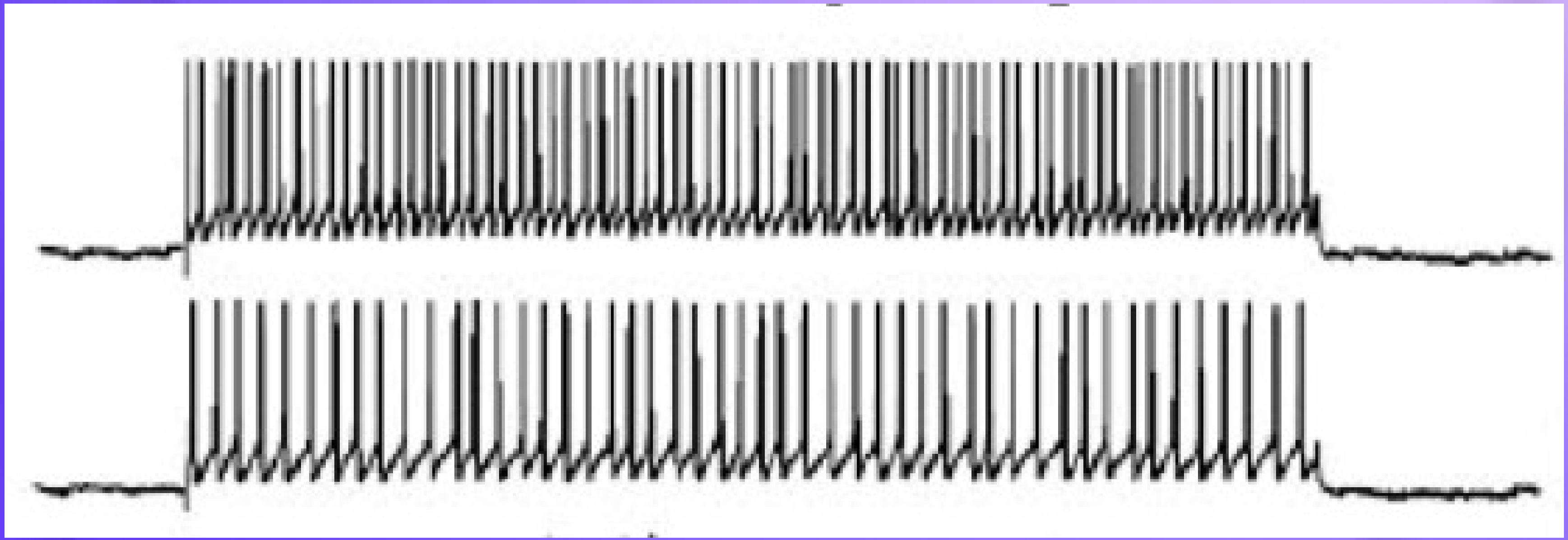
"Allosteric" NMDA Captures STDP
(including higher-order and time integration effects)





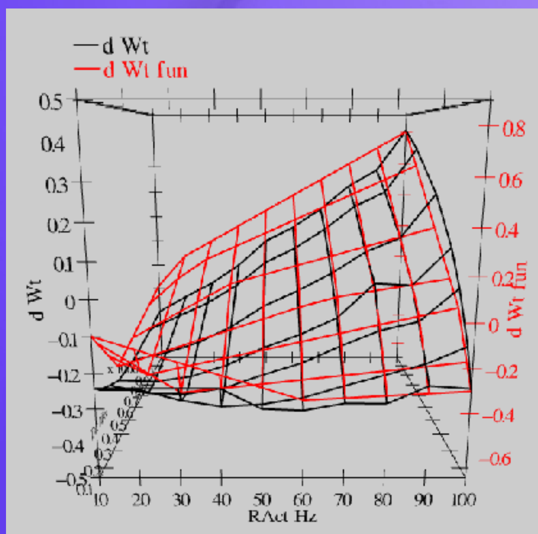


What About Real Spike Trains?

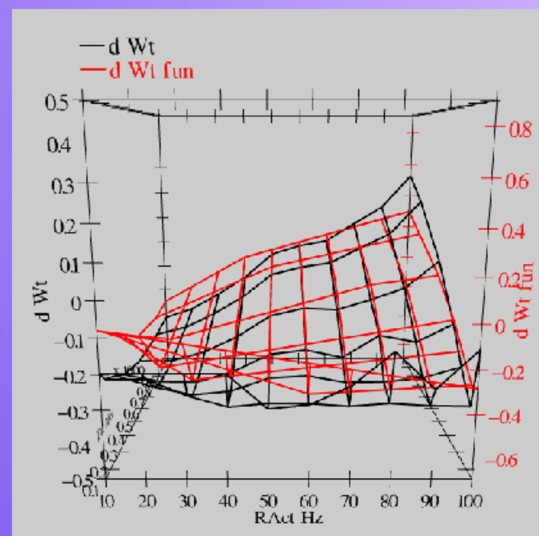


Extended Spike Trains = Emergent Simplicity

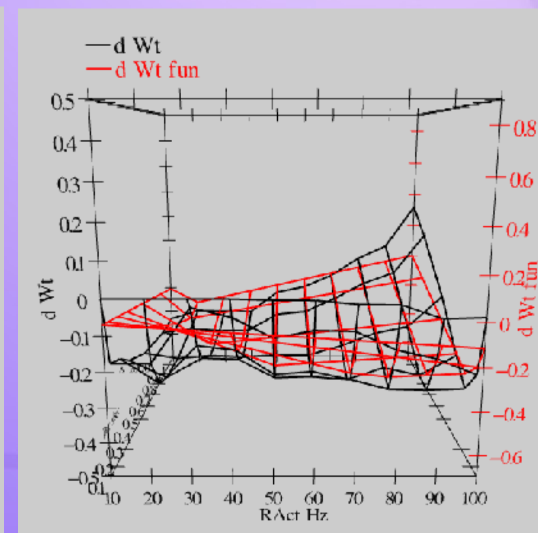
S = 100Hz



S = 50Hz

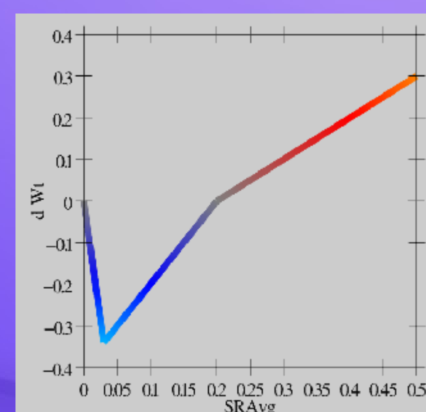


S = 20Hz



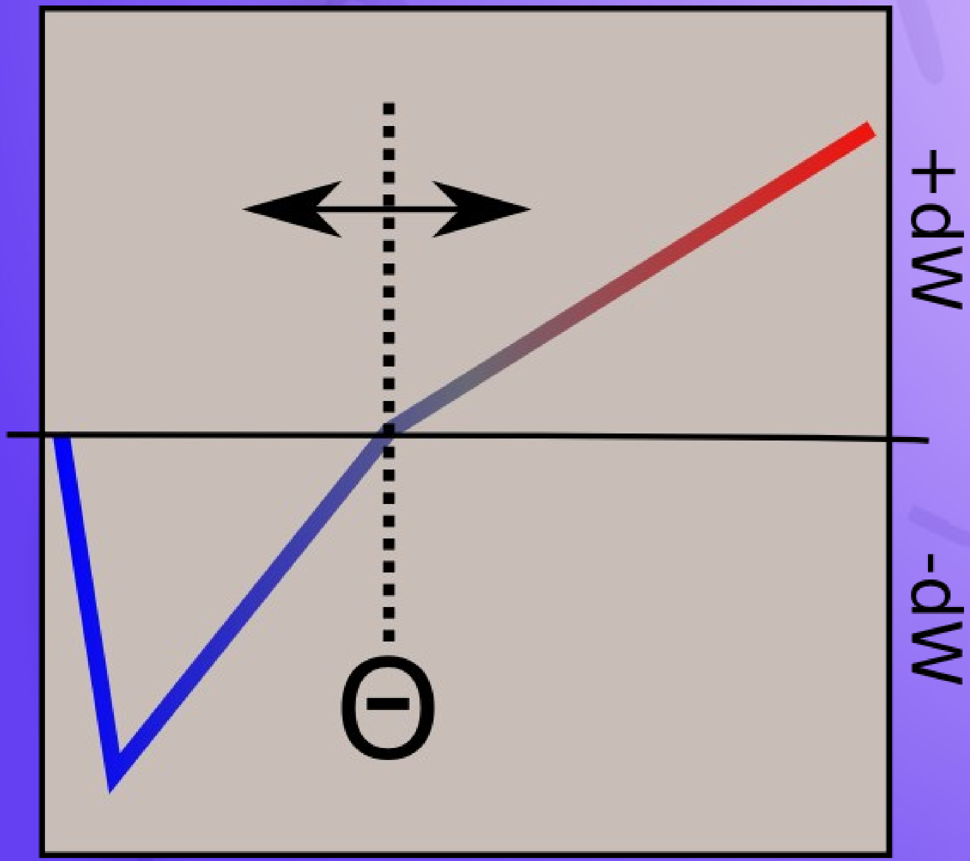
dW = f(send * recv) =

(spike rate * duration)



r=.894

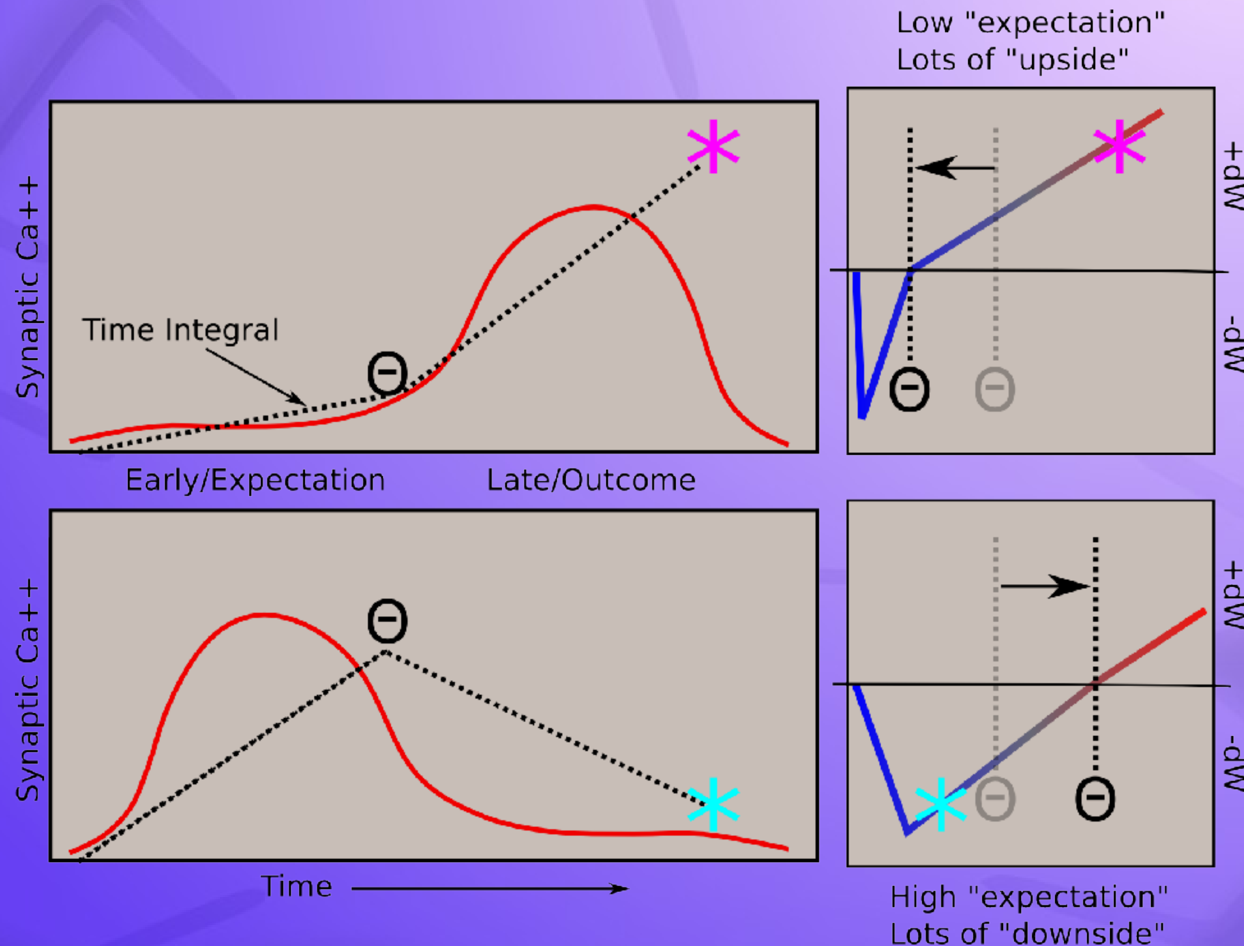
Linearized BCM



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

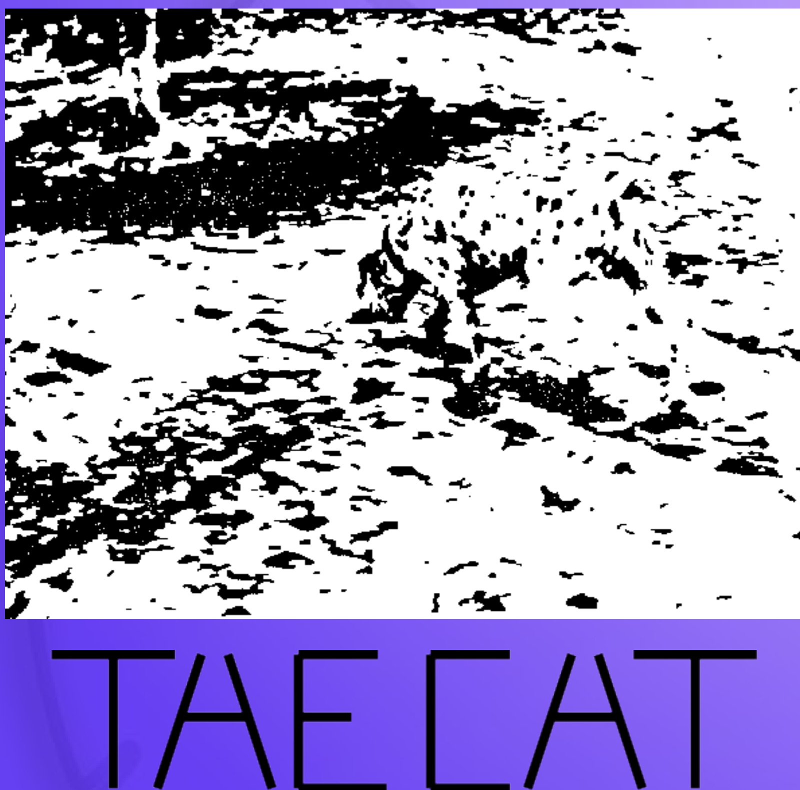
    (homeostatic)

Fast Threshold Adaptation: Late Trains Early



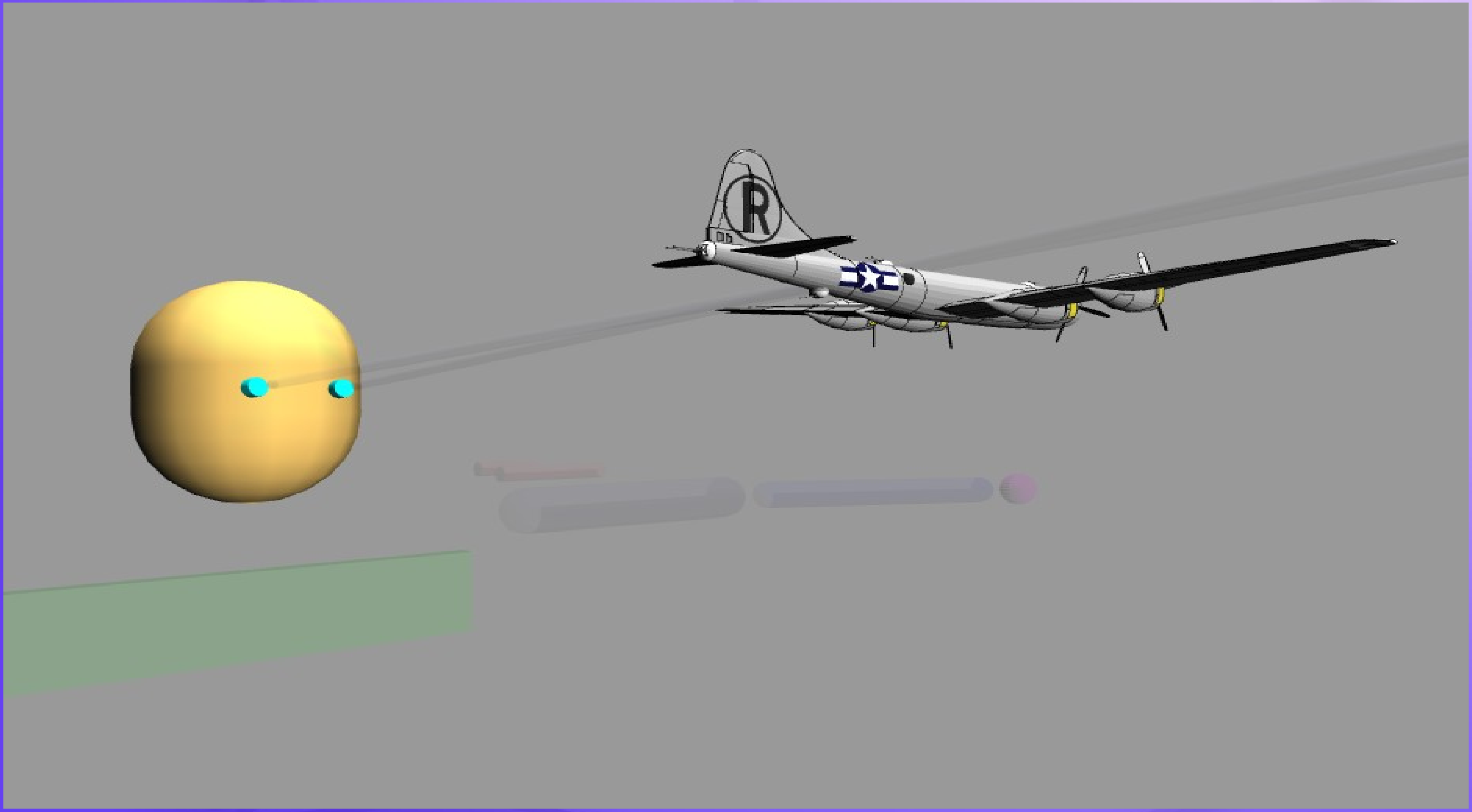
Essence of Err-Driven: dW = outcome - expectation

Neocortical Bidirectional Connectivity (Attractors)

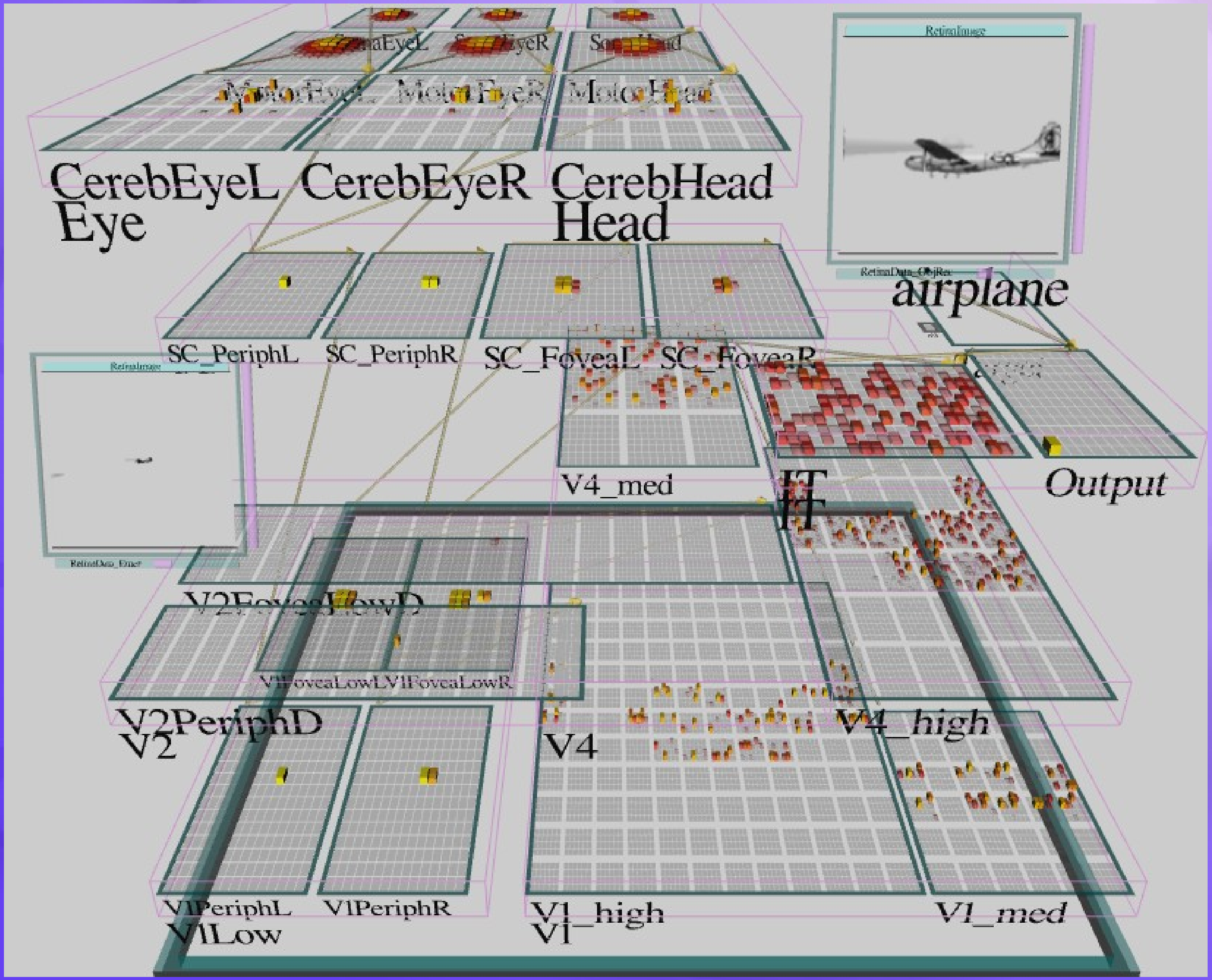


- Constraint satisfaction: higher-level interpretation feeds back to constrain lower-level feature detectors
- Error-driven learning: conveys err signals

Emer Demo



Emer's Brain (Gaze + ObjRec)



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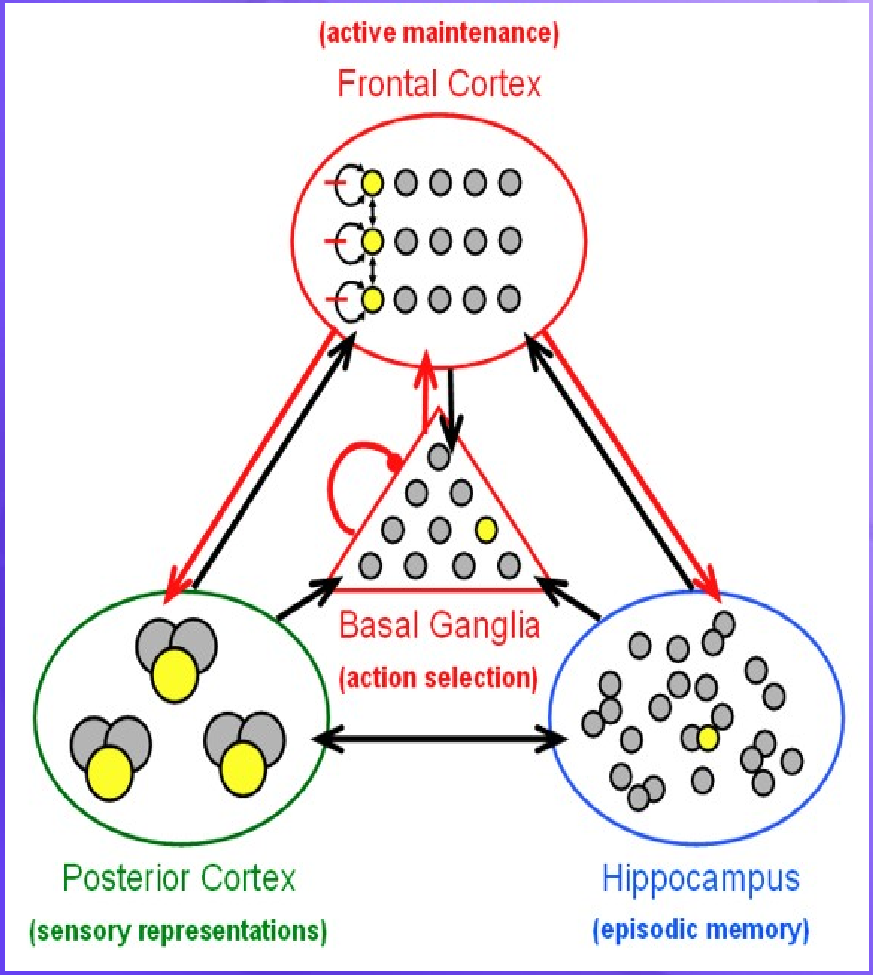
Leabra Tripartite Architecture



- Common neural mechs
- But specializations to resolve computational tradeoffs (e.g., fast, distinct learning vs. slow, integrative learning)
- Control flows from BG action selection to PFC updating to top-down bias

Thanks To

Rich Ivry – lots of fun discussion at Yali's!

CCN Lab

- Brad Aisa (Auditory)
- Tom Hazy (Learning)
- Seth Herd (Learning)
- Dave Jilk (Vision, eCortex)
- Kenneth Latimer (Vision)
- Brian Mingus (Motor)
- Wolfgang Pauli (Attention)
- Dean Wyatte (Vision)

Funding

- ONR – McKenna & Bello
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- NIMH R01-MH069597
- AFOSR
- DARPA

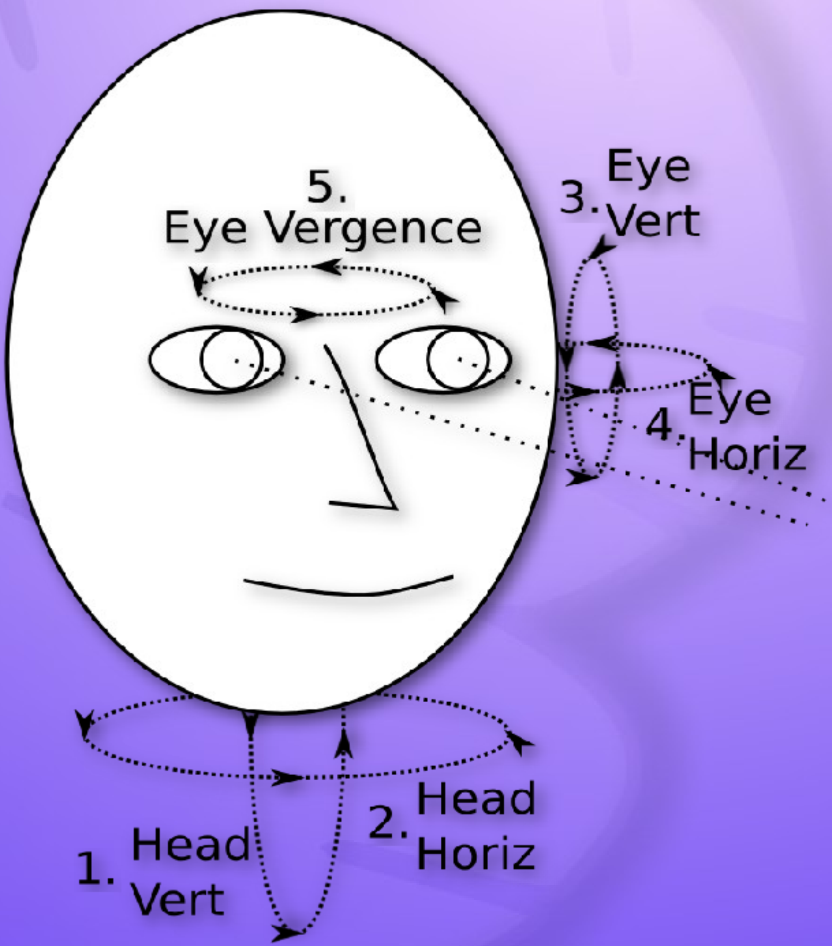
Extras

Object Recognition is Hard

- Large amount of shape variability within and between categories
- Huge amount of view-based variability (position, orientation, size, rotation)

Learning to Look is Non-Trivial

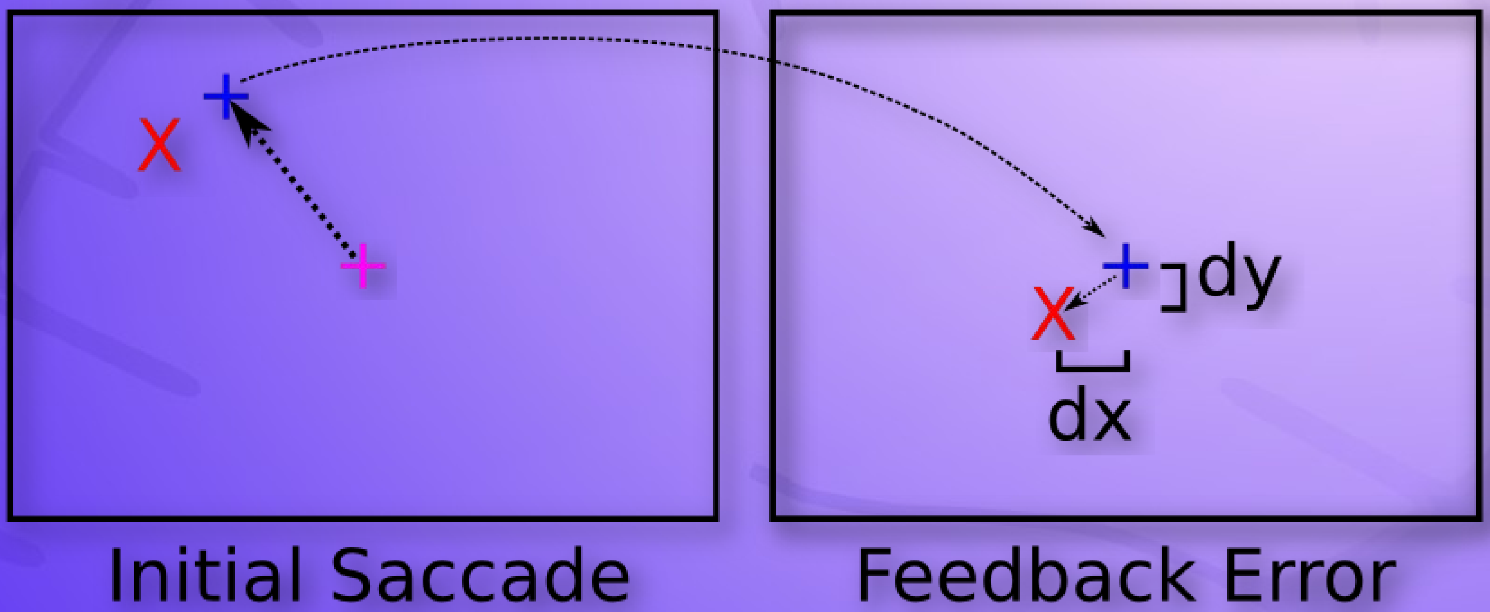
- 5 DOF -> 3 dimensions
- New gaze contingent on current positions
- Head & eye coordination



How Emer’s Brain Works

1. Learning to Look
   - How a “dumb” signal can be smart (Kawato et al)
1. Recognizing Objects
   - Multi-modal learning signals in a bidirectionally-connected, hierarchically-organized network
1. Spike-based Learning
   - Bridging the gap between biology and cognition

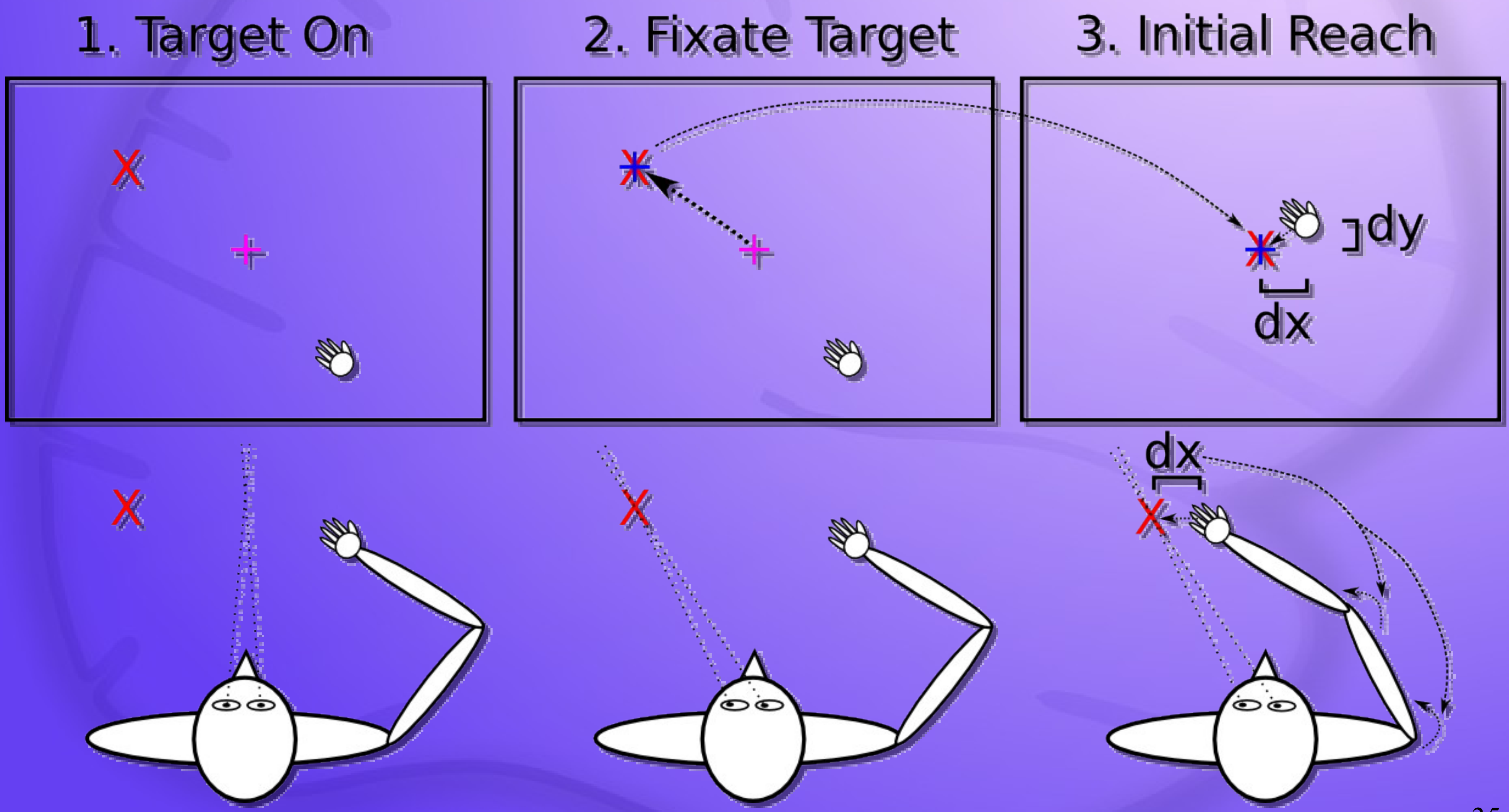
Learning to Look: Integrating over a “dumb” signal



Feedback error is in ***sensory*** coordinates but applied directly to ***motor*** signal

(dumb = wrong coords, but only sensory is available; Kawato et al)

Looking to Reach: Same Error Signal, Different Muscles



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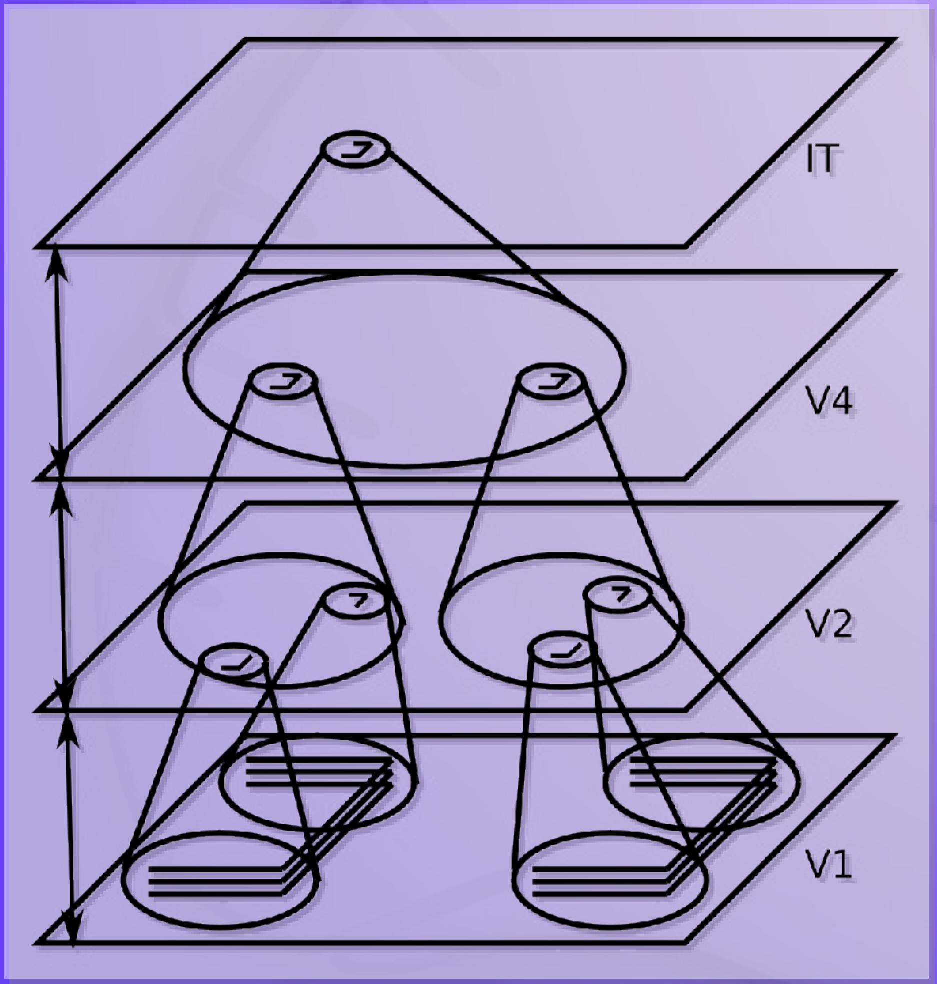
Invariant Object Recognition



- Hierarchy of increasing:
  - Feature complexity
  - Spatial invariance
- Strong match to RF's in corresponding brain areas

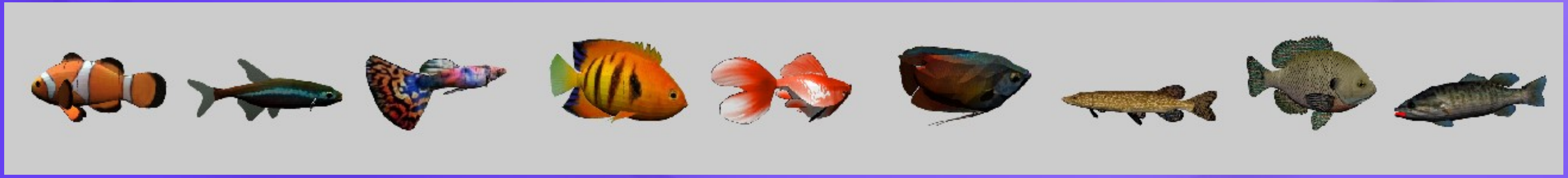
(Fukushima, 1980; Poggio, Riesenhuber, et al…)

3D Object Recognition Test

- From Google SketchUp Warehouse
- 100 categories
- 8+ objects per categ
- 2 objects left out for testing
- +/- 20° horiz depth rotation + 180° flip
- 0-30° vertical depth rotation
- 14° 2D planar rotations
- 25% scaling
- 30% planar translations

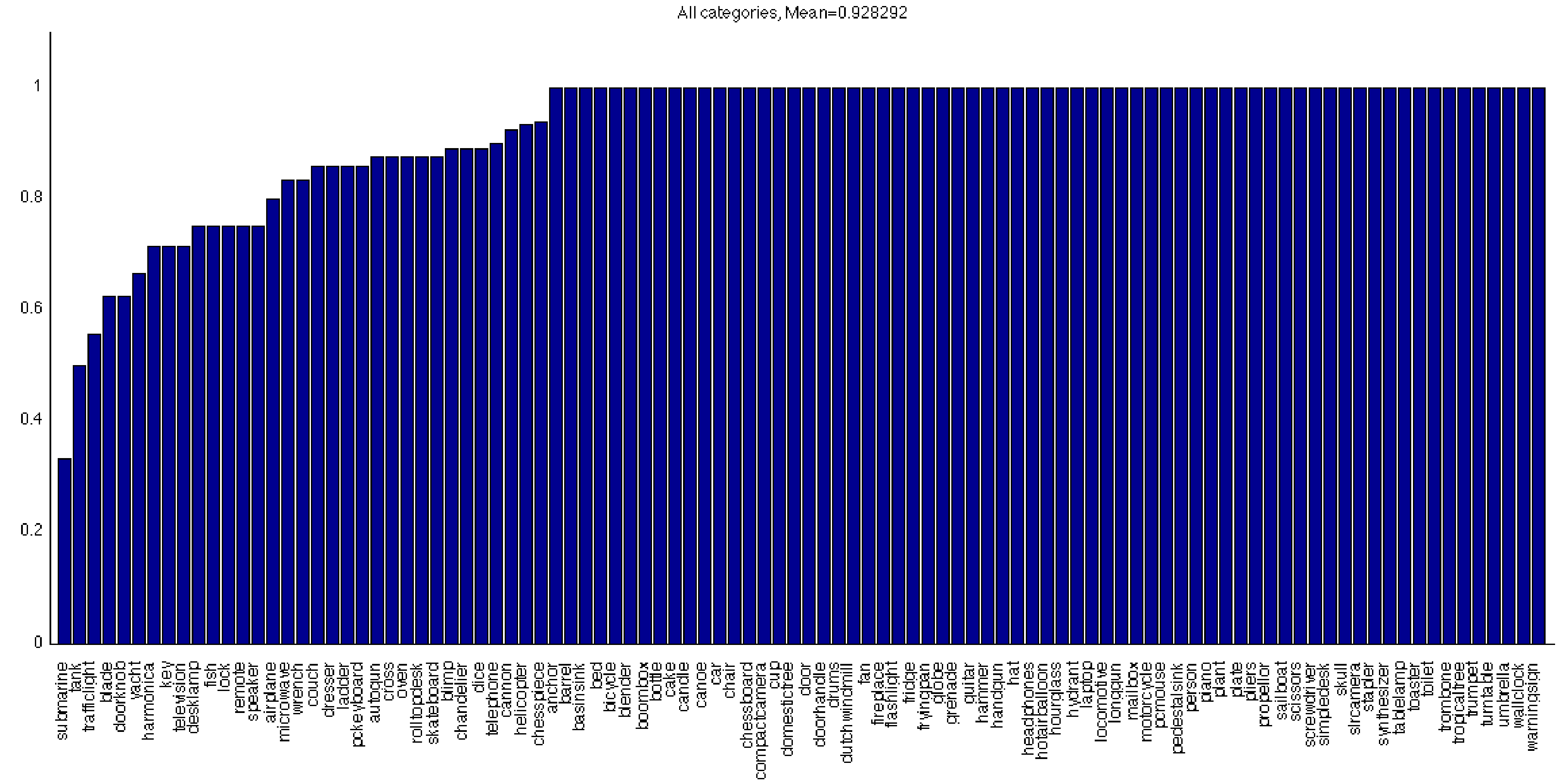
- Objects in Car Category

- Objects in Fish Category

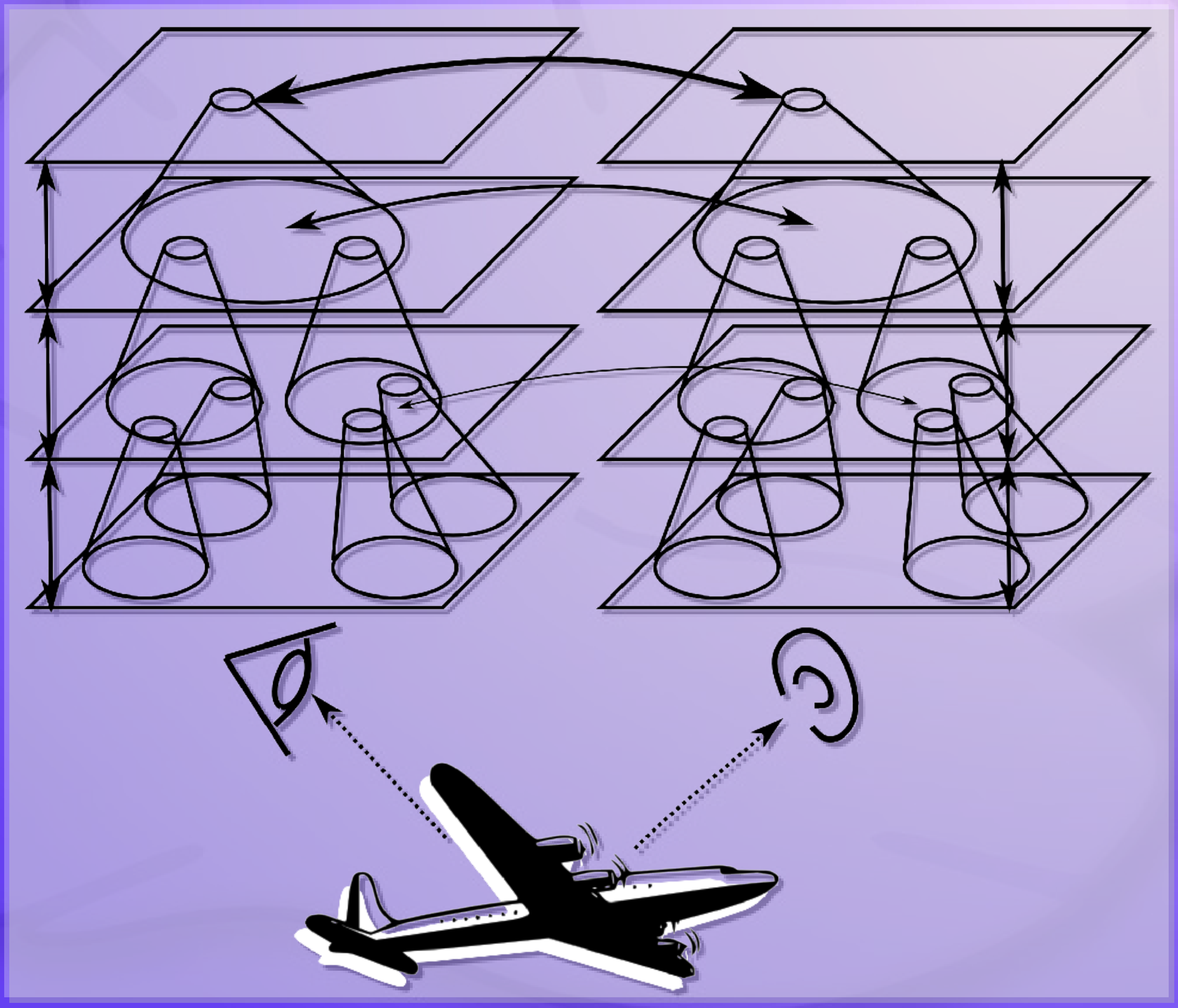


- Depth & lighting variations for one object

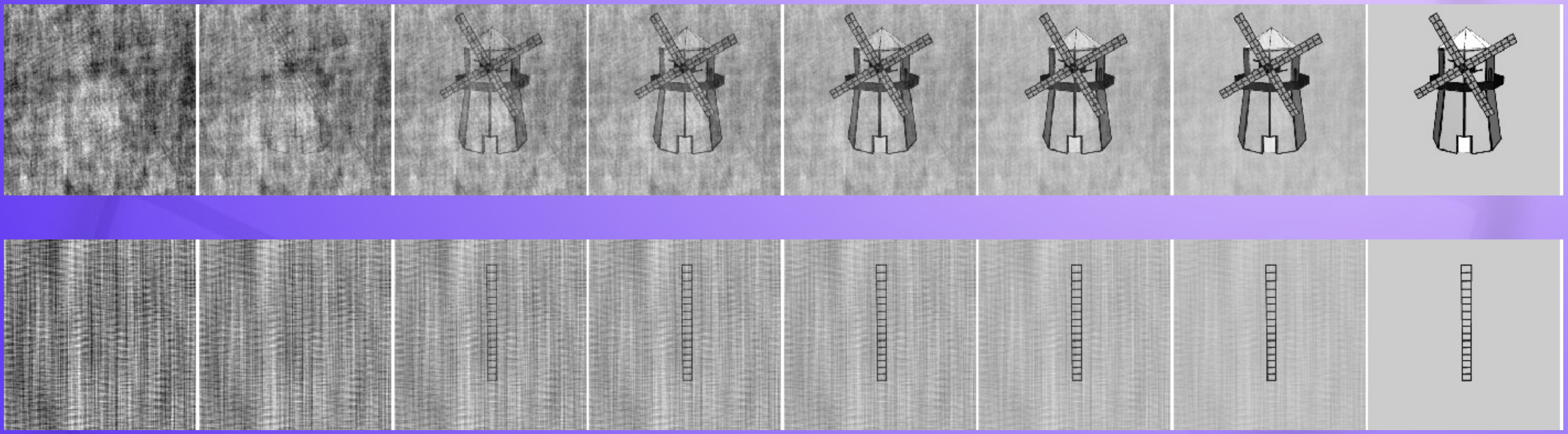
Generalization Results: 92.8%



Bidirectional Multimodal Training

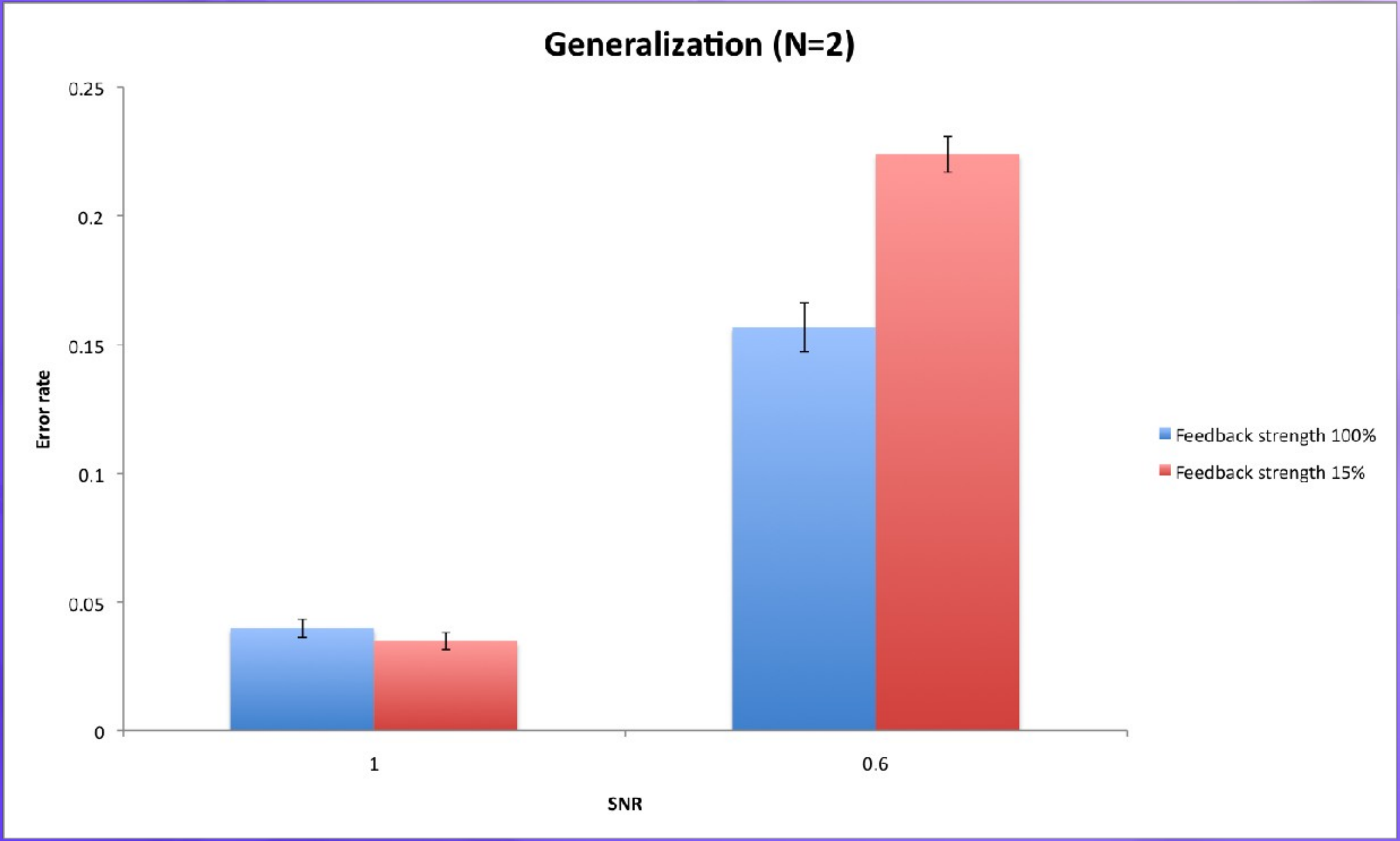


Benefit of Bidirectionality: Noise Robustness



Noise matched to image spatial frequency structure.

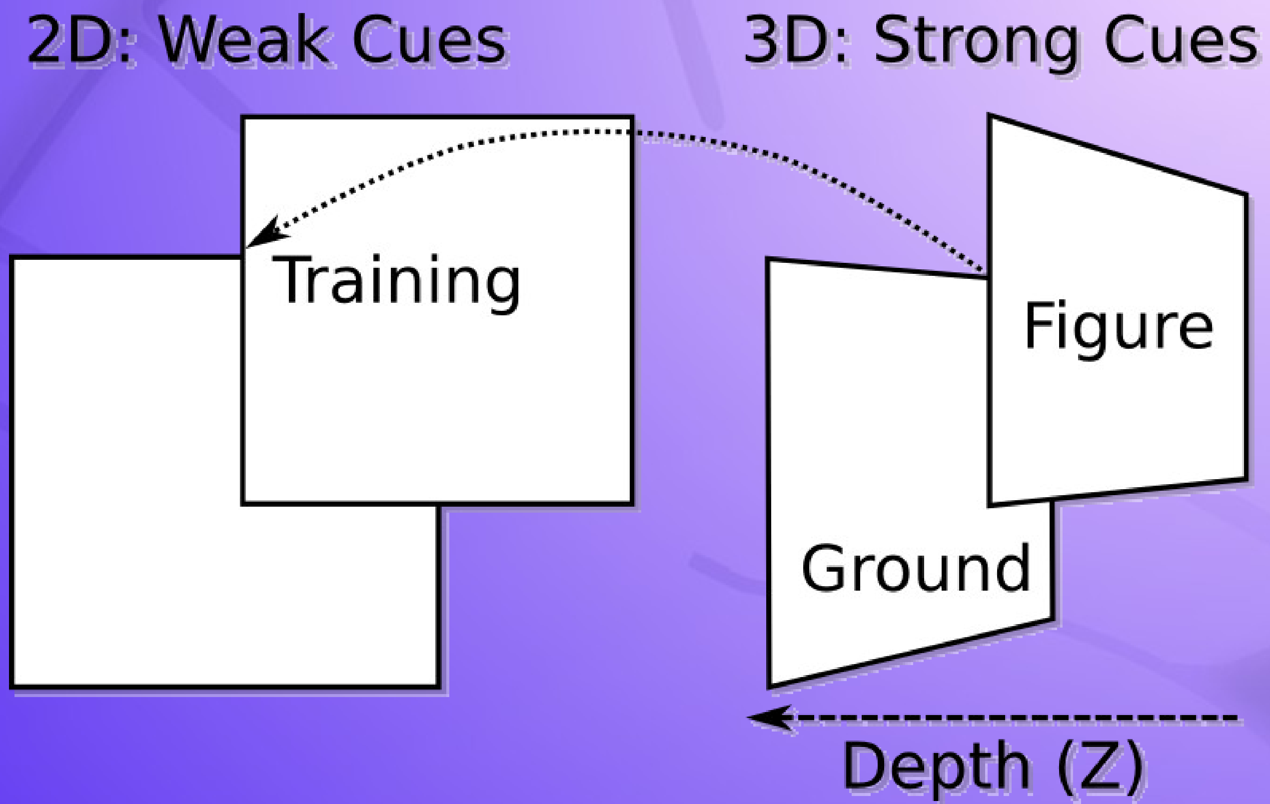
Benefit of Bidirectionality: Noise Robustness



Cluttered Backgrounds

- Performance degrades significantly
- Need figure-ground segregation – in V2

Embodied Figure Ground Learning



- Binocular foveation ➔ disparity ➔ 3D depth
- 3D depth trains 2D depth/occlusion cues

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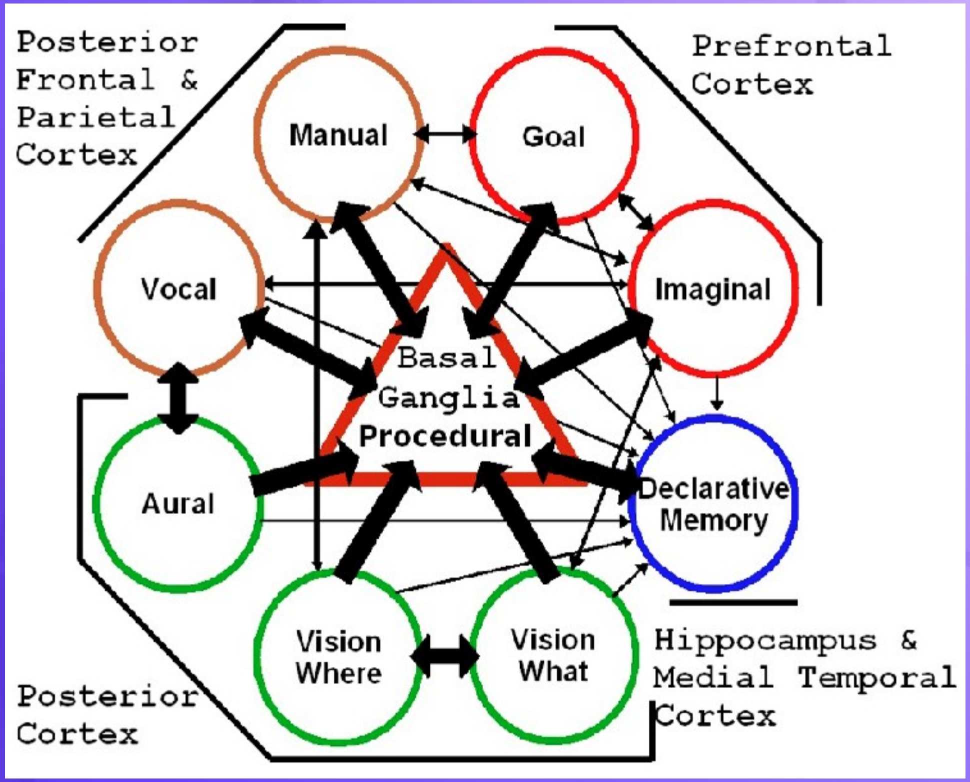
Embodiment = Rich Continuous Source of Learning Signals

- Every gaze is an automatic training signal
- Multiple modalities driven by same environment
  - Visual fixation trains motor reaching
  - Object foveation ←→ naming mutual training
- Binocular foveation → disparity → 3D depth → trains 2D depth → figure-ground segregation → object recognition in cluttered scenes

The Common Sense Problem

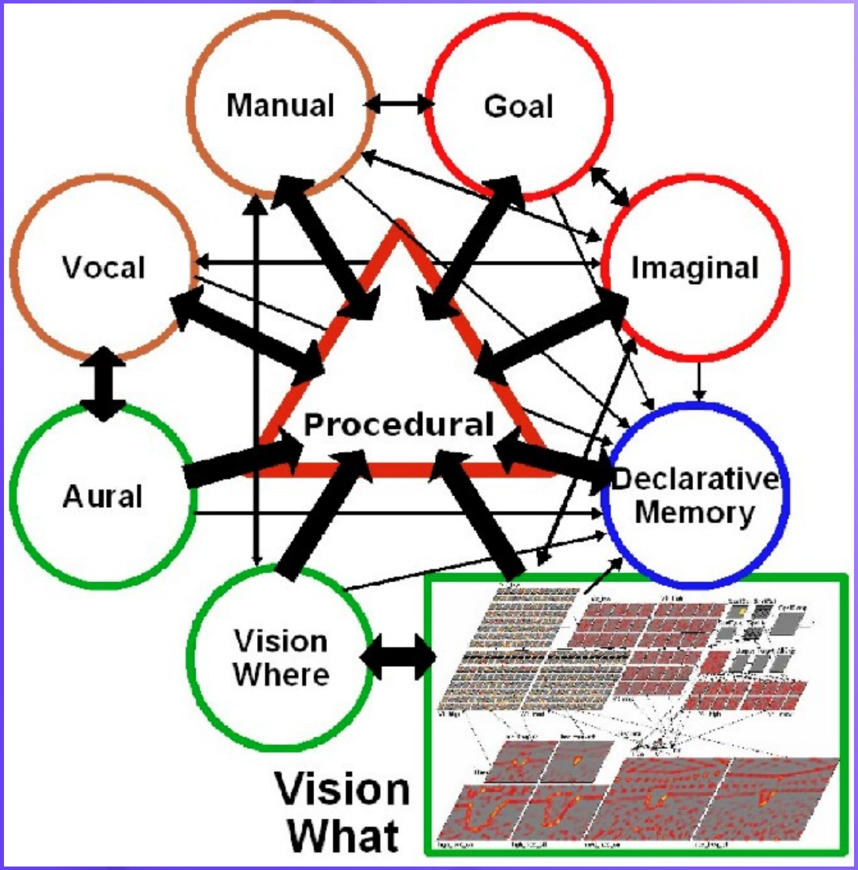
- Thesis: Human common sense depends on intensive learning about physical world
- More abstract cognitive functions build upon this sensory-motor foundation (Barsalou et al)
- Need this common sense to truly understand natural language and interact with people

SAL = Synthesis of ACT-R & Leabra



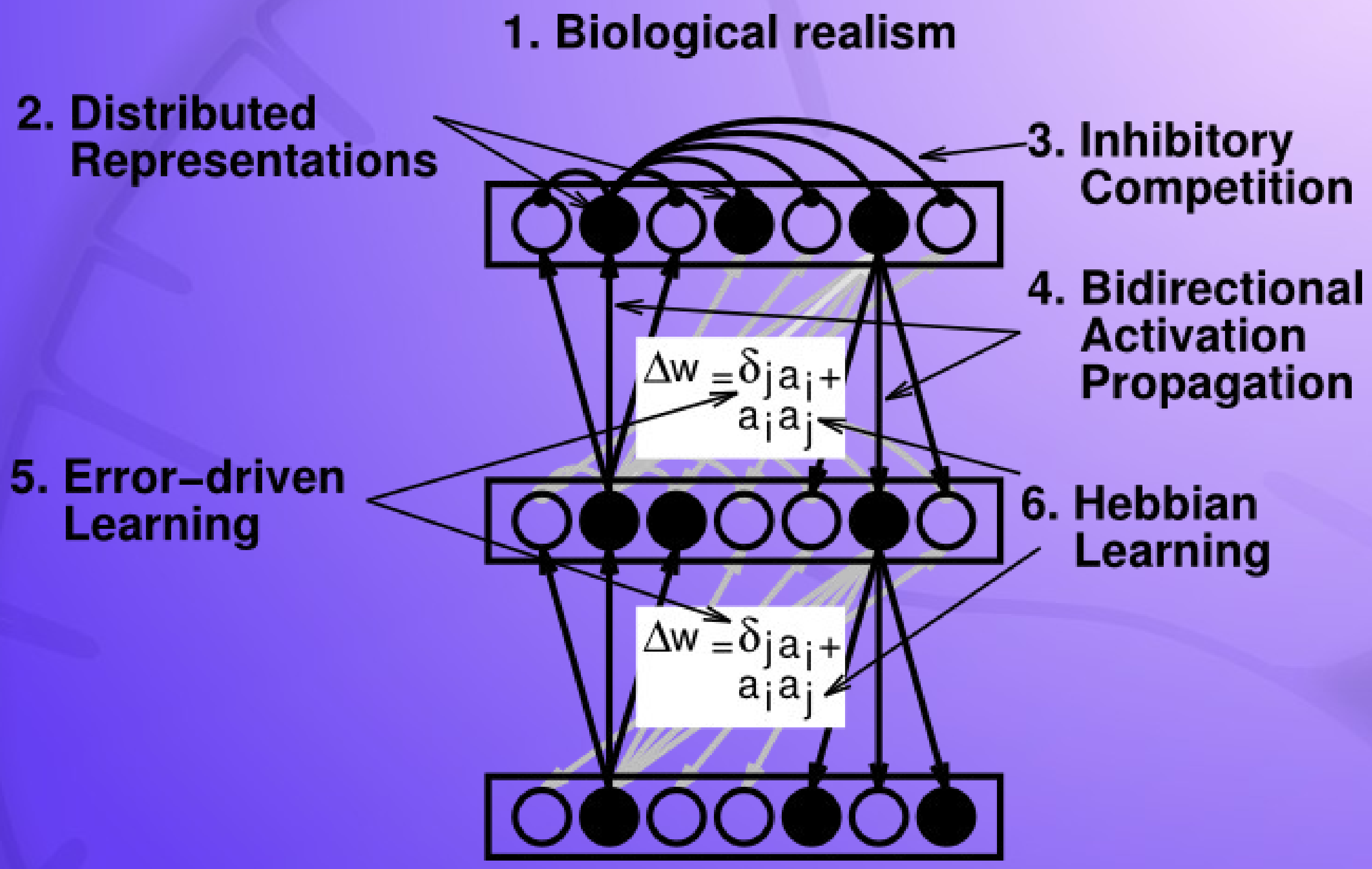
- Very close mapping between ACT-R and Leabra archs
- Productive ongoing collaboration to explore & develop SAL.

Simple Modular SAL



- Replace ACT-R module with Leabra visual system
- Achieves mutual benefits quickly
- But not as satisfying as a fuller synthesis..

The Leabra Algorithm



Same algorithm (and mostly params) can simulate ~100 different cognitive phenomena!