Towards an integration of deep learning and neuroscience

A preliminary attempt at an integrative "survey" of where we stand

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Machine Learning Meets Biology Workshop
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Machine learning and neuroscience speak different languages today…

ML	Neuro
Gradient-based optimization	Circuits
Supervised learning	Representations
Augmenting neural nets with external memories	Computational motifs
	"the neural code"

Key messages (still very much hypotheses):

These are not as far apart as we think

Modern ML, suitably modified, may provide a partial framework for theoretical neuro

"Atoms of computation" framework (outdated)

biological specializations

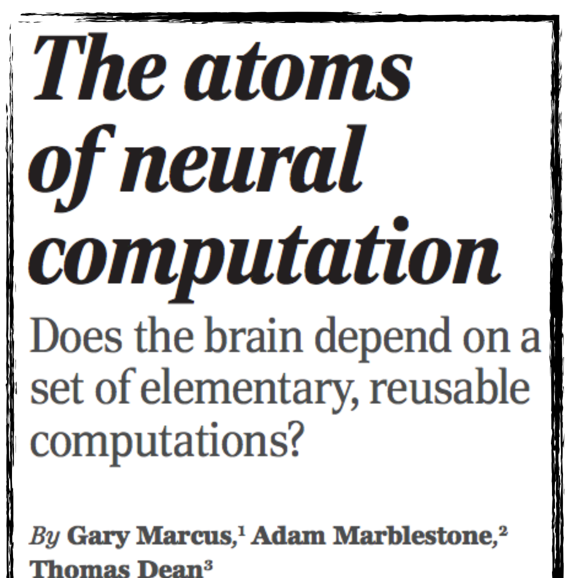
<>

different circuits

<>

different computations

Computation	Algorithmic/ representational realization	Neural implementation(s)	Brain location(s)
Rapid perceptual classification	Receptive fields, pooling and local contrast normalization [51,55]	Hierarchies of simple and complex cells [56]	Visual system
Complex spatiotemporal pattern recognition	Bayesian belief propagation [19,57]	Feedforward and feedback pathways in cortical hierarchy [19]	Sensory hierarchies
Learning efficient coding of inputs	Sparse coding [58]	Thresholding and local competition [59]	Sensory and other systems
Working memory	Continuous or discrete attractor states in networks [60,61]	Persistent activity in recurrent networks [62]	Prefrontal cortex
Decision making	Temporal-difference reinforcement learning algorithms [63,64]; actor-critic models [65]	Cortically implemented Bayesian inference networks combined with temporal difference reinforcement learning via the dopamine system and action selection systems in the basal gangla [66]	Prefrontal cortex
	Winner-take-all networks [67]	Recurrent networks coupled via lateral inhibition [67]	Prefrontal cortex
Gating of information flow	Context-dependent tuning of activity in recurrent network dynamics [68]	Recurrent neural networks implementing line attractors and selection vectors [68]	Prefrontal cortex
	Shifter circuits [69]	Divergent excitatory relays and input-selective shunting inhibition in dendrites [69]	Visual system
Gain control	Divisive normalization [52]	Shunting inhibition in networks or balanced background synaptic excitation and inhibition [70]	Common across many cortical areas
Sequencing of events over time [71]	Feed-forward cascades; Serial working memories [72]	Synfire chains [73-75]; Thalamo-cortico-striatal loops [76,77]	Common across many cortical areas
Representation and transformation of variables	Population coding [78]	Time-varying firing rates of cosine-tuned neurons representing dot products with encoding vectors	Motor cortex
Variable binding	Holographic reduced representations [49,79]	Circular convolution of vectors represented by neural population codes	Cortical areas involved in sequential or symbolic processing
	Dynamic binding [80,81]	Neural synchronization [82]	


The atoms of neural computation

Does the brain depend on a set of elementary, reusable computations?

By **Gary Marcus,[1] Adam Marblestone,[2] Thomas Dean[3]**

Objection to a "list of neural computations"

"The big, big lesson from neural networks is that there exist computational systems (artificial neural networks) for which *function only weakly relates to structure*...

A neural network needs a cost function and an optimization procedure to be fully described; and an optimized neural network's computation is more predictable from this cost function than from the dynamics or connectivity of the neurons themselves."

Greg Wayne (DeepMind) in response to Atoms of Neural Computation paper

Three hypotheses for linking neuroscience and ML

1) Existence of cost functions:
the brain optimizes cost functions (~ as powerfully as backprop)

2) Diversity of cost functions:
the cost functions are diverse, area-specific and systematically regulated in space and time
(not a single "end-to-end" training procedure)

3) Embedding within a structured architecture:
optimization occurs within a specialized architecture containing pre-structured systems (e.g., memory systems, routing systems) that support efficient optimization

Three <u>hypotheses</u> for linking neuroscience and ML

1) Existence of cost functions:

the brain optimizes cost functions (~ as powerfully as backprop)

<u>Not</u> just the trivial "neural dynamics can be *described* in terms of cost function(s)"… it actually has <u>machinery</u> to <u>do</u> optimization

2) Diversity of cost functions:

the cost functions are diverse, area-specific and systematically regulated in space and time
(not a single "end-to-end" training procedure)

3) Embedding within a structured architecture:

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Three **hypotheses** for linking neuroscience and ML

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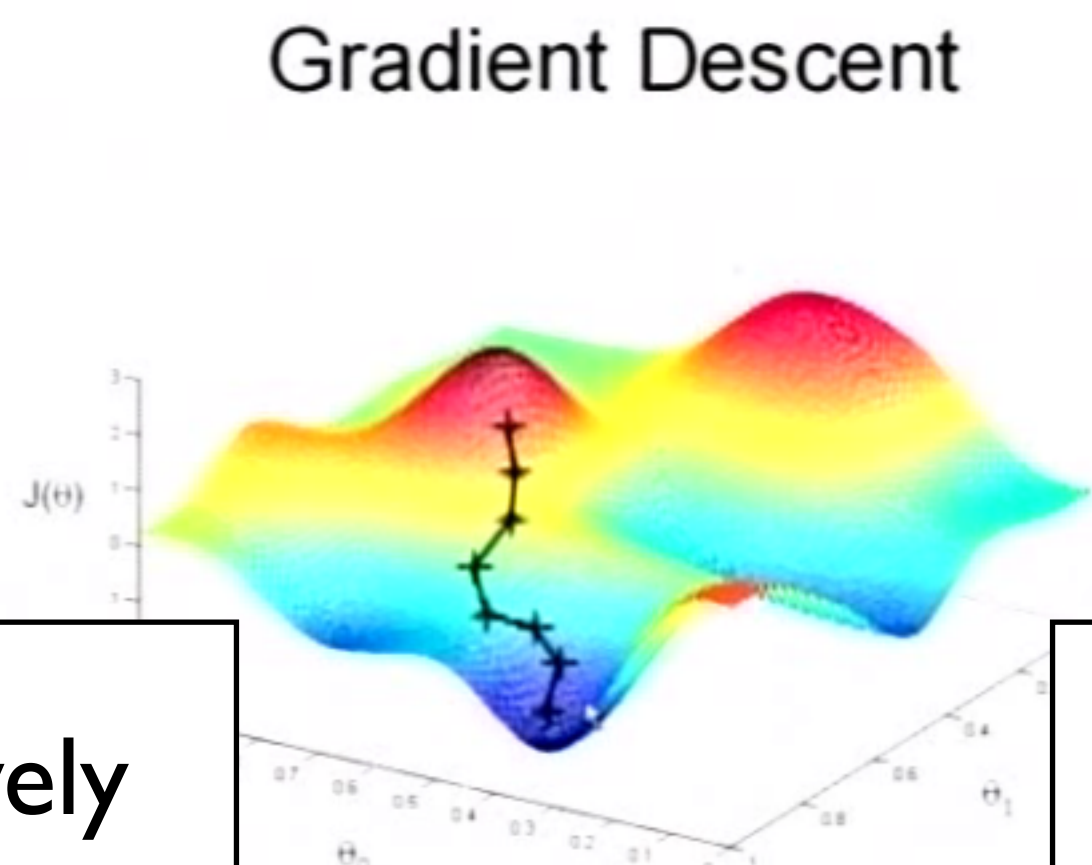


Relatively unstructured network

Trained relatively unstructured network

1) Existence of cost functions:

Ways to perform optimization in a neural network

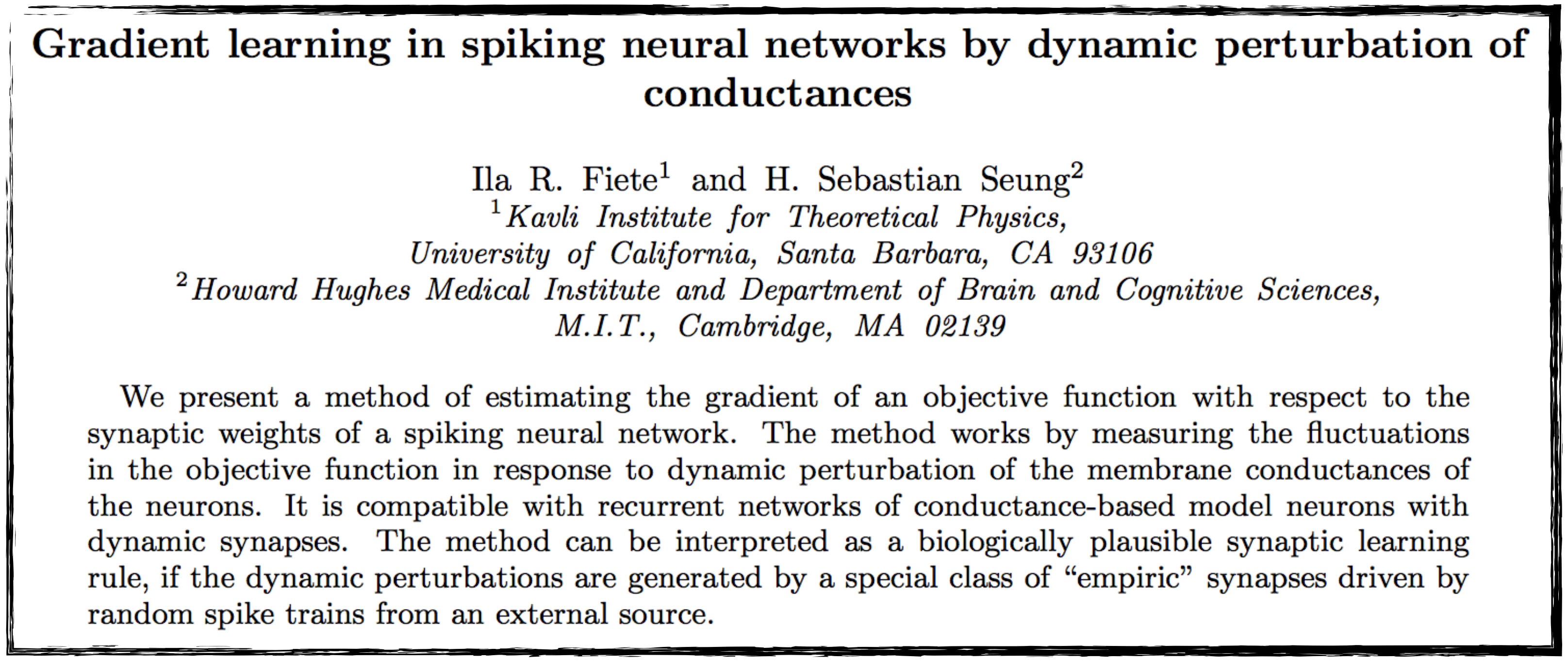
Back-propagation	*efficient, exact gradient computation by propagating errors through multiple layers*
Node perturbation Serial Parallel	*slow, high-variance gradient computation*
Weight perturbation Serial Parallel	*slow, high-variance gradient computation*

1) Existence of cost functions:

Back-propagation is much more efficient and precise, ***but*** *computational neuroscience has mostly rejected it*

It has instead focused on local synaptic plasticity rules, or occasionally on weight or node perturbation

Example:



Gradient learning in spiking neural networks by dynamic perturbation of conductances

Ila R. Fiete[1] and H. Sebastian Seung[2]
[1] *Kavli Institute for Theoretical Physics, University of California, Santa Barbara, CA 93106*
[2] *Howard Hughes Medical Institute and Department of Brain and Cognitive Sciences, M.I.T., Cambridge, MA 02139*

We present a method of estimating the gradient of an objective function with respect to the synaptic weights of a spiking neural network. The method works by measuring the fluctuations in the objective function in response to dynamic perturbation of the membrane conductances of the neurons. It is compatible with recurrent networks of conductance-based model neurons with dynamic synapses. The method can be interpreted as a biologically plausible synaptic learning rule, if the dynamic perturbations are generated by a special class of "empiric" synapses driven by random spike trains from an external source.

1) Existence of cost functions:

Neural nets and the brain

It is hardly surprising that such achievements have produced a heady sense of euphoria. But is this what the brain actually does? Alas, the back-drop nets are unrealistic in almost every respect, as indeed some of their inventors have admitted. They usually violate the rule that the outputs of a single neuron, at least in the neocortex, are either excitatory synapses or inhibitory ones, but not both[12]. It is also extremely difficult to see how neurons would implement the back-prop algorithm. Taken at its face value this seems to require the rapid transmission of information backwards along the axon, that is, antidromically from each of its synapses. It seems highly unlikely that this actually happens in the brain. Attempts to make more realistic nets to do this[13], though ingenious, seem to me to be very forced. Moreover the theorists working

NATURE VOL. 337 12 JANUARY 1989 COMMENTARY 129

The recent excitement about neural networks

Francis Crick

The remarkable properties of some recent computer algorithms for neural networks seemed to promise a fresh approach to understanding the computational properties of the brain. Unfortunately most of these neural nets are unrealistic in important respects.

1) **Existence of cost functions**:

Do you really need information to flow “backwards along the axon”?

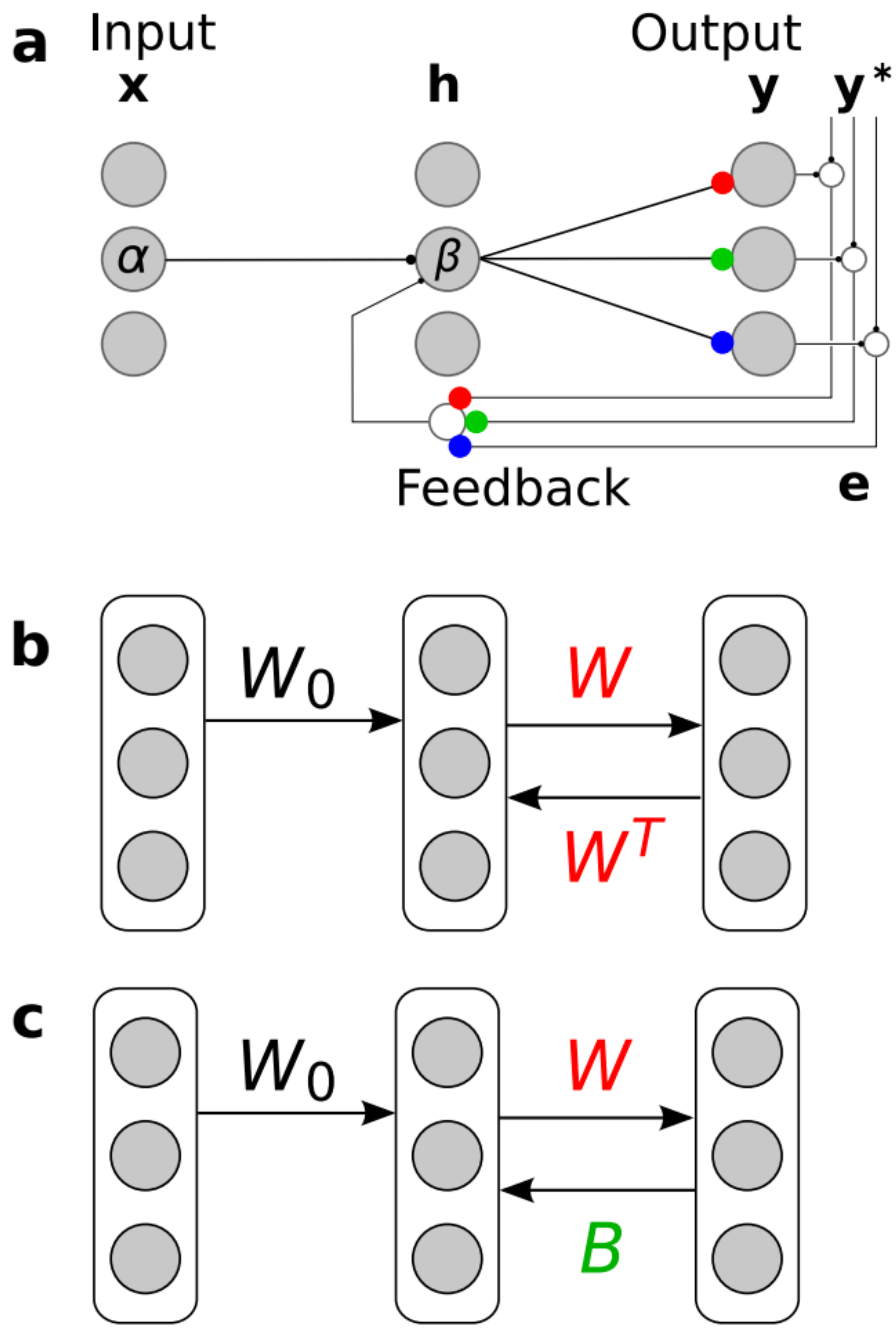
Or more generally, is the “weight transport” problem a genuine one?

I) Existence of cost functions:

Random feedback weights support learning in deep neural networks

Timothy P. Lillicrap, Daniel Cownden, Douglas B. Tweed, Colin J. Akerman

(Submitted on 2 Nov 2014)



transpose(**W**) x **e**
gets fed back
into the hidden units

B x **e**
gets fed back
into the hidden units

I) Existence of cost functions:

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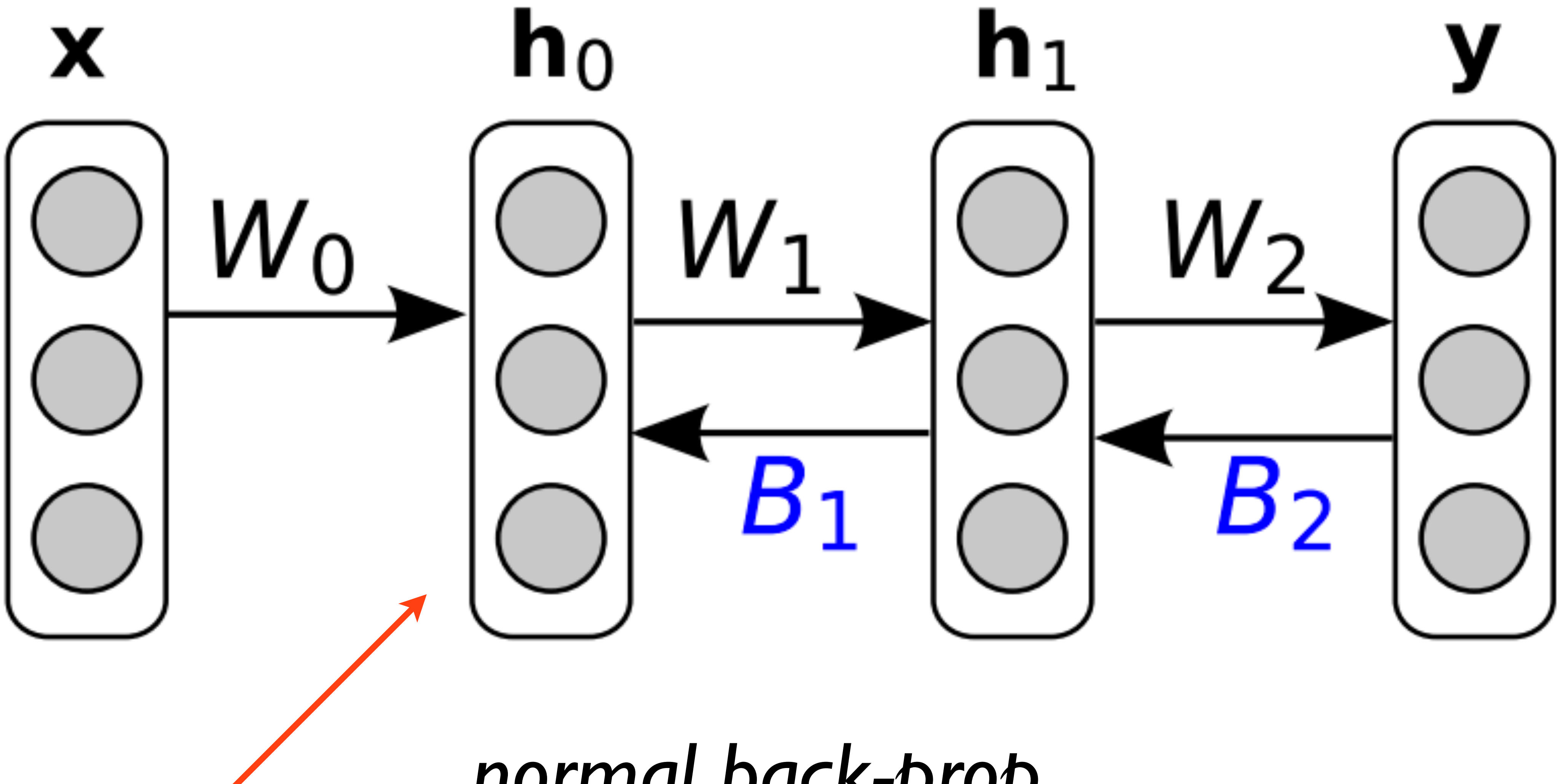


normal back-prop

$\Delta \mathbf{h}^0_{\mathrm{BP}} = W_1^T((W_2^T \mathbf{e}) \circ \mathbf{h}'_1)$, where $\circ$ is element-wise multiplication

fixed random feedback weights

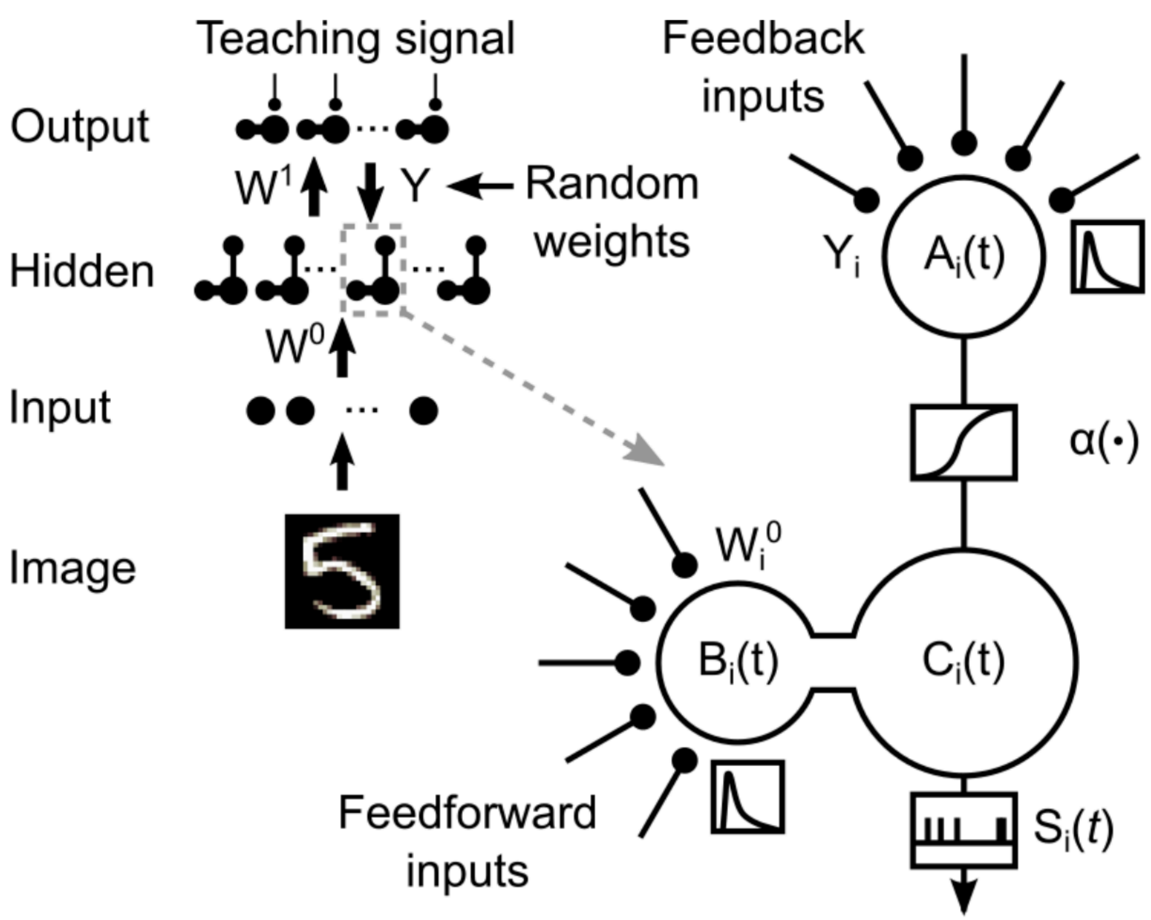
$\Delta \mathbf{h}^0_{\mathrm{FA}} = B_1((B_2 \mathbf{e}) \circ \mathbf{h}'_1)$, where B_1 and B_2 are random matrices

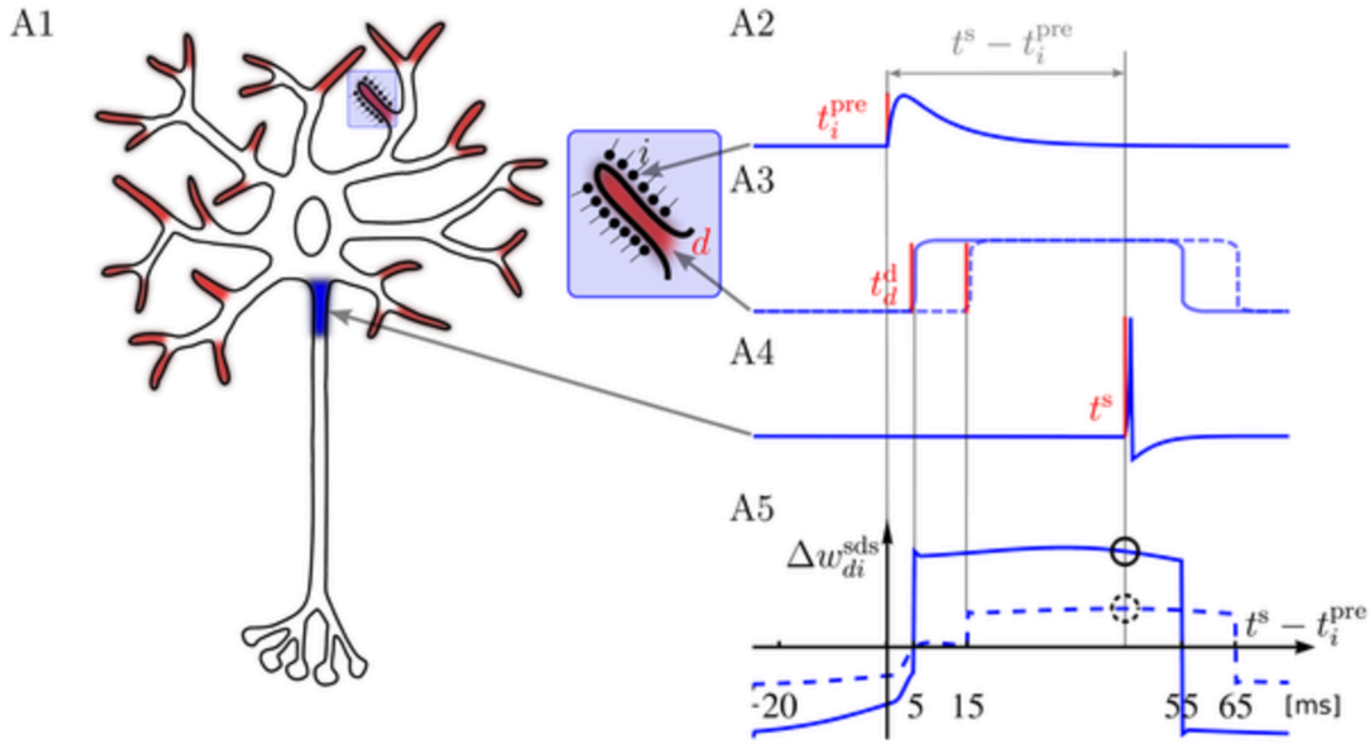
I) Existence of cost functions:

Use multiple dendritic compartments to store both "activations" and "errors"

soma voltage ~ activation

dendritic voltage ~ error derivative





Supervised and Unsupervised Learning with Two Sites of Synaptic Integration

KONRAD P. KÖRDING AND PETER KÖNIG

Institute of Neuroinformatics, ETH/UNI Zürich, Winterthurerstr. 190, 8057 Zürich, Switzerland

Deep learning with segregated dendrites

Jordan Guergiuev[1,2], Timothy P. Lillicrap[4], Blake A. Richards[1,2,3,*]

Somato-dendritic Synaptic Plasticity and Error-backpropagation in Active Dendrites

Mathieu Schiess, Robert Urbanczik, Walter Senn

1) Existence of cost functions:

Or use temporal properties of the neuron to encode both signals

firing rate ~ activation

d(firing rate)/dt ~ error derivative

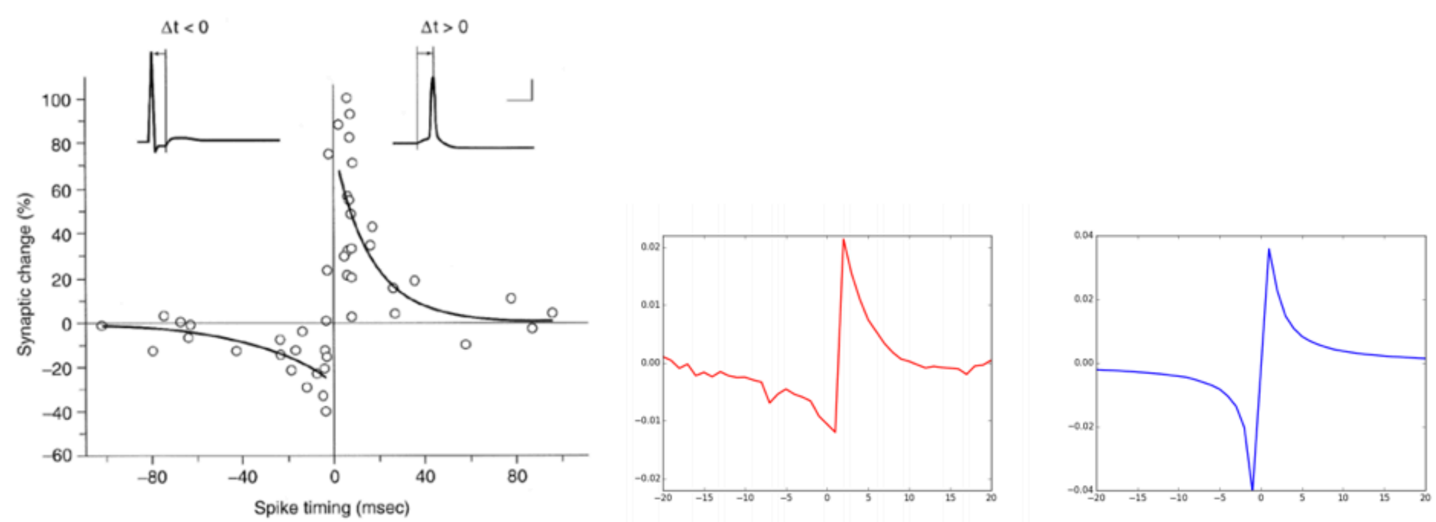


Figure 1: Left: Biological observation of STDP weight change, vertical axis, for different spike timing differences (post minus pre), horizontal axis. From Shepherd (2003), with data from Bi and Poo (2001). Compare with the result of the simulations using the objective function proposed here (middle).
Middle and right:Spike-based simulation shows that when weight updates follow SGD on the proposed predictive objective function, we recover the biologically observed relationship between spike timing difference (horizontal axis, postsynaptic spike time minus presynaptic spike time) and the weight update (vertical axis). Middle: the weight updates are obtained with the proposed update rule (Eq. 1). Right: the weight updates are obtained using the nearest neighbor STDP rule. Compare with the biological finding, left.

STDP as presynaptic activity times rate of change of postsynaptic activity

Yoshua Bengio, Thomas Mesnard, Asja Fischer, Saizheng Zhang, Yuhuai Wu

See also similar claims by Hinton

I) Existence of cost functions:

Removing the two-phase and globally-coordinated aspects of back-prop

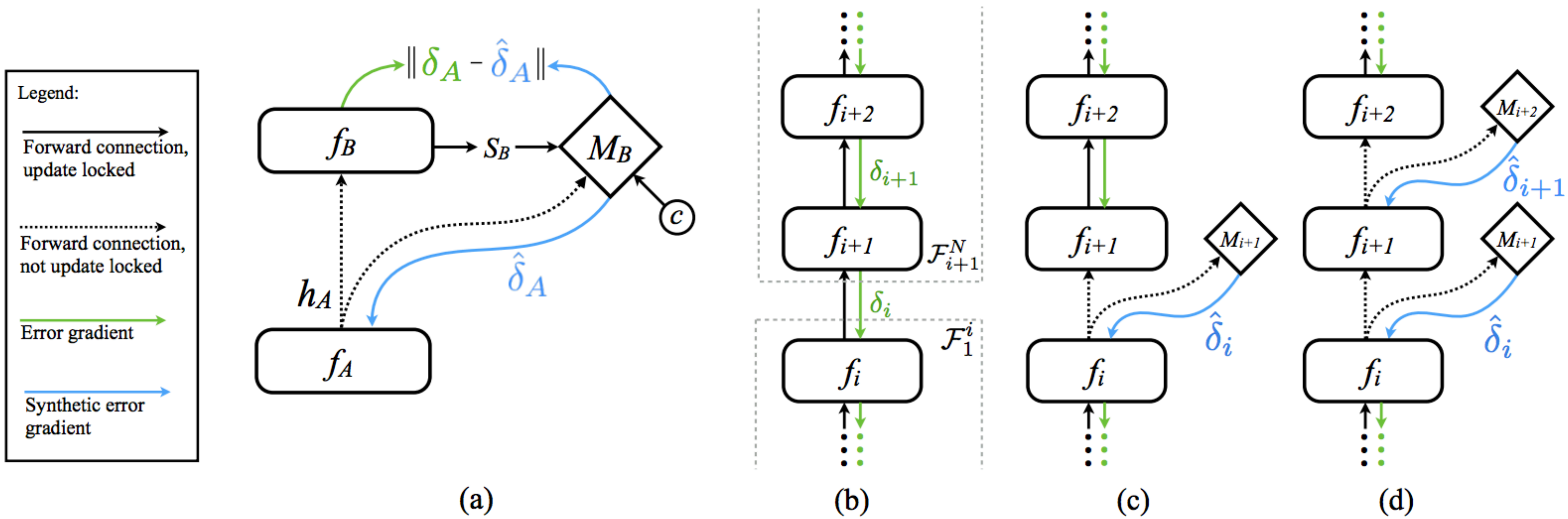


Figure 1: (a) General communication protocol between A and B. After receiving the message h_A from A, B can use its model of A, M_B, to send back *synthetic gradients* $\hat{\delta}_A$ which are trained to approximate real error gradients δ_A. Note that A does not need to wait for any extra computation after itself to get the correct error gradients, hence decoupling the backward computation. The feedback model M_B can also be conditioned on any privileged information or context, c, available during training such as a label. (b-d) DNI applied to feed-forward networks. (b) A section of a vanilla feed-forward neural network $\mathcal{F}_1^N$. (c) Incorporating one synthetic gradient model for the output of layer i. This results in two sub-networks $\mathcal{F}_1^i$ and $\mathcal{F}_{i+1}^N$ which can be updated independently. (d) Incorporating multiple synthetic gradient models after every layer results in N independently updated layers.

Decoupled Neural Interfaces using Synthetic Gradients

Max Jaderberg **Wojciech Marian Czarnecki** **Simon Osindero**

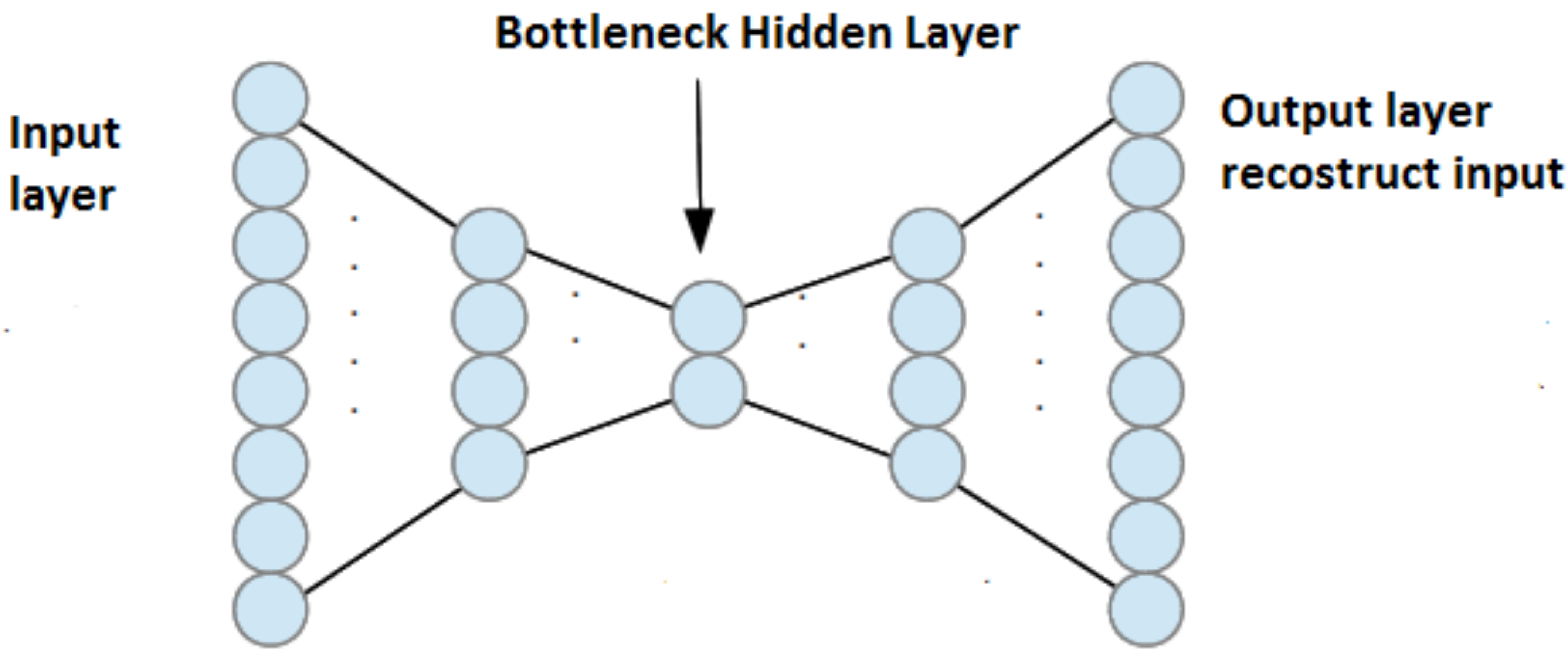
Oriol Vinyals **Alex Graves** **Koray Kavukcuoglu**

1) Existence of cost functions:

But isn't gradient descent only compatible with "supervised" learning?

No! Lots of unsupervised learning paradigms operate via gradient descent…

classic auto-encoder



1) Existence of cost functions:

But isn't gradient descent only compatible with "supervised" learning?

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filling in

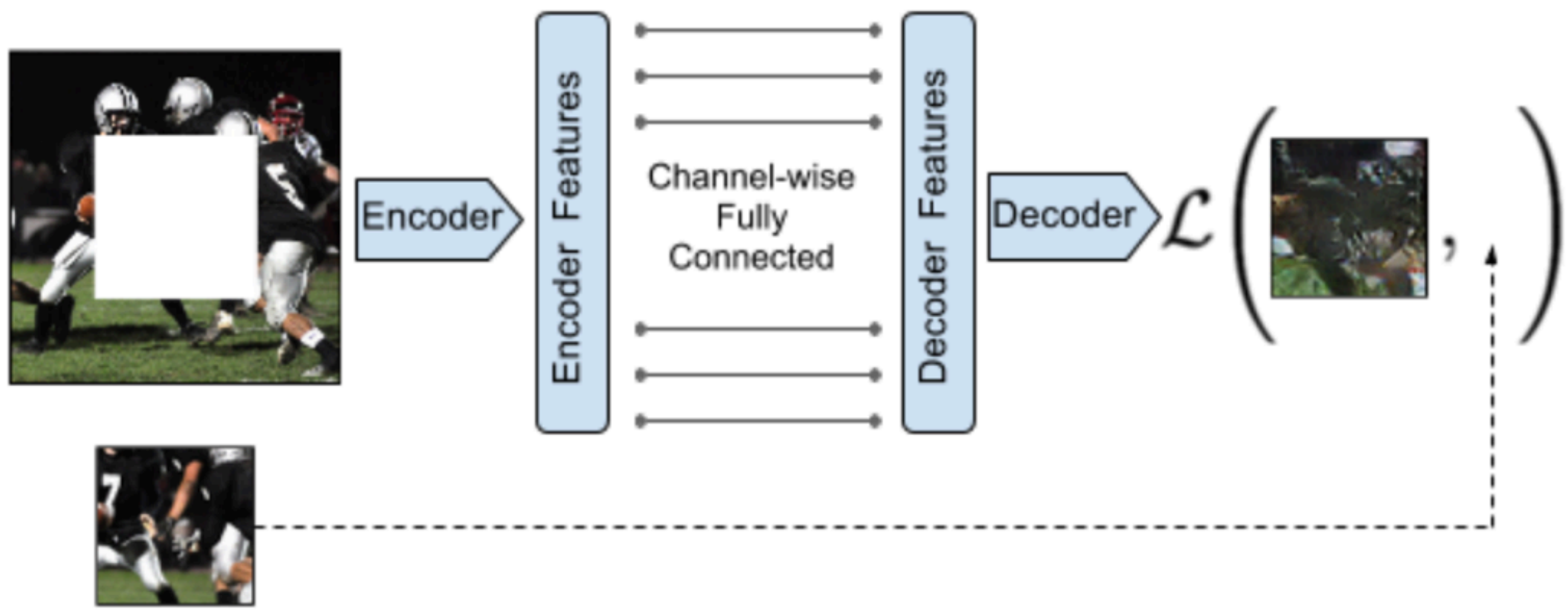

Figure 2: Context Encoder. The context image is passed through the encoder to obtain features which are connected to the decoder using channel-wise fully-connected layer as described in Section 3.1. The decoder then produces the missing regions in the image.

Context Encoders: Feature Learning by Inpainting

Deepak Pathak   Philipp Krähenbühl   Jeff Donahue   Trevor Darrell   Alexei A. Efros
University of California, Berkeley
{pathak,philkr,jdonahue,trevor,efros}@cs.berkeley.edu

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prediction of the next frame of a movie

UNDERSTANDING VISUAL CONCEPTS WITH CONTINUATION LEARNING

William F. Whitney, Michael Chang, Tejas Kulkarni, and Joshua B. Tenenbaum
Department of Brain and Cognitive Science
Massachusetts Institute of Technology
{wwhitney,mbchang,tejask,jbt}@mit.edu

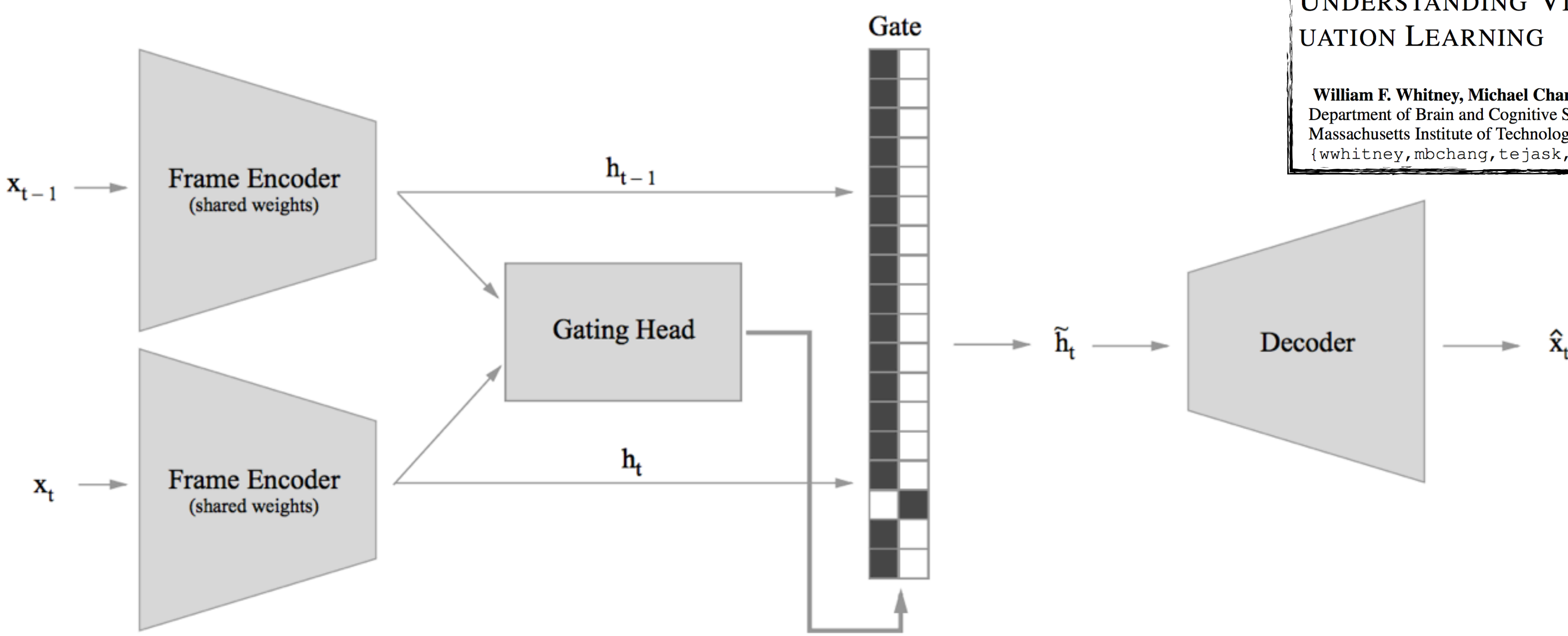

Figure 1: The gated model. Each frame encoder produces a representation from its input. The gating head examines both these representations, then picks one component from the encoding of time t to pass through the gate. All other components of the hidden representation are from the encoding of time $t-1$. As a result, each frame encoder predicts what it can about the next frame and encodes the "unpredictable" parts of the frame into one component.

1) Existence of cost functions:

But isn't gradient descent only compatible with "supervised" learning?

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prediction of the next frame of a movie

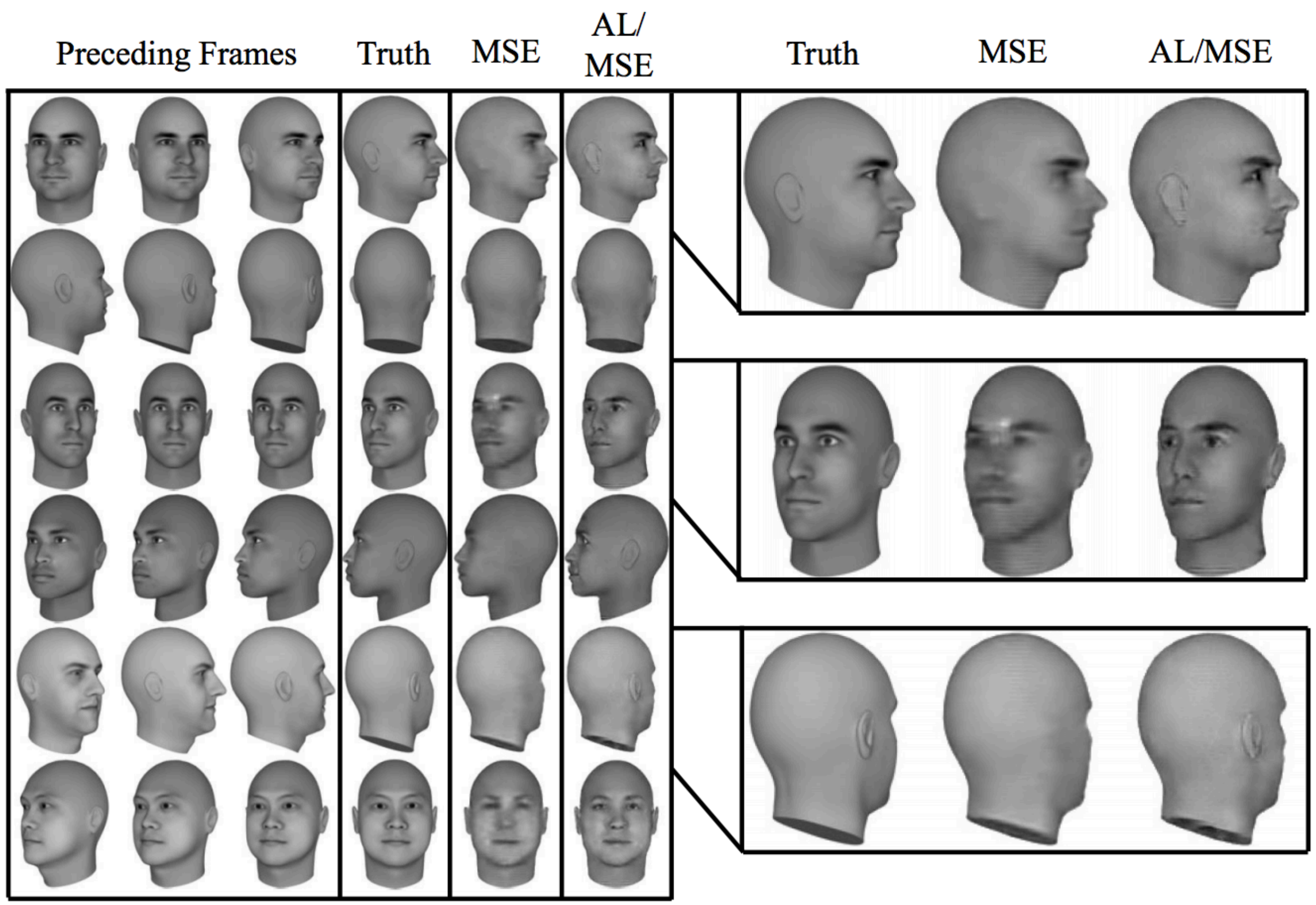


Figure 3: Example predictions for the rotating faces dataset. Predictions for models trained with MSE and a weighted MSE and adversarial loss (AL) are shown.

Unsupervised Learning of Visual Structure using Predictive Generative Networks

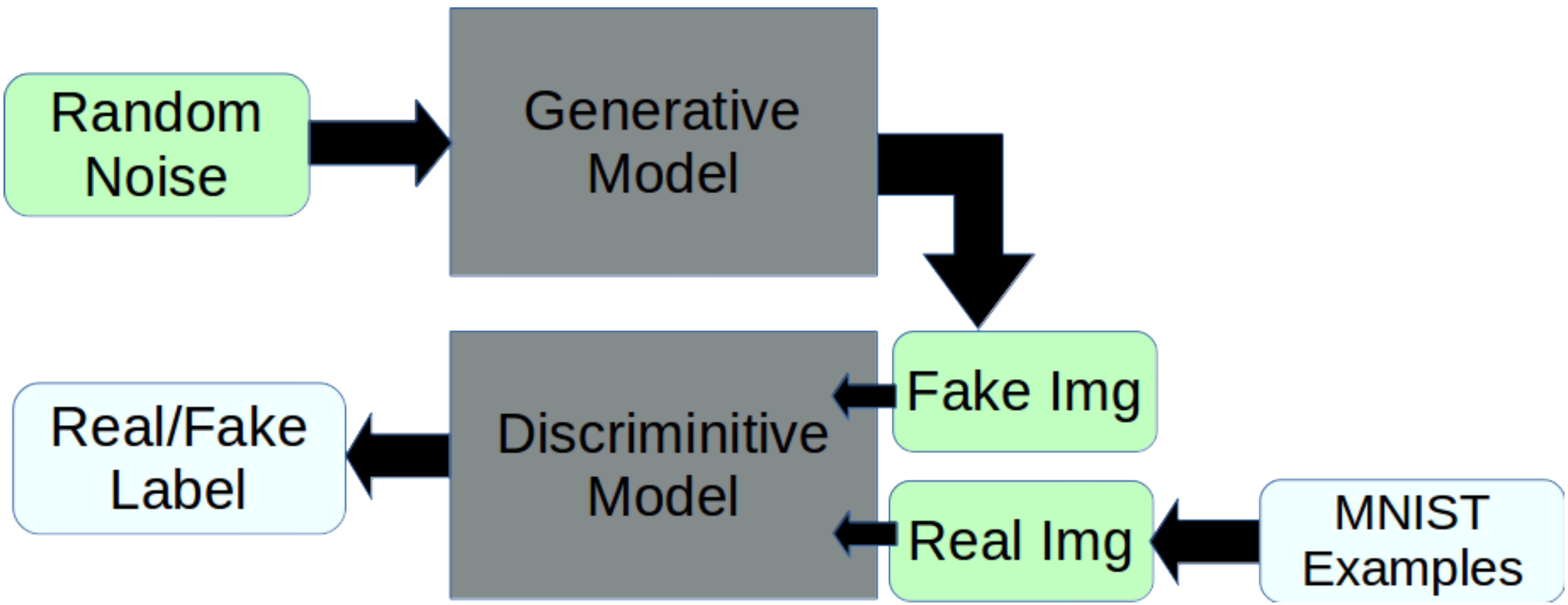
William Lotter, Gabriel Kreiman, David Cox

1) **Existence of cost functions**:

But isn't gradient descent only compatible with "supervised" learning?

No! Lots of unsupervised learning paradigms operate via gradient descent…

generative adversarial network

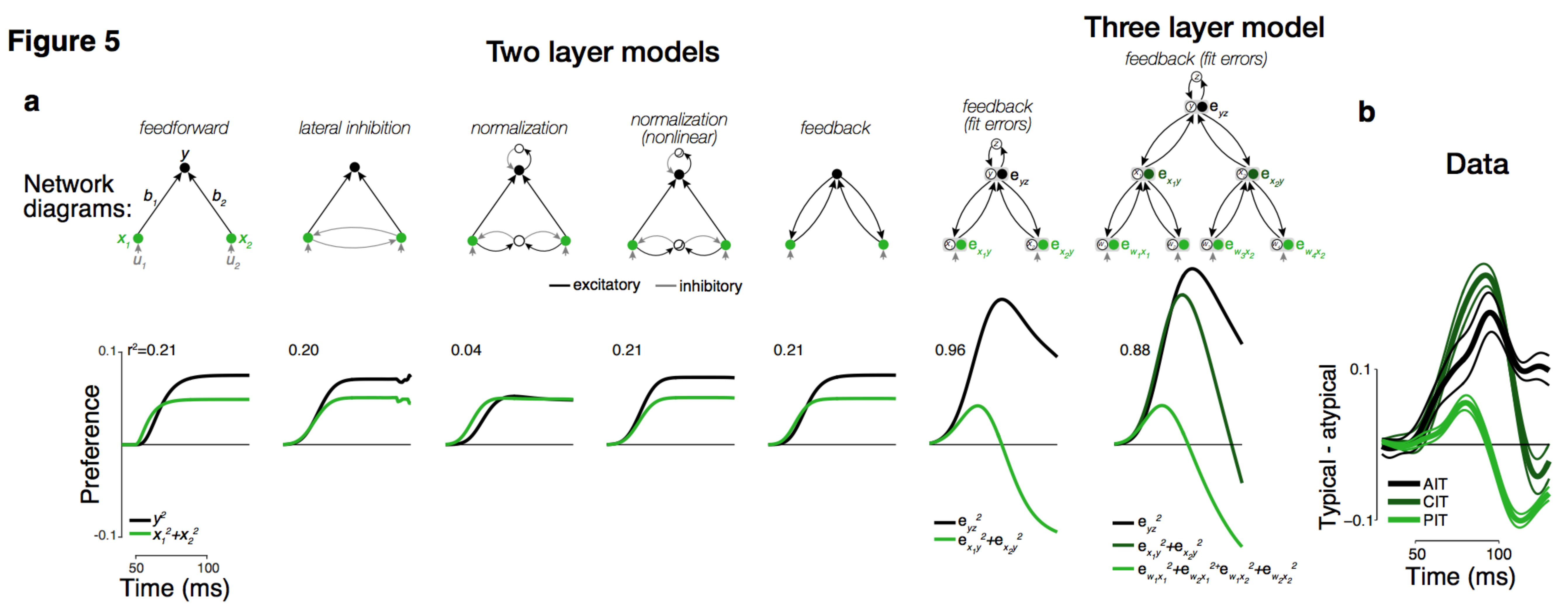


I) Existence of cost functions:

Signatures of error signals being computed in the visual hierarchy?!

Evidence that the ventral stream codes the errors used in hierarchical inference and learning

Elias B. Issa, Charles F. Cadieu, James J. DiCarlo



Does not yet tell us whether it is something like backprop, or whether these signals are used for learning vs. inference…

1) Existence of cost functions:

Take Away

The brain *could* efficiently compute approximate gradients of its multi-layer weight matrix via propagating credit through multiple layers of neurons

Diverse *potential* mechanisms available leveraging:

Dendritic computation

Timing-dependent plasticity

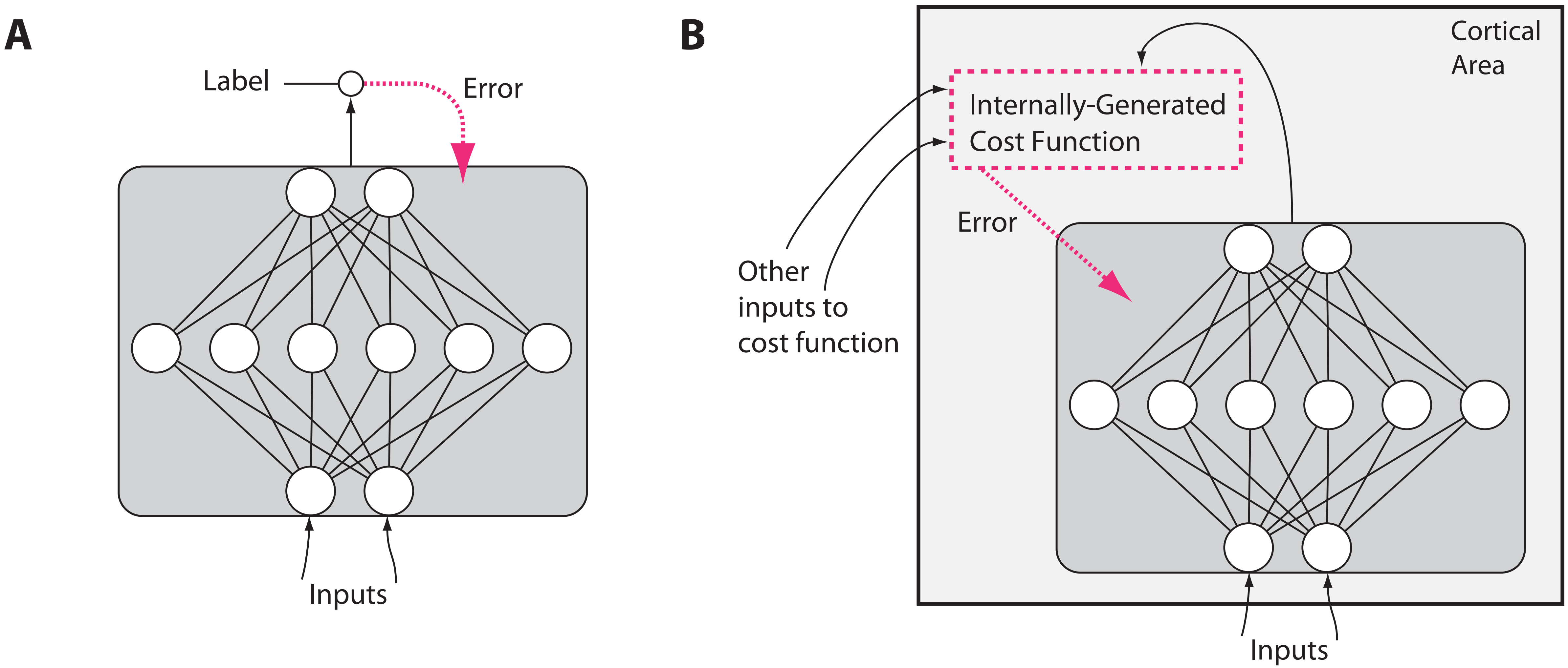
…

Such a core capability for error-driven learning could underpin diverse supervised and unsupervised learning paradigms

Three hypotheses for linking neuroscience and ML

2) Biological fine-structure of cost functions:

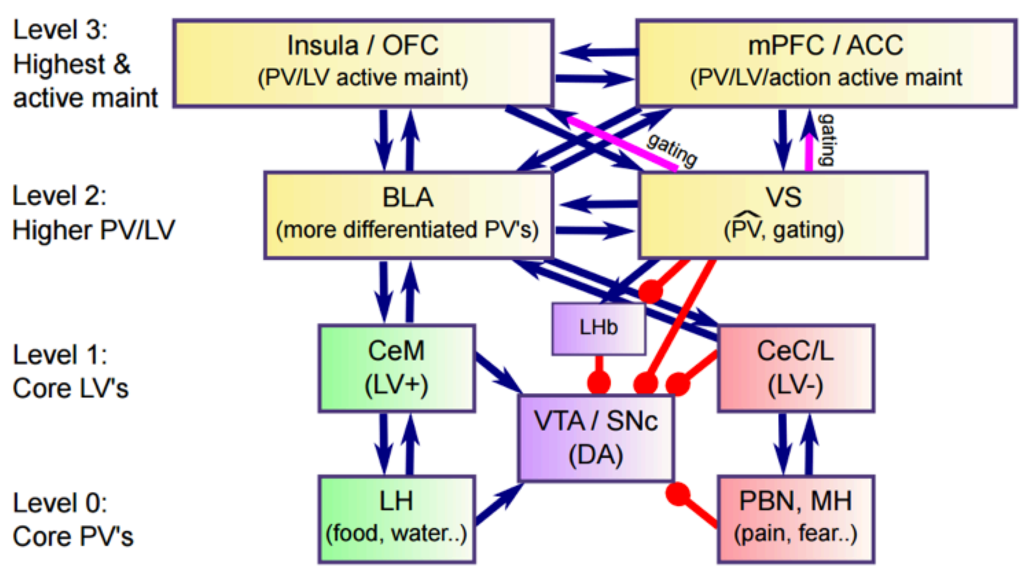
the cost functions are diverse, area-specific and systematically regulated in space and time

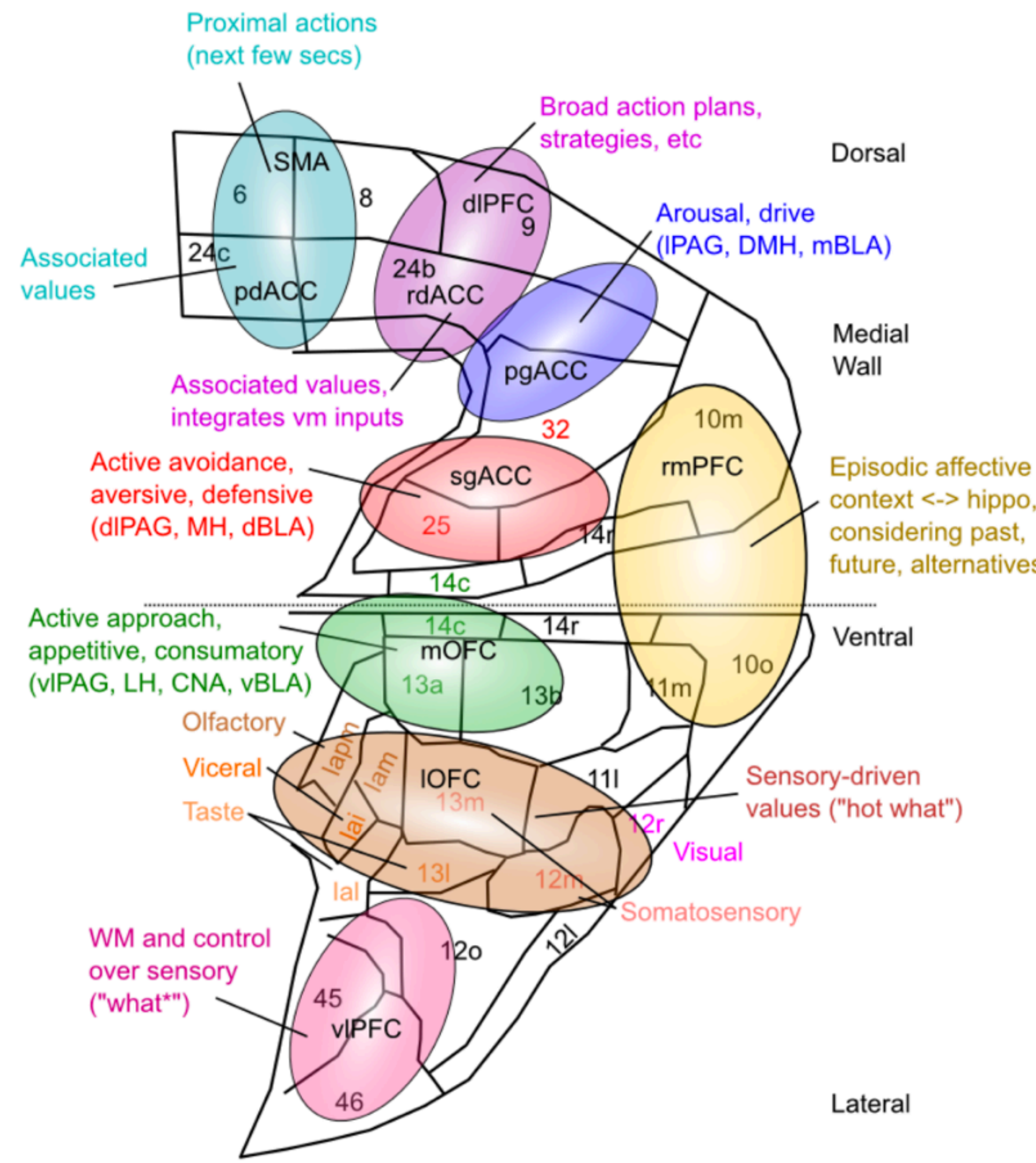


2) Biological fine-structure of cost functions:

the cost functions are diverse, area-specific and systematically regulated in space and time

Global "value functions" vs. *multiple local internal cost functions*

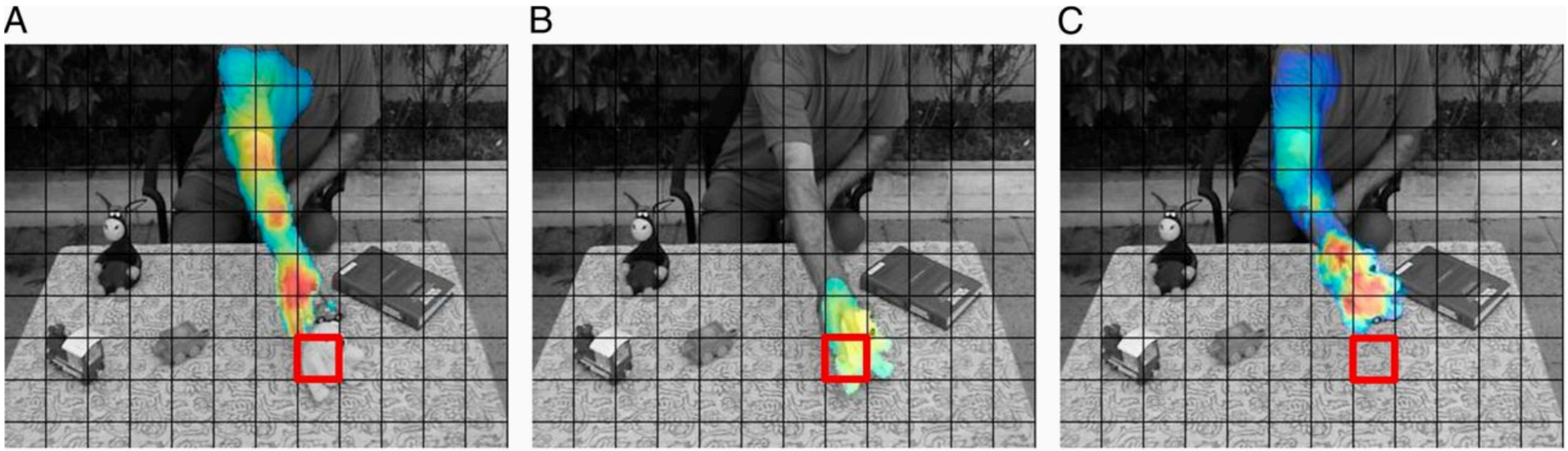




These diagrams describe a global "value function" for "end-to-end" training of the entire brain…
but these aren't the whole story!

Randal O'Reilly

Internally-generated **bootstrap cost functions**: *against* “end to end” training



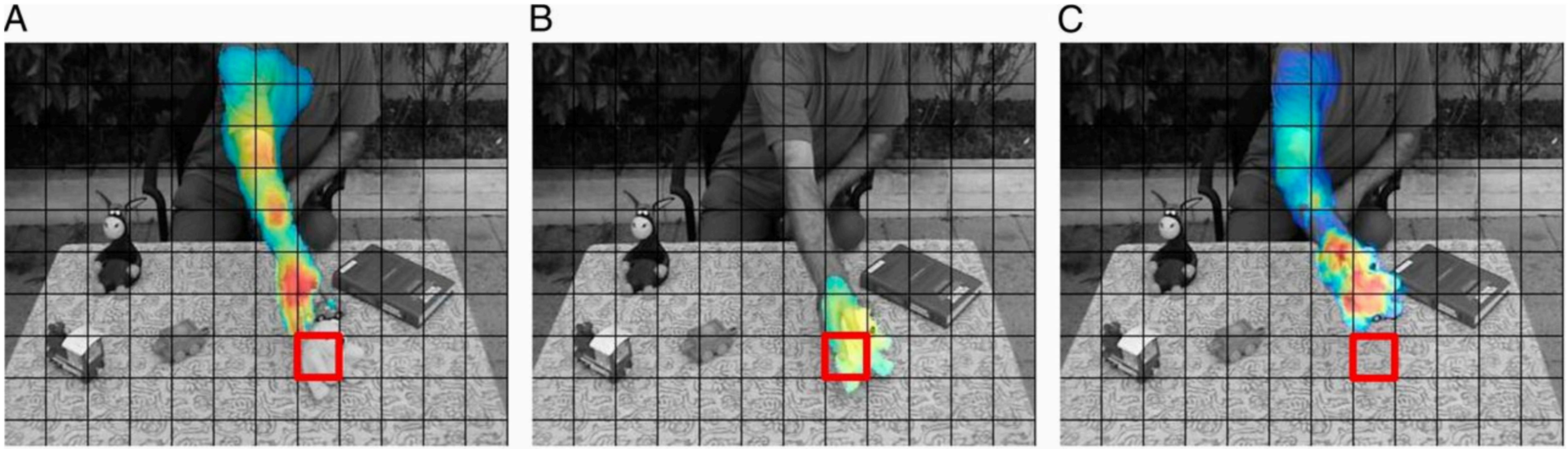
Simple optical flow calculation provides an *internally generated “bootstrap” training signal* for hand recognition

Optical flow: bootstraps hand recognition
Hands + faces: bootstraps gaze direction recognition
Gaze direction (and more): bootstraps more complex social cognition

From simple innate biases to complex visual concepts

Shimon Ullman[1,2], Daniel Harari[1], and Nimrod Dorfman[1]

Internally-generated **bootstrap cost functions**: *against* "end to end" training



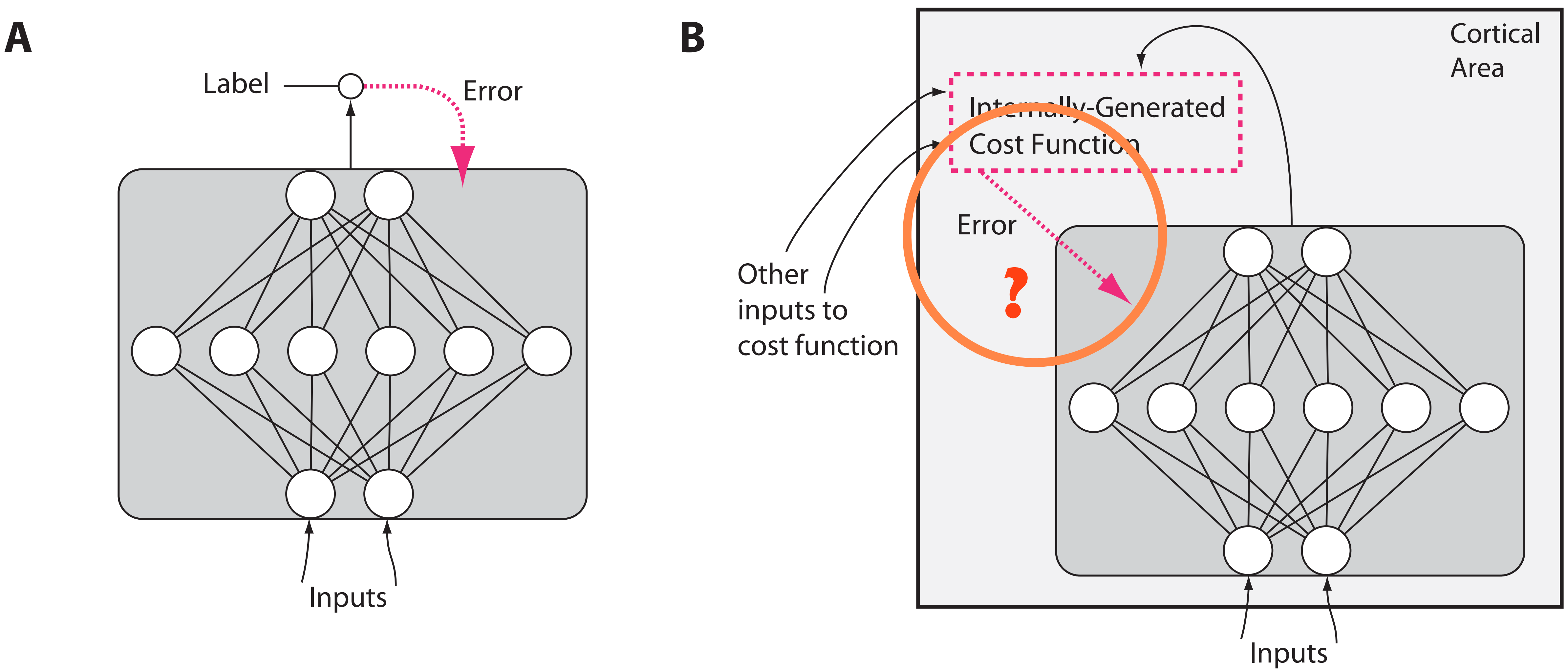
Generalizations of this idea could be a key architectural principle for how the biological brain would generate and use ***internal*** *training signals (a form of "weak label")*

From simple innate biases to complex visual concepts

Shimon Ullman[1,2], Daniel Harari[1], and Nimrod Dorfman[1]

But how are internal cost functions *represented* and *delivered*?

<u>Normal backprop</u>: need a full vectorial target pattern to train towards
<u>Reinforcement</u>: problems of credit assignment are even worse



***<u>Possibility</u>**: The brain may re-purpose deep **reinforcement** learning to optimize diverse internal cost functions, which are computed internally and delivered as scalars*

Ways of making deep *RL* efficient

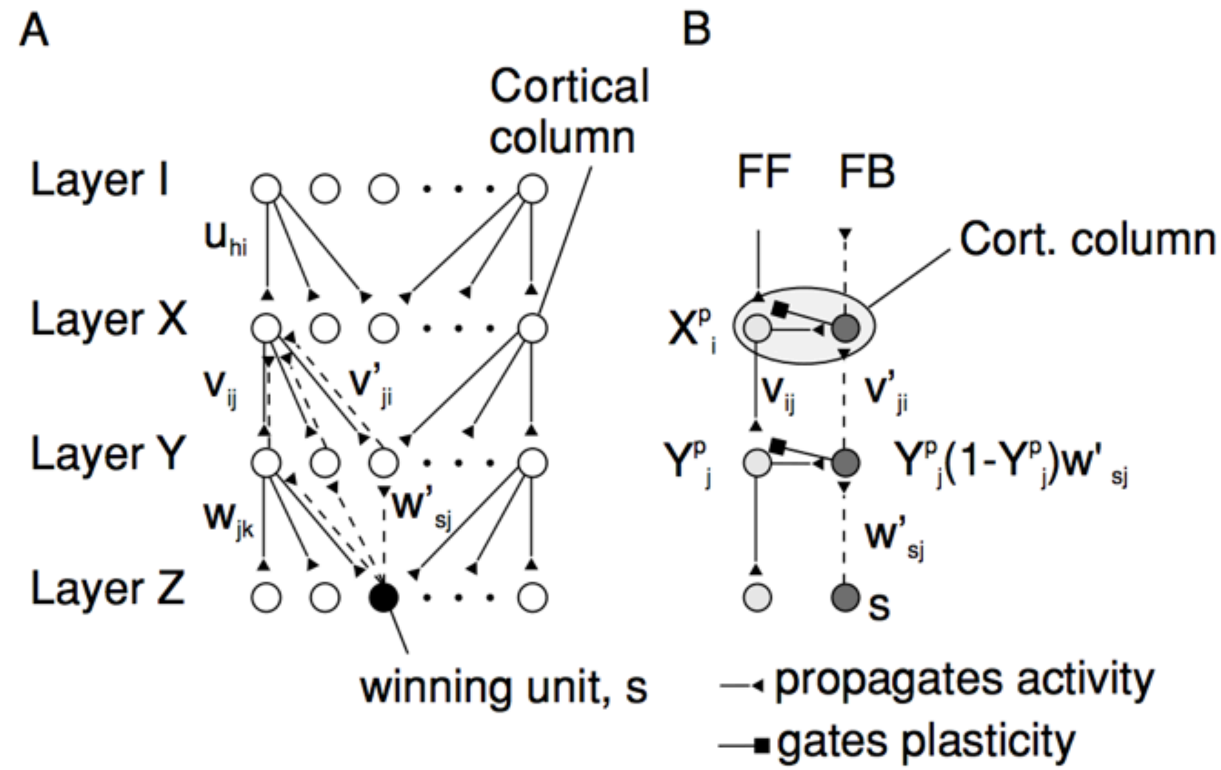


Figure 4: Generalization of AGREL to networks with more than three layers. (A) Feedforward connections u, v, and w propagate activity from the input layer I through two hidden layers to the output layer Z. The winning output unit, s, feeds back to units in layer Y through connections w'_{sj}. All units in Y that receive feedback from Z propagate it to layer X through feedback connections v'_{ji}. (B) Units of AGREL are hypothesized to correspond to cortical columns that contain FF neurons (light gray circles) that propagate activity to the next higher layer as well as FB neurons (dark gray) that propagate activity to the previous layer. FB neurons gate plasticity in the FF pathway, but they do not directly influence the activity of FF neurons (connection with square).

Neural Comput. 2005 Oct;17(10):2176-214.

Attention-gated reinforcement learning of internal representations for classification.

Roelfsema PR[1], van Ooyen A.

Ways of making deep *RL* efficient

Algorithm 1 Deep Q-learning with Experience Replay

Initialize replay memory $\mathcal{D}$ to capacity N
Initialize action-value function Q with random weights
for episode $= 1, M$ **do**
  Initialise sequence $s_1 = \{x_1\}$ and preprocessed sequenced $\phi_1 = \phi(s_1)$
  for $t = 1, T$ **do**
    With probability ϵ select a random action a_t
    otherwise select $a_t = \max_a Q^*(\phi(s_t), a; \theta)$
    Execute action a_t in emulator and observe reward r_t and image x_{t+1}
    Set $s_{t+1} = s_t, a_t, x_{t+1}$ and preprocess $\phi_{t+1} = \phi(s_{t+1})$
    Store transition $(\phi_t, a_t, r_t, \phi_{t+1})$ in $\mathcal{D}$
    Sample random minibatch of transitions $(\phi_j, a_j, r_j, \phi_{j+1})$ from $\mathcal{D}$
    Set $y_j = \begin{cases} r_j & \text{for terminal } \phi_{j+1} \\ r_j + \gamma \max_{a'} Q(\phi_{j+1}, a'; \theta) & \text{for non-terminal } \phi_{j+1} \end{cases}$
    Perform a gradient descent step on $(y_j - Q(\phi_j, a_j; \theta))^2$ according to equation 3
  end for
end for

"biologically plausible"?

Playing Atari with Deep Reinforcement Learning

Volodymyr Mnih, Koray Kavukcuoglu, David Silver, Alex Graves, Ioannis Antonoglou, Daan Wierstra, Martin Riedmiller

A complex molecular and cellular basis for reinforcement-based training in *primary* visual cortex

Reinforcement in striatum: VTA dopaminergic projections
Reinforcement in cortex: basal forebrain cholinergic projections

with a *glial* intermediate!

A Cholinergic Mechanism for Reward Timing within Primary Visual Cortex

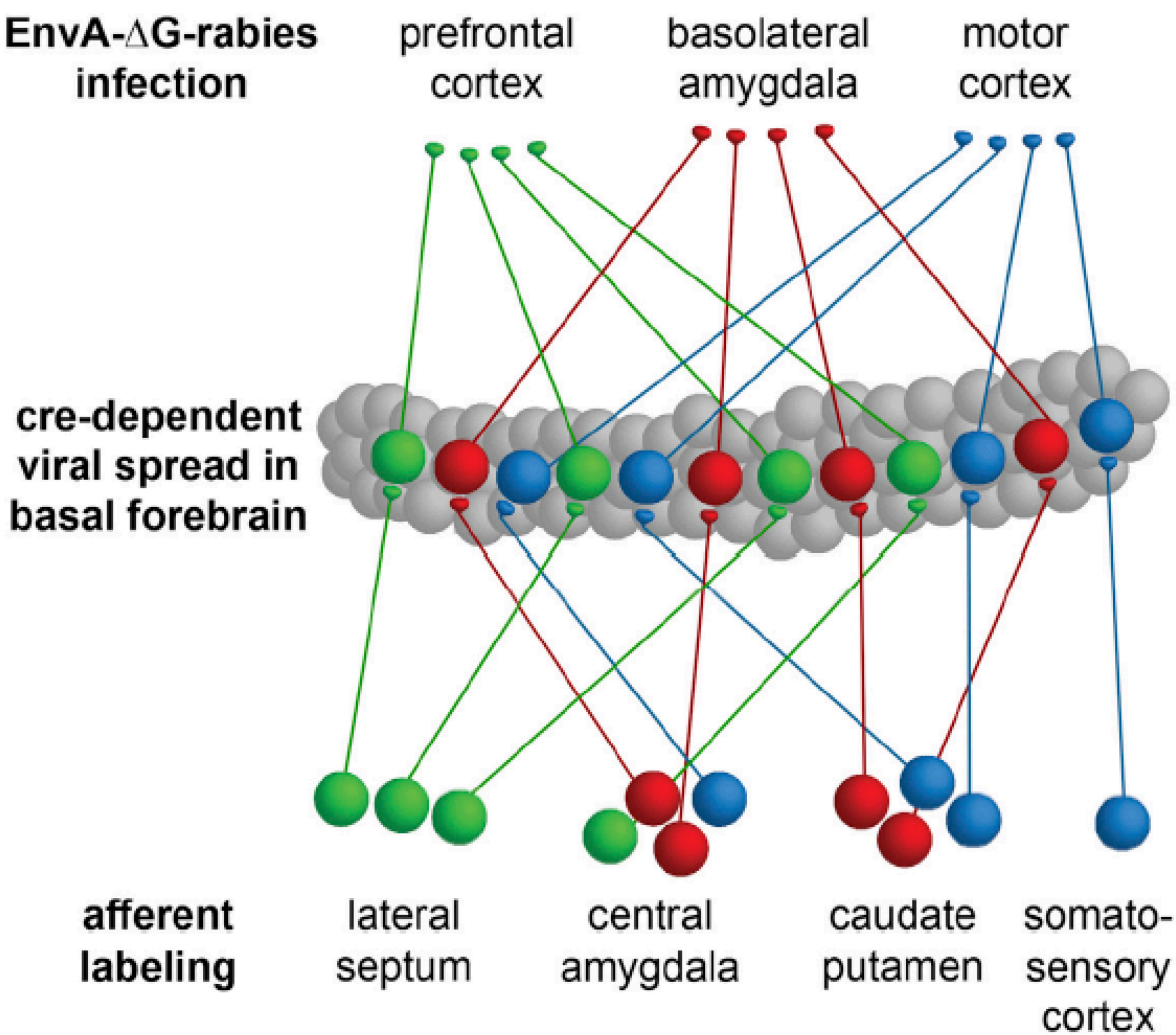
Alexander A. Chubykin[3], Emma B. Roach[3], Mark F. Bear, Marshall G. Hussain Shuler
[3] These authors contributed equally to this work

Nucleus basalis-enabled stimulus-specific plasticity in the visual cortex is mediated by astrocytes (i.e., glia not neurons)

Naiyan Chen[a,1], Hiroki Sugihara[a,1], Jitendra Sharma[a,b], Gertrudis Perea[a], Jeremy Petravicz[a], Chuong Le[a], and Mriganka Sur[a,2]

Where are the cost functions:
Cholinergic transmission to cortex from basal forebrain?

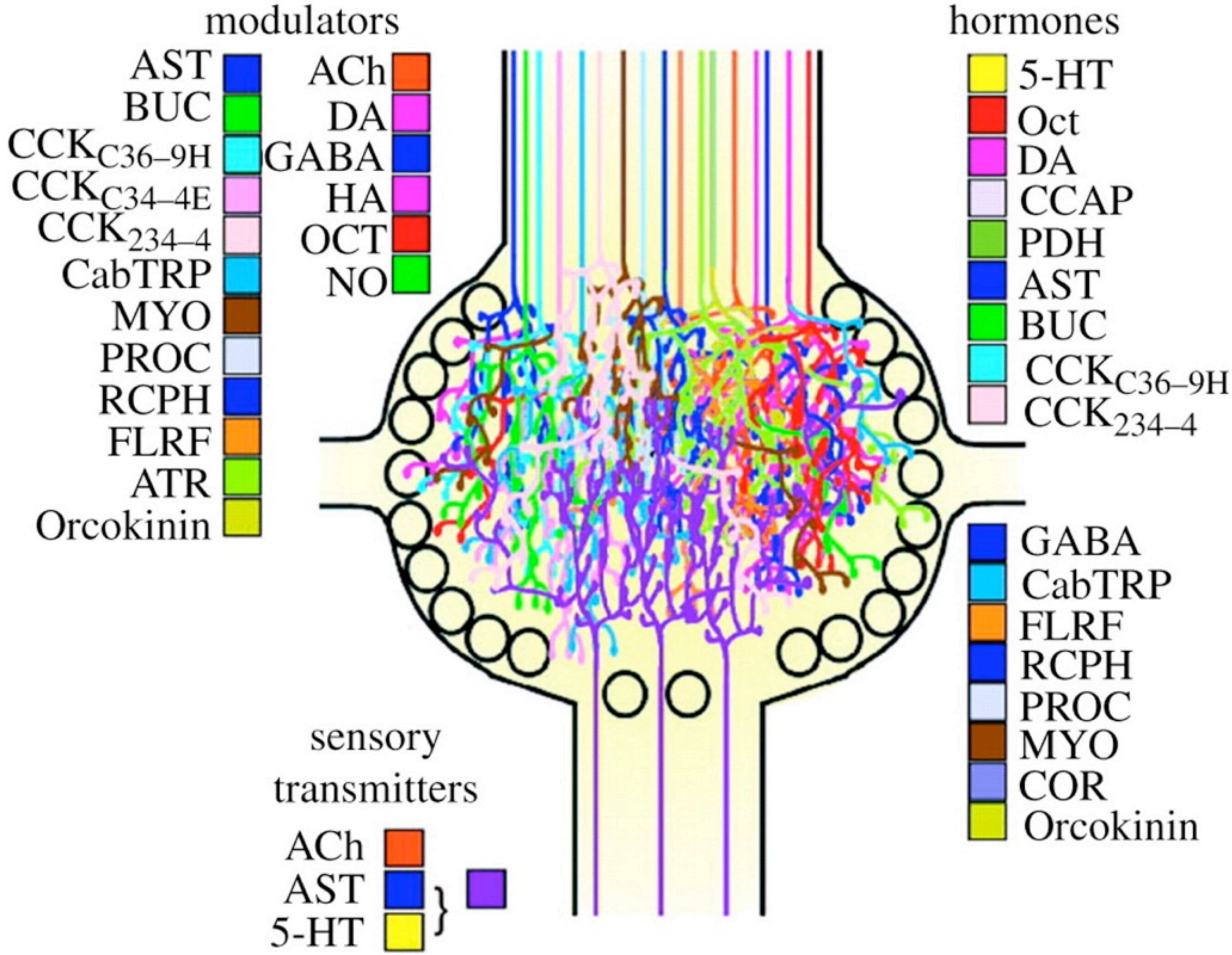
Reinforcement in striatum: VTA dopaminergic projections
Reinforcement in cortex: basal forebrain cholinergic projections



The Input-Output Relationship of the Cholinergic Basal Forebrain

Matthew R. Gielow[1] and Laszlo Zaborszky[1,2,*]

Where are the cost functions:
A diversity of reinforcement-like signals?



Classic work by Eve Marder in the crab stomatogastric ganglion

Where are the cost functions:
Motor intention efference copies via thalamus?

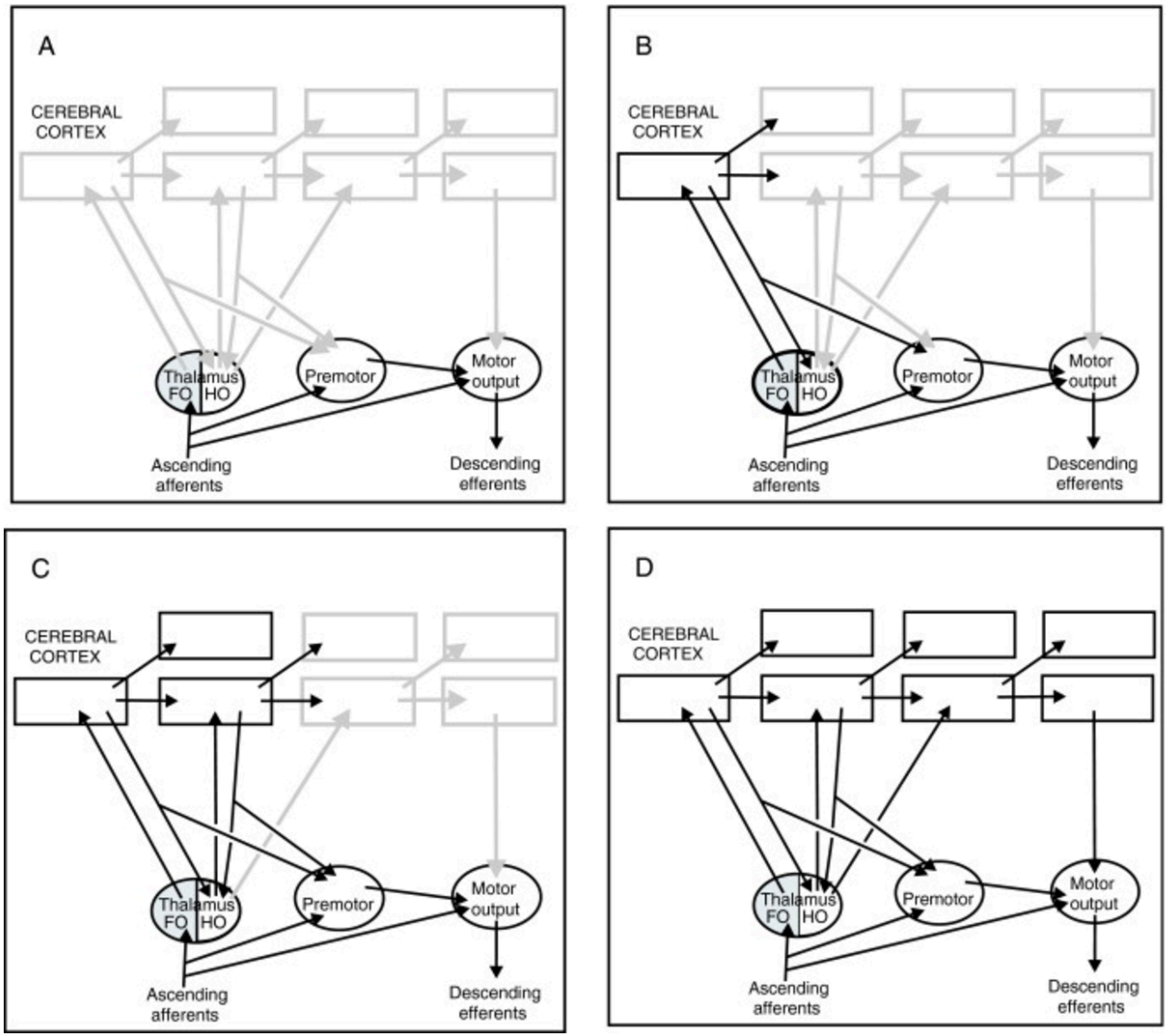
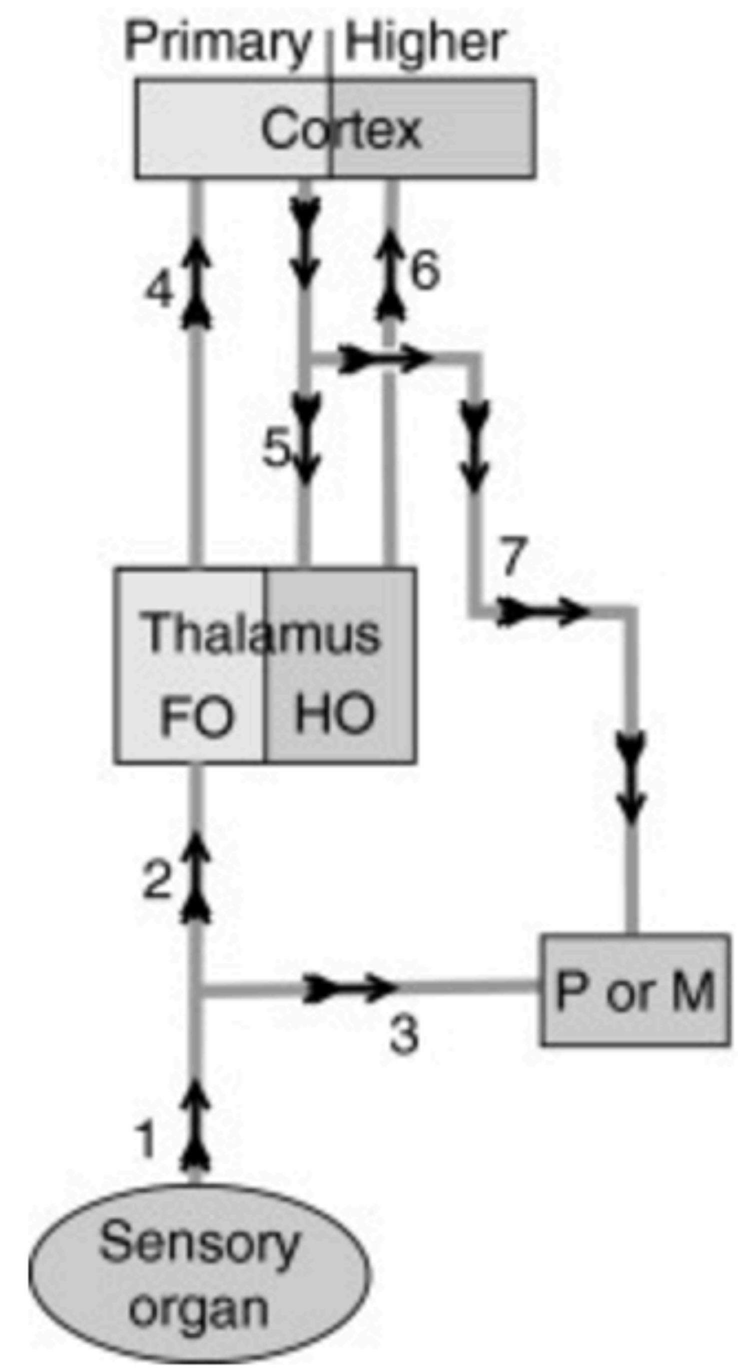


Fig. 11.
Schema to show the sequence of development of the connections illustrated in Fig. 3. A–D show a chronological sequence, with black lines indicating mature and grey lines indicating immature pathways.



Sherman and Guillery:
"Anatomical pathways that link perception and action"

Where are the cost functions:
Storage of temporal context in thalamus for predictive learning?

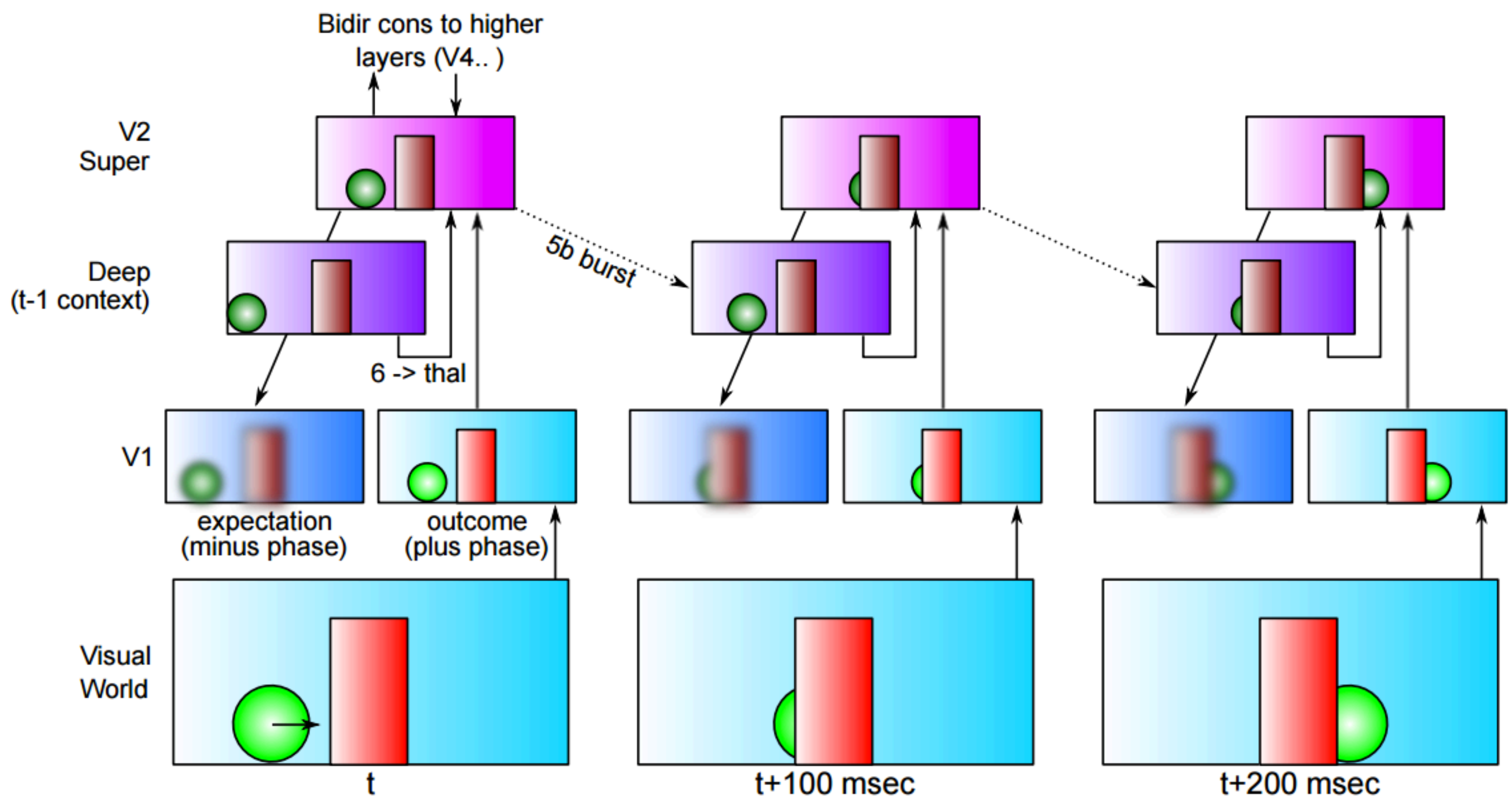


Figure 1: The temporal evolution of information flow in a LeabraTI model predicting visual sequences, over a period of three alpha cycles of 100 msec each. The Deep context maintains the prior 100 msec information while the Superficial generates a prediction (in the minus phase) about what will happen next. Learning occurs in comparing this prediction with the plus phase outcome, which generates an updated activity pattern in the Super layers. Thus, prediction error is a temporally extended quantity, not coded explicitly in individual neurons.

Learning Through Time in the Thalamocortical Loops

Randall C. O'Reilly, Dean Wyatte, John Rohrlich

Where are the cost functions:
Storage of temporal context in thalamus for predictive learning?

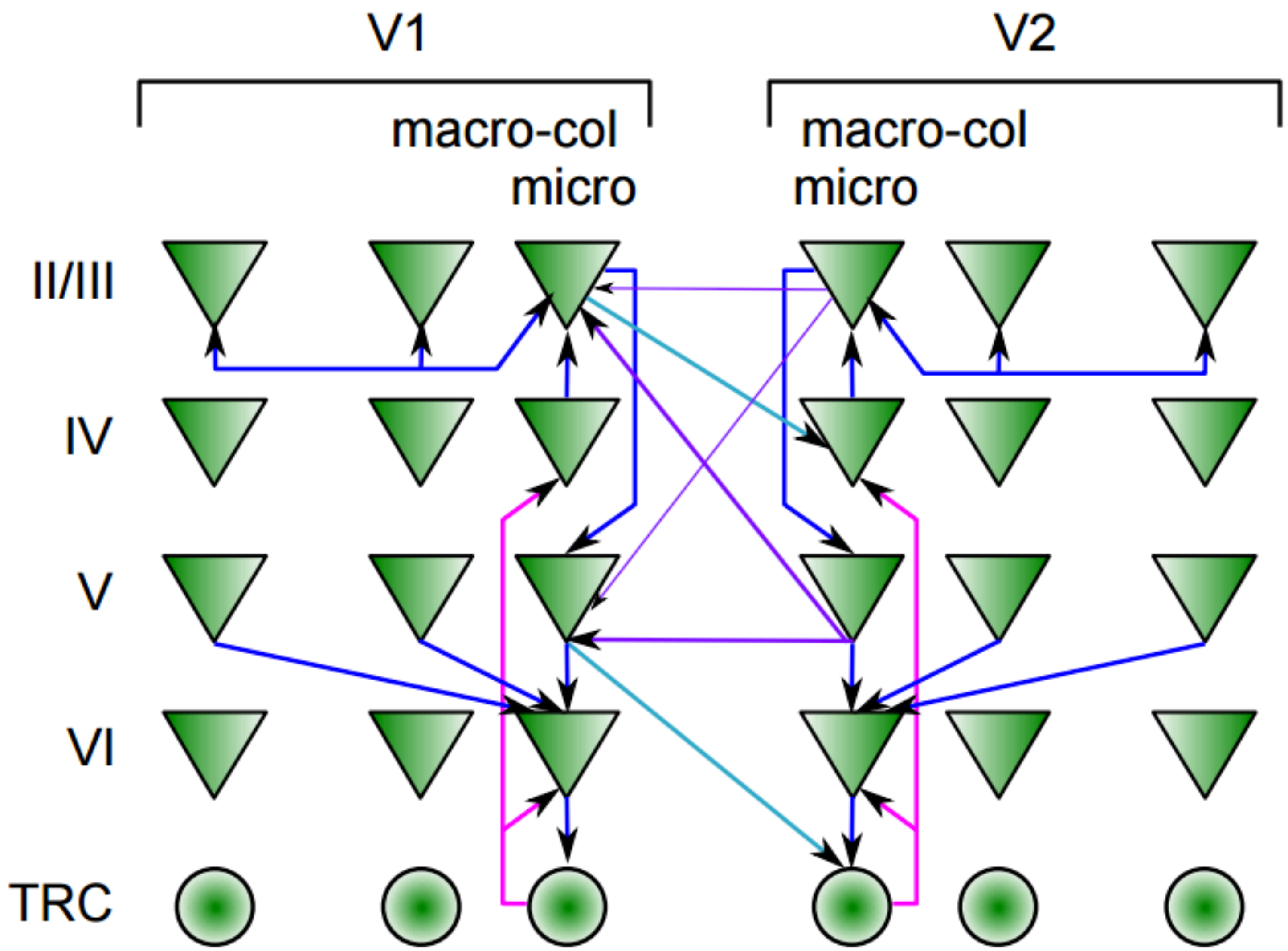


Figure 2: Anatomical connectivity supporting the LeabraTI model. Super (II/III) layers have extensive connectivity within and between areas, and do the primary information processing. Deep layer V integrates contextual information within and between areas, and 5b bursting neurons only update the sustained context, in layer VI, every 100 msec. These layer VI tonically firing neurons sustain the context through recurrent projections through the thalamic relay cells (TRC), which also communicate the context up to the Super neurons (via IV) to support generation of the next prediction.

Learning Through Time in the Thalamocortical Loops

Randall C. O'Reilly, Dean Wyatte, John Rohrlich

2) Biological fine-structure of cost functions:
the cost functions are diverse, area-specific and systematically regulated in space and time

Take Away

Not a single "end-to-end" cost function for the entire brain

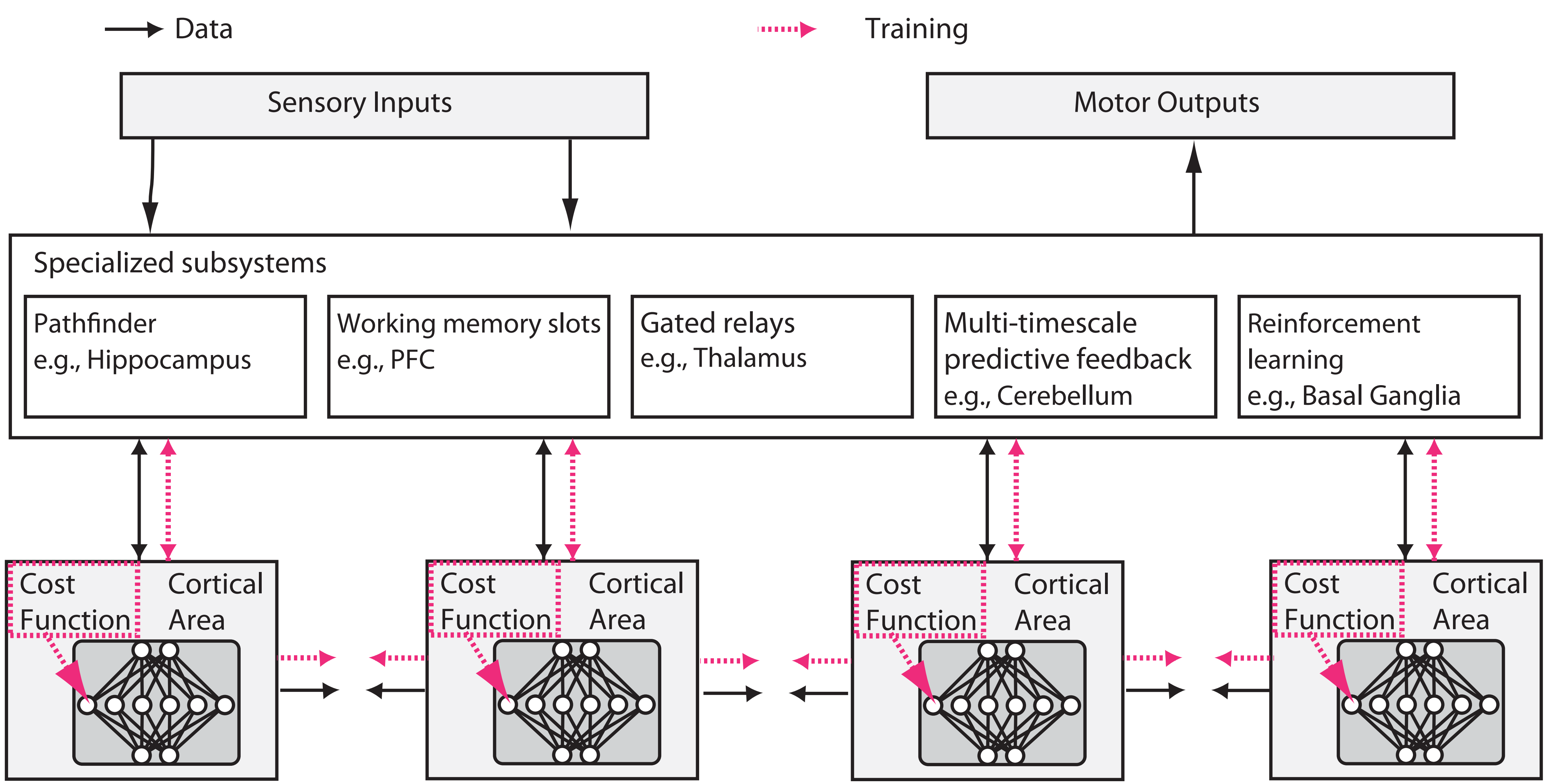
A series of cost functions generated internally and deployed to particular brain areas at particular times
in a genetically and developmentally regulated fashion

Bootstrapping of learning based on heuristics and weak labels ("prior knowledge" encoded into the training process)

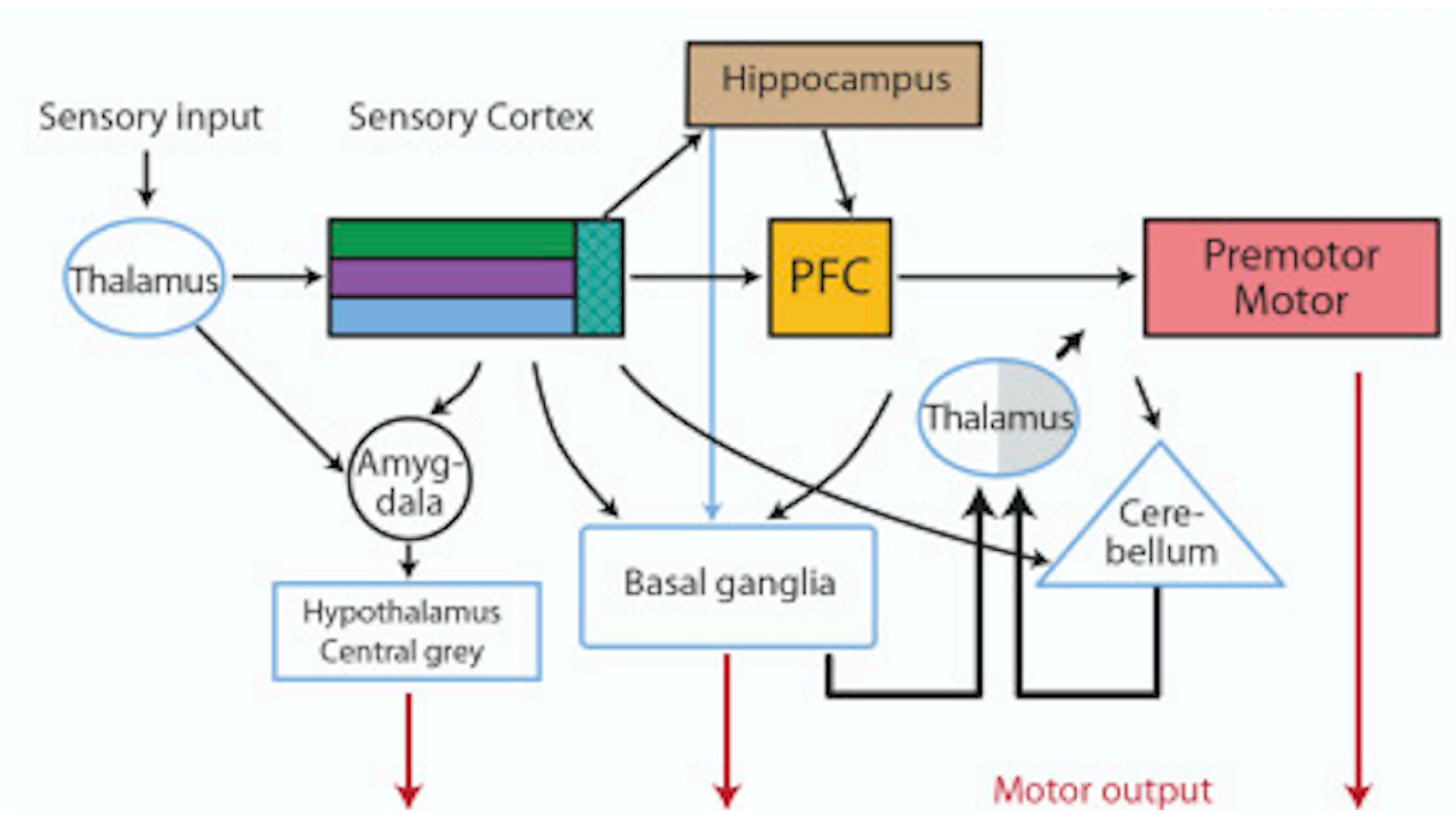
Reinforcement system may be re-purposed for diverse internal cost functions, and coupled with multi-layer credit assignment in deep networks

Three <u>hypotheses</u> for linking neuroscience and ML

3) Embedding within a pre-structured architecture:
the brain contains dedicated, specialized systems for efficiently solving key problems whose solutions are not easily bootstrapped by learning, such as information routing and variable binding



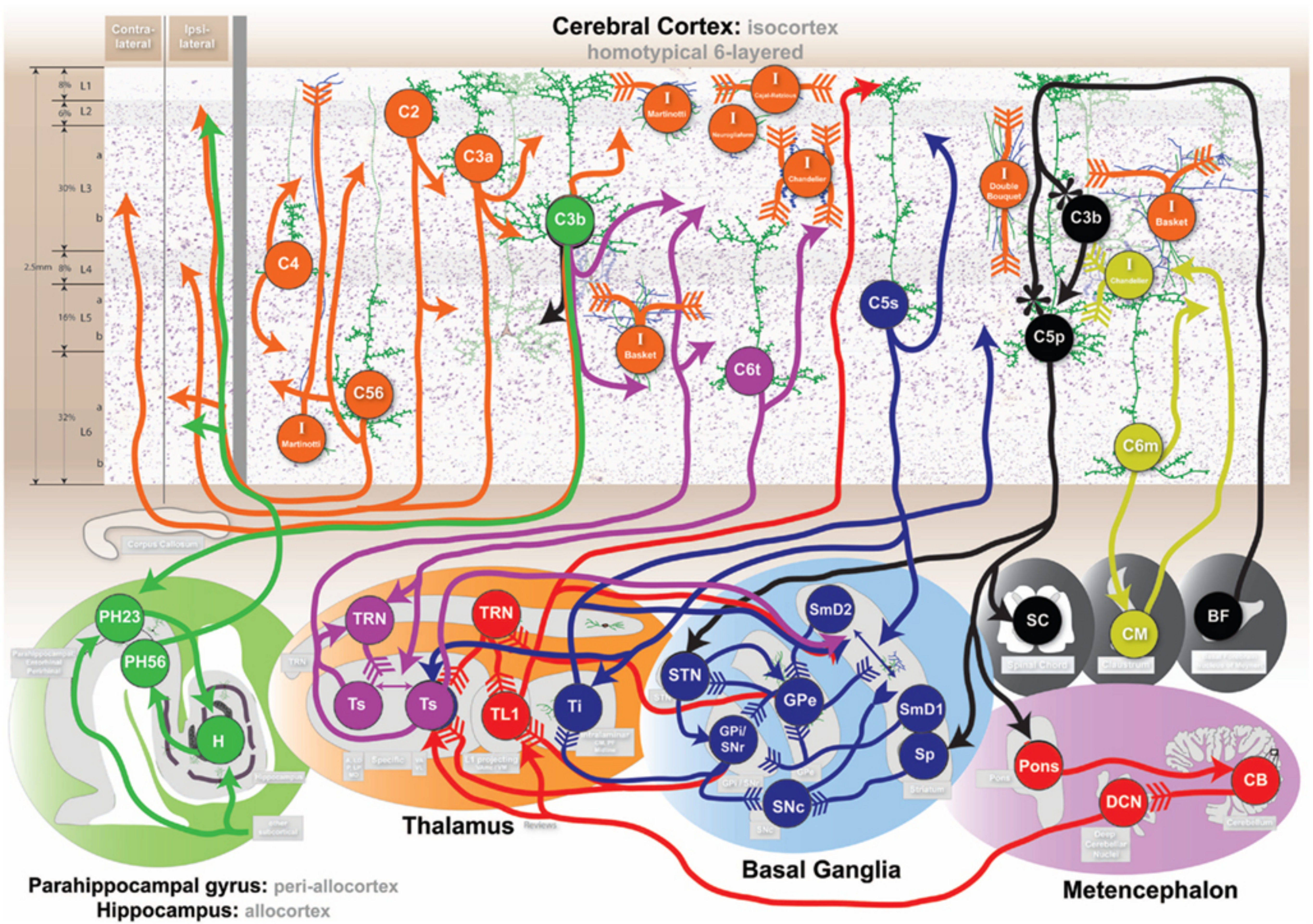
Neuroscience broadly has found an array of specialized structures



Perspective

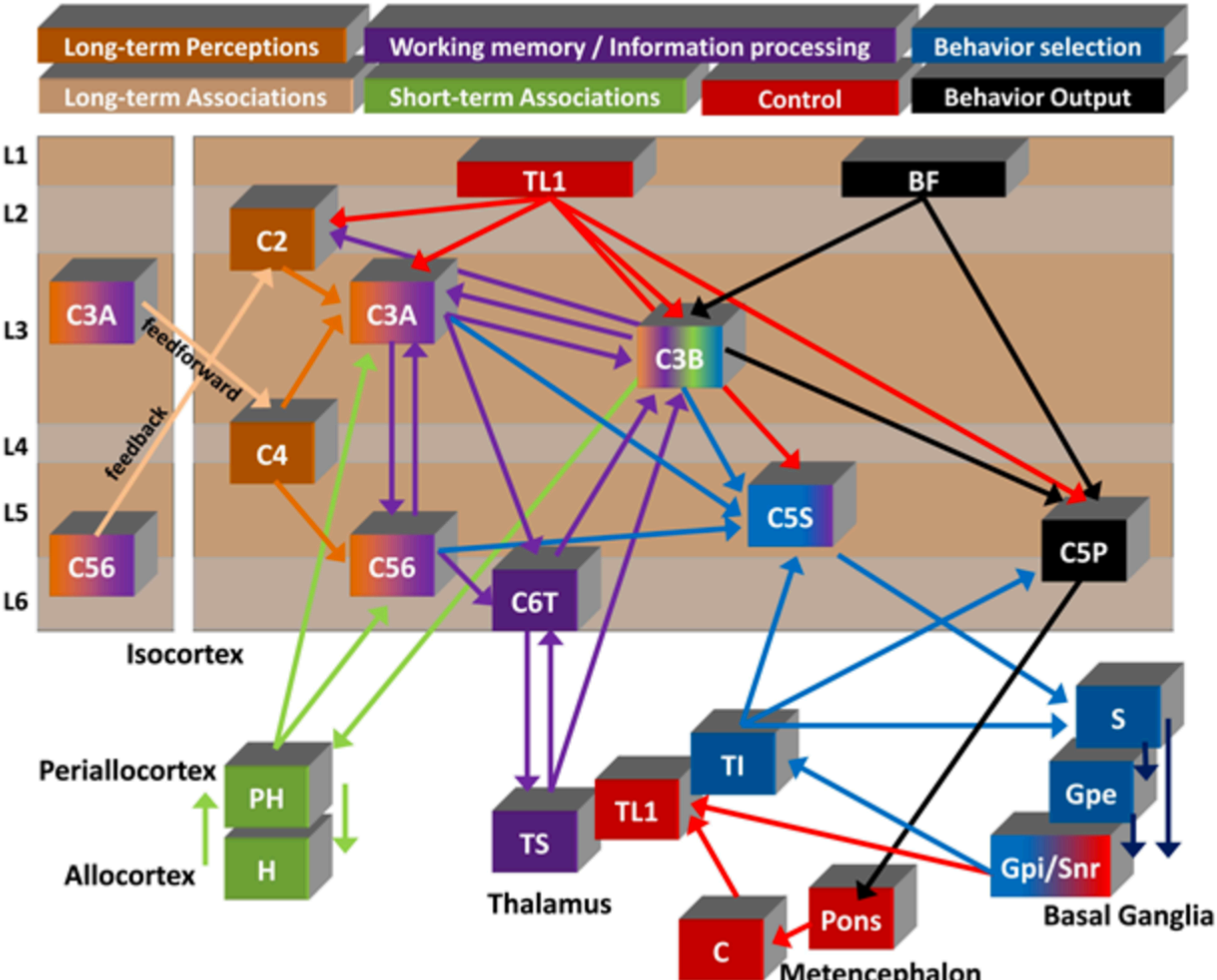
The Challenge of Understanding the Brain: Where We Stand in 2015

John Lisman[1]



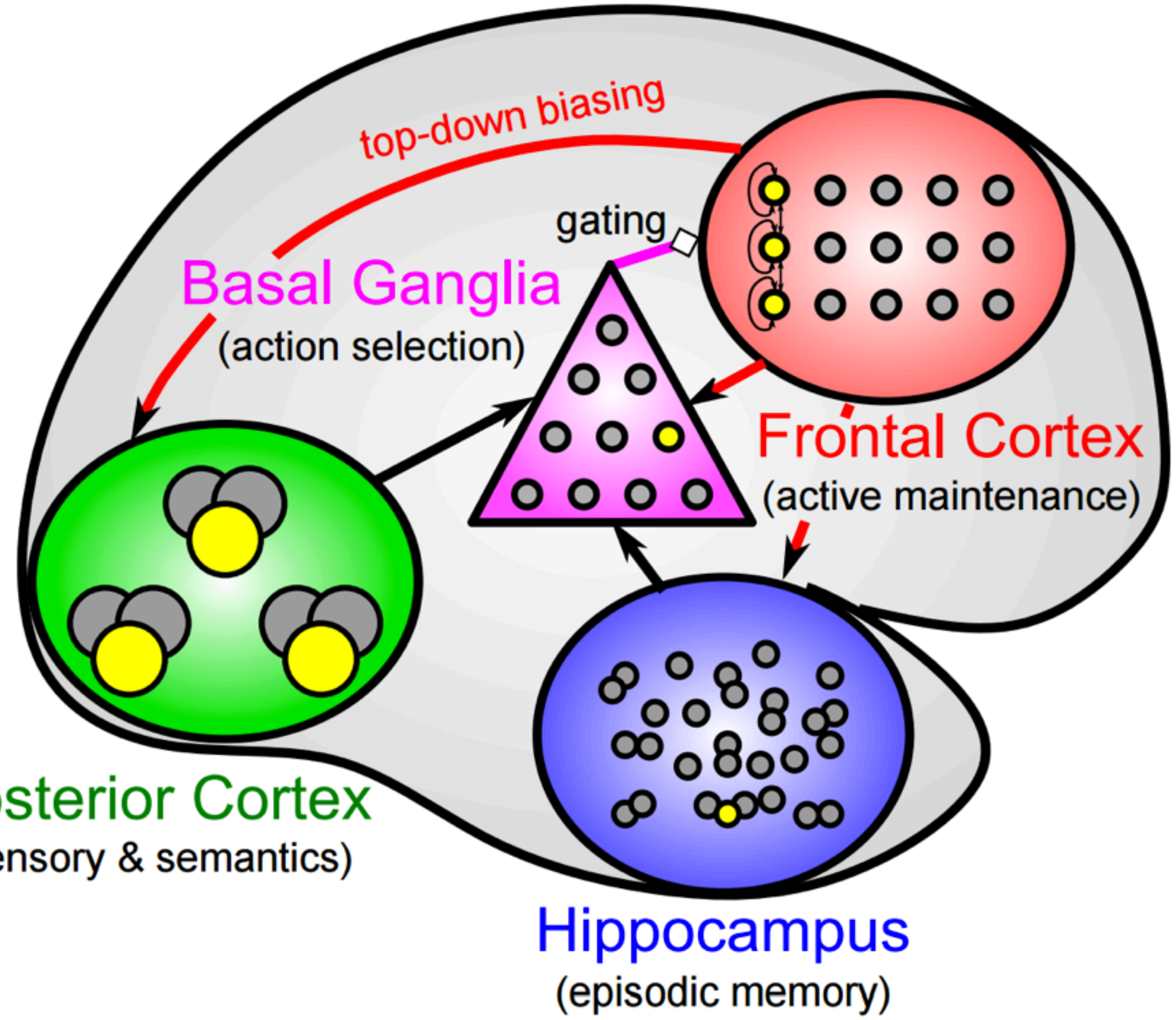
Solari and Stoner 2011

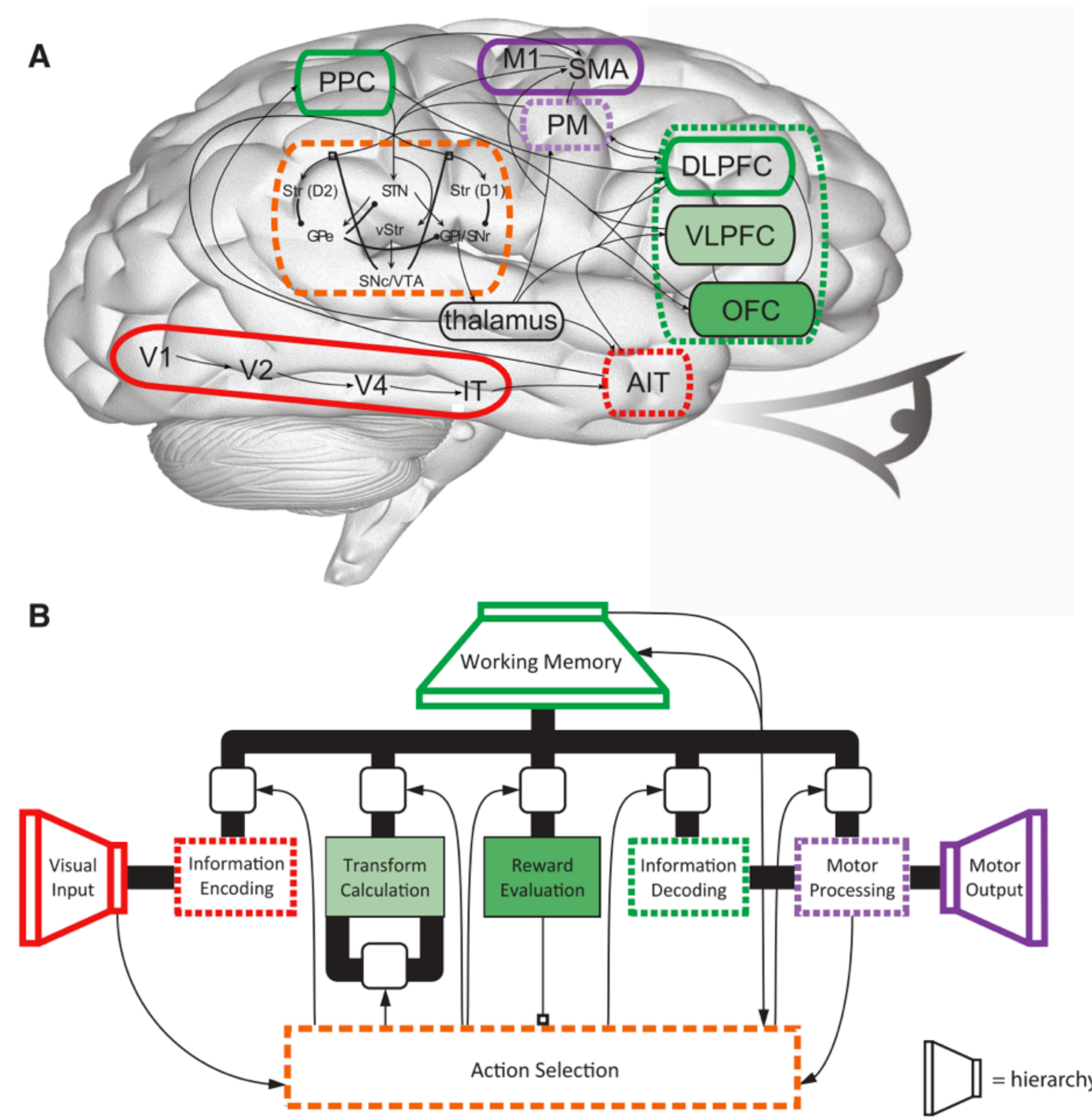
Solari and Stoner cognitive model



Solari and Stoner 2011

Integrated "biological" cognitive architectures: LEABRA and SPAUN





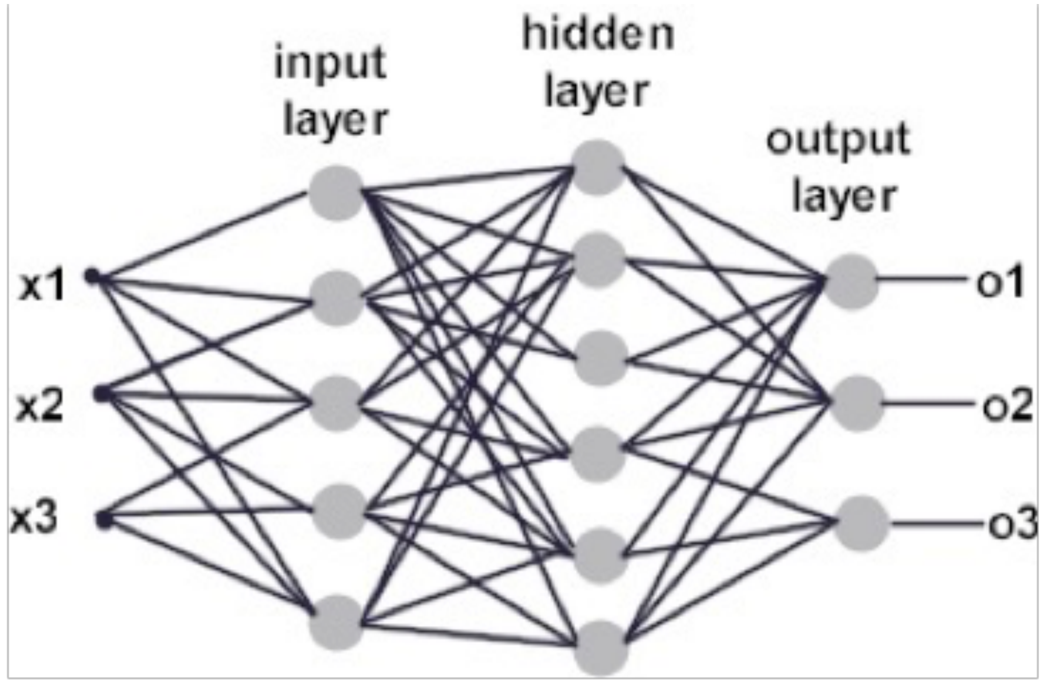
Interesting but do not show "powerful" AI performance

The Leabra Cognitive Architecture:
How to Play 20 Principles with Nature and Win!

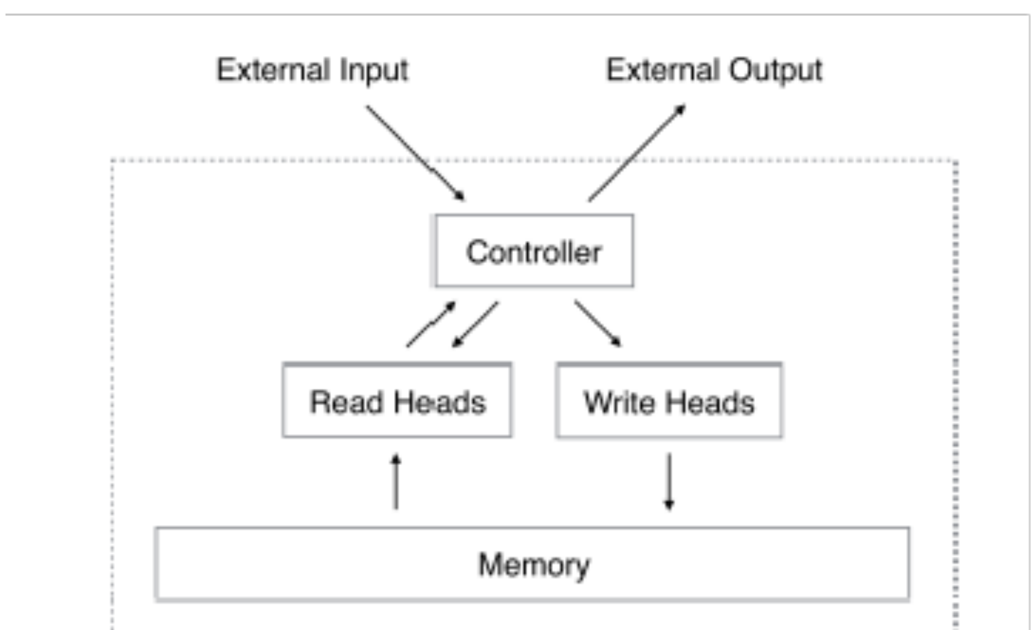
Randall C. O'Reilly, Thomas E. Hazy, and Seth A. Herd
Department of Psychology and Neuroscience
University of Colorado Boulder
345 UCB
Boulder, CO 80309
randy.oreilly@colorado.edu

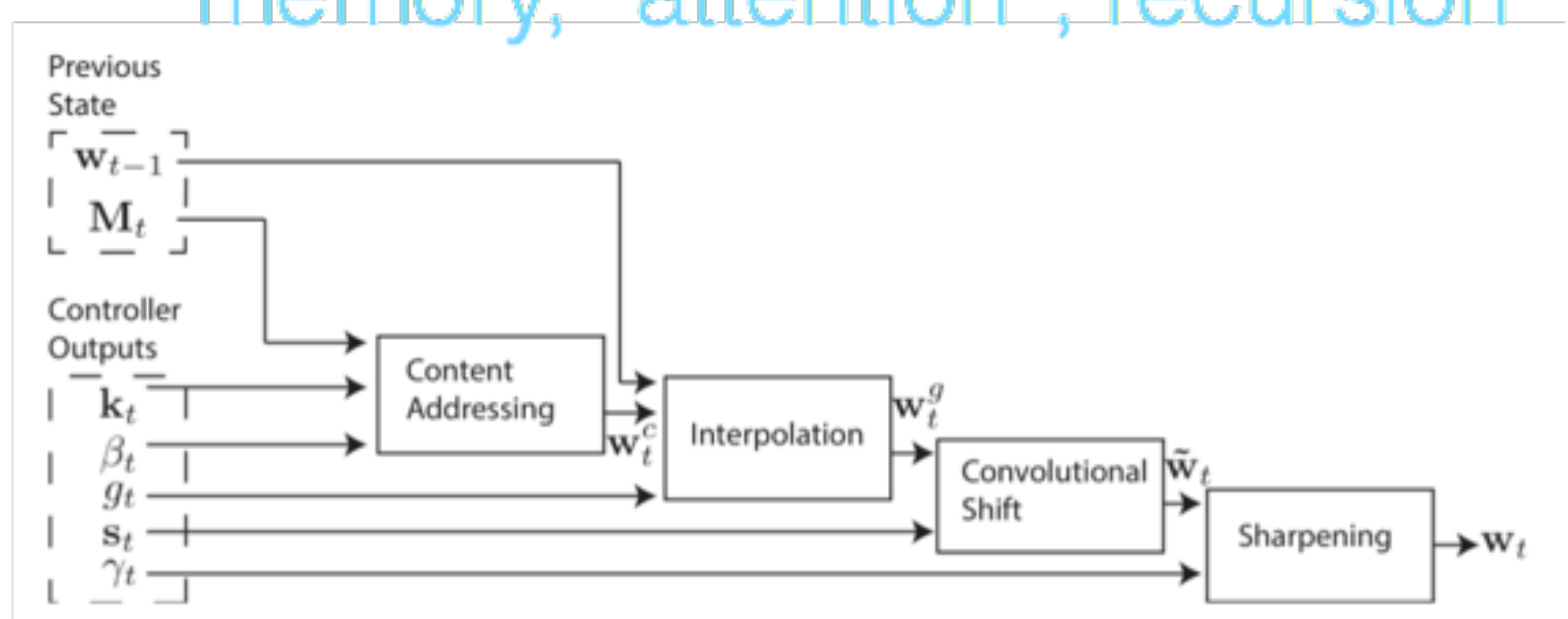
A Large-Scale Model of the Functioning Brain
Chris Eliasmith *et al.*
Science **338**, 1202 (2012);
DOI: 10.1126/science.1225266

Compare: Emerging structured machine learning architectures



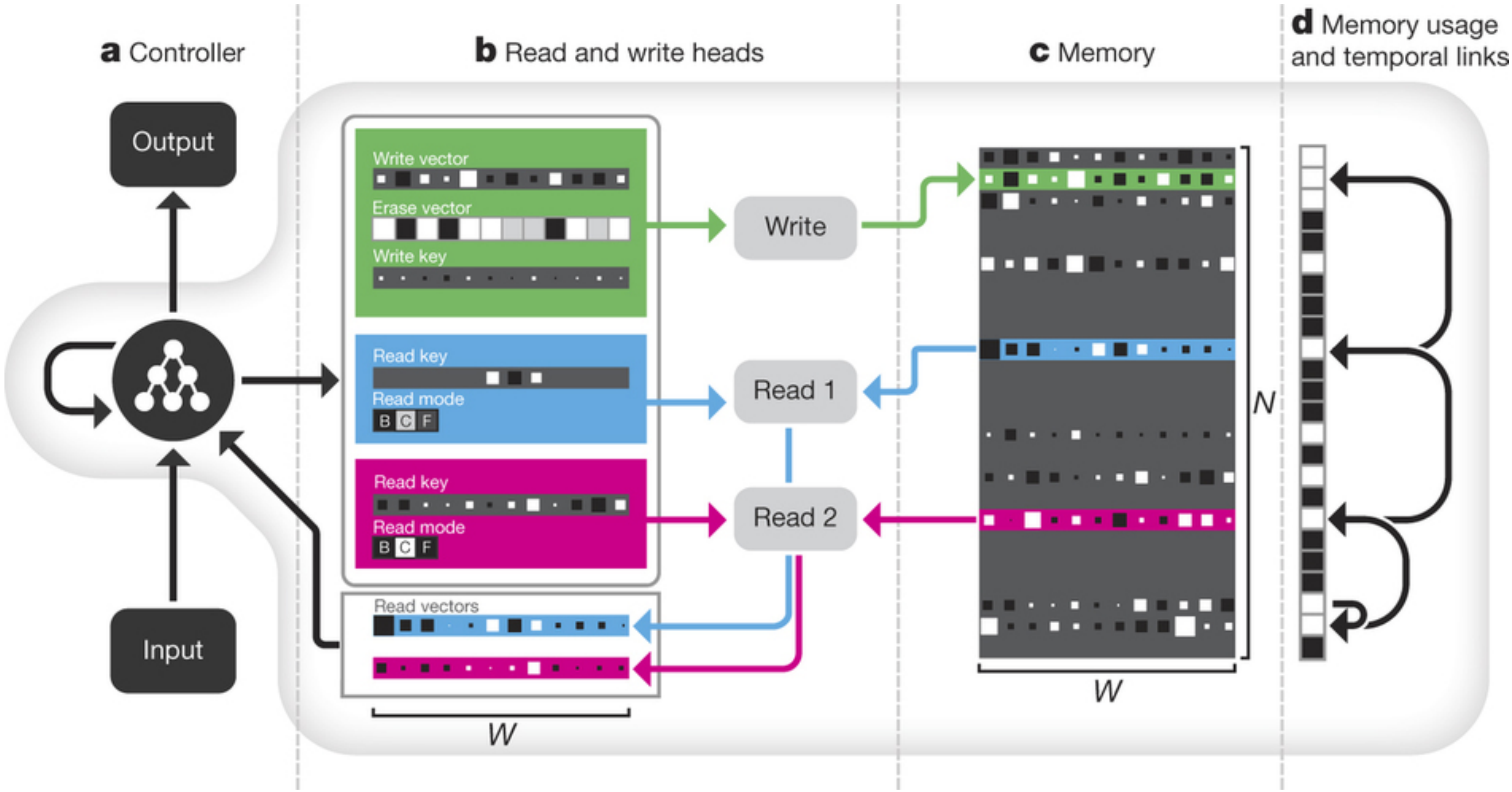
memory, “attention”, recursion





Graves, Wayne, Danihelka (2014)

<u>Compare</u>: Emerging structured machine learning architectures

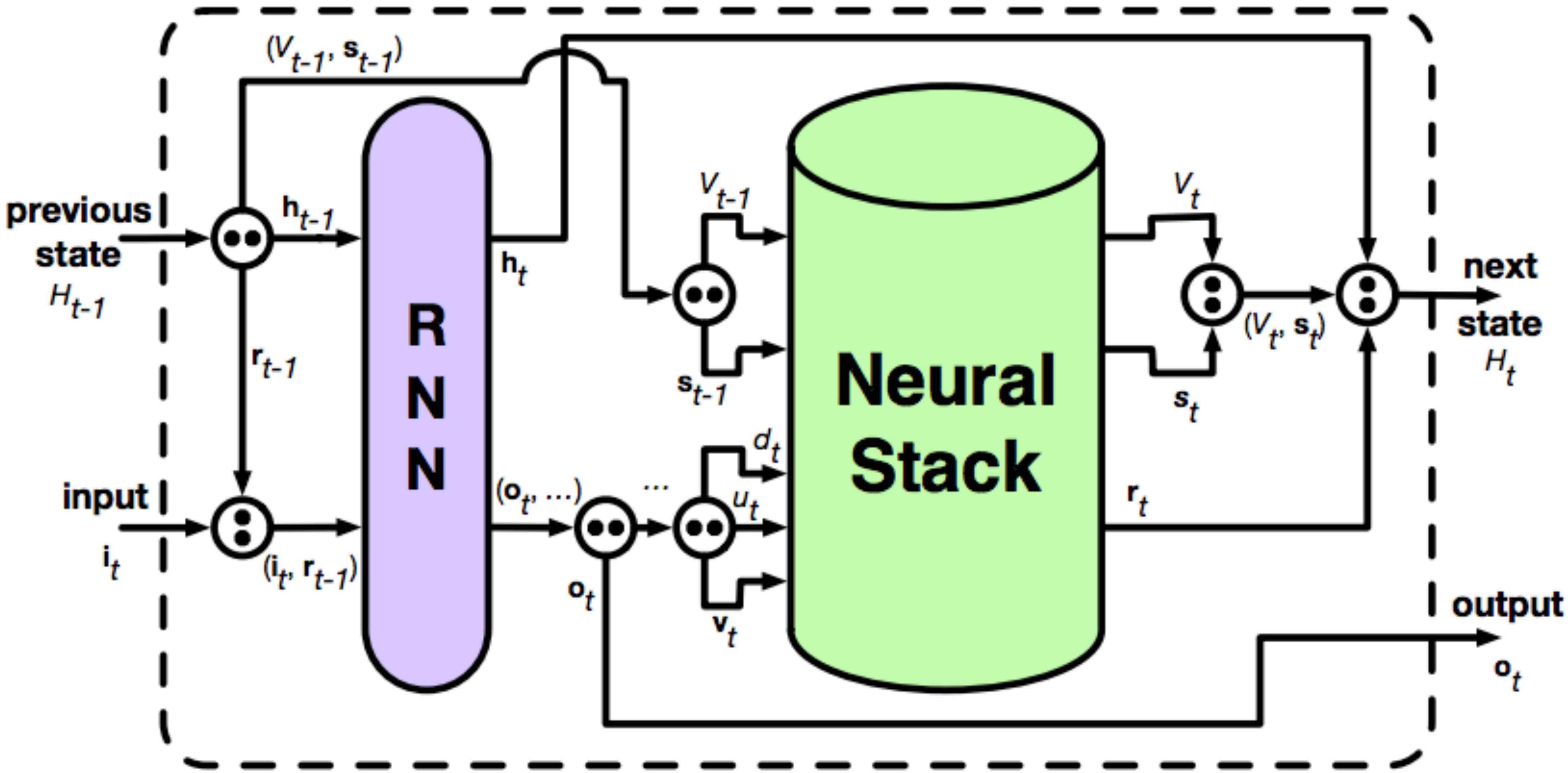


Memory system is already somewhat hippocampus-inspired…

Hybrid computing using a neural network with dynamic external memory

Alex Graves, Greg Wayne, Malcolm Reynolds, Tim Harley, Ivo Danihelka, Agnieszka Grabska-Barwińska, Sergio Gómez Colmenarejo, Edward Grefenstette, Tiago Ramalho, John Agapiou, Adrià Puigdomènech Badia, Karl Moritz Hermann, Yori Zwols, Georg Ostrovski, Adam Cain, Helen King, Christopher Summerfield, Phil Blunsom, Koray Kavukcuoglu & Demis Hassabis

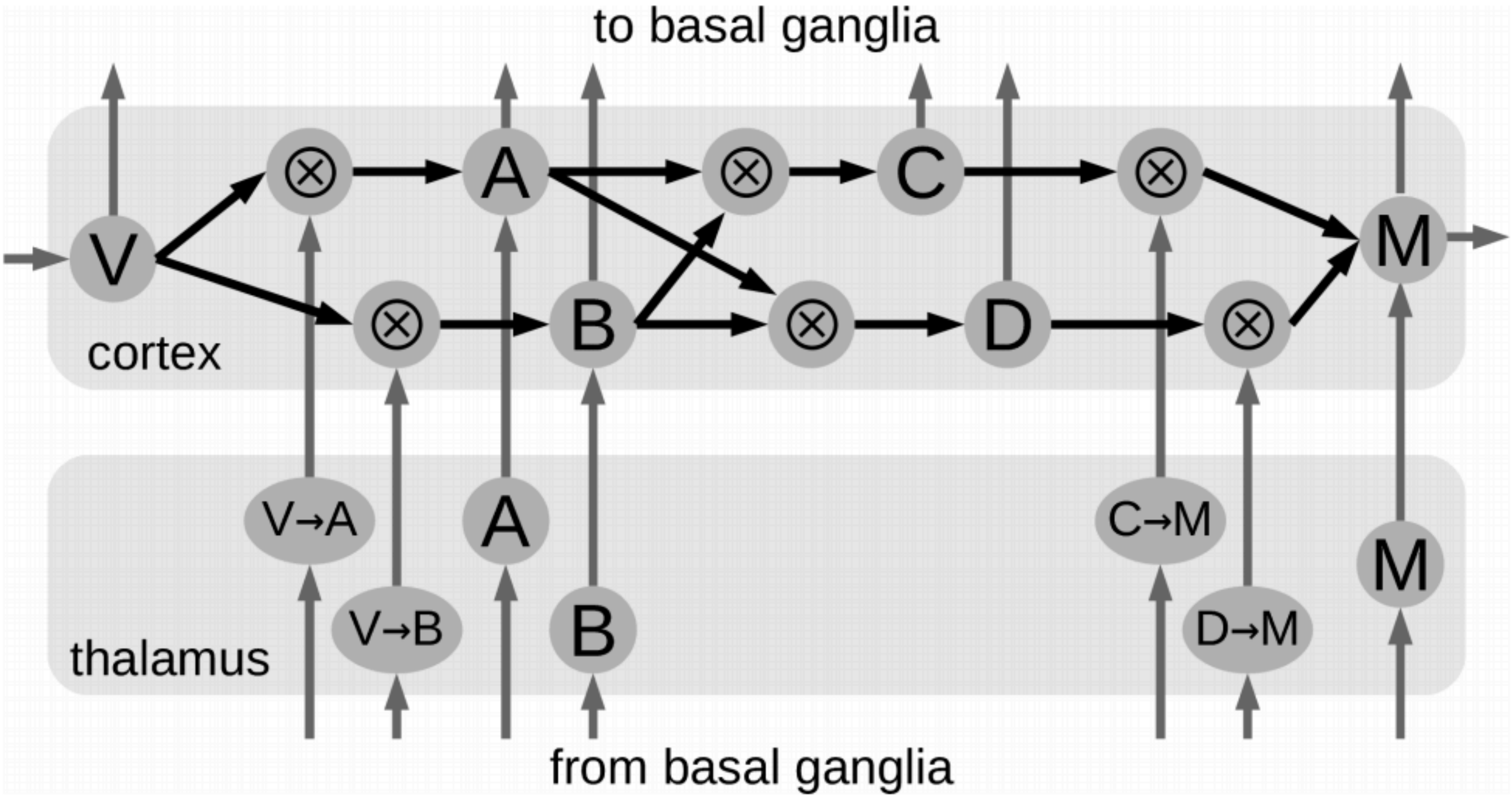
Compare: Emerging structured machine learning architectures



(c) RNN Controlling a Stack

Figure 1: Illustrating a Neural Stack's Operations, Recurrent Structure, and Control

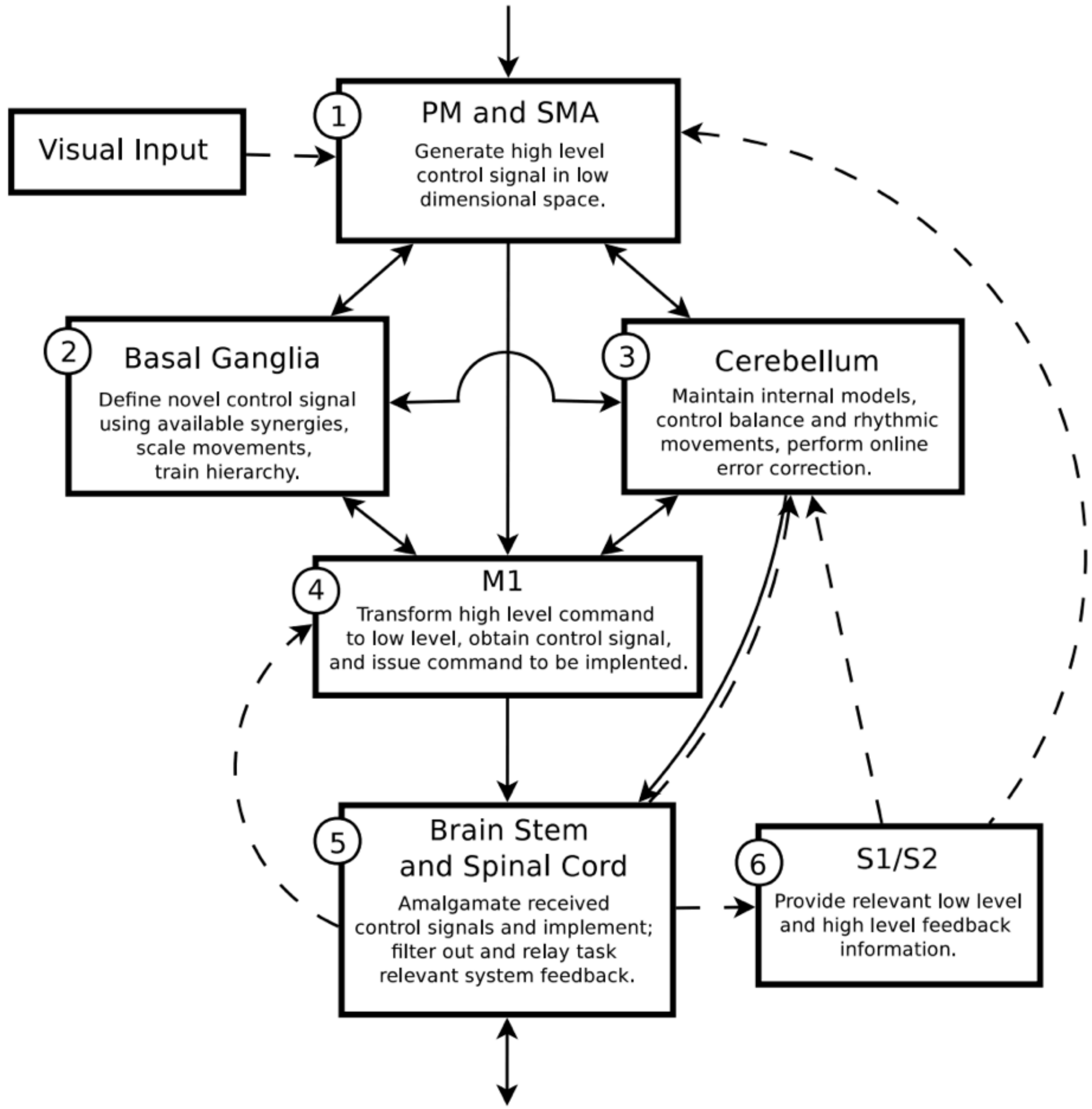
Pre-structured architectures in the brain: to make learning efficient?



thalamic gating of "copy and paste" operations between cortical working memory buffers, executing a sequence of steps controlled by the basal ganglia

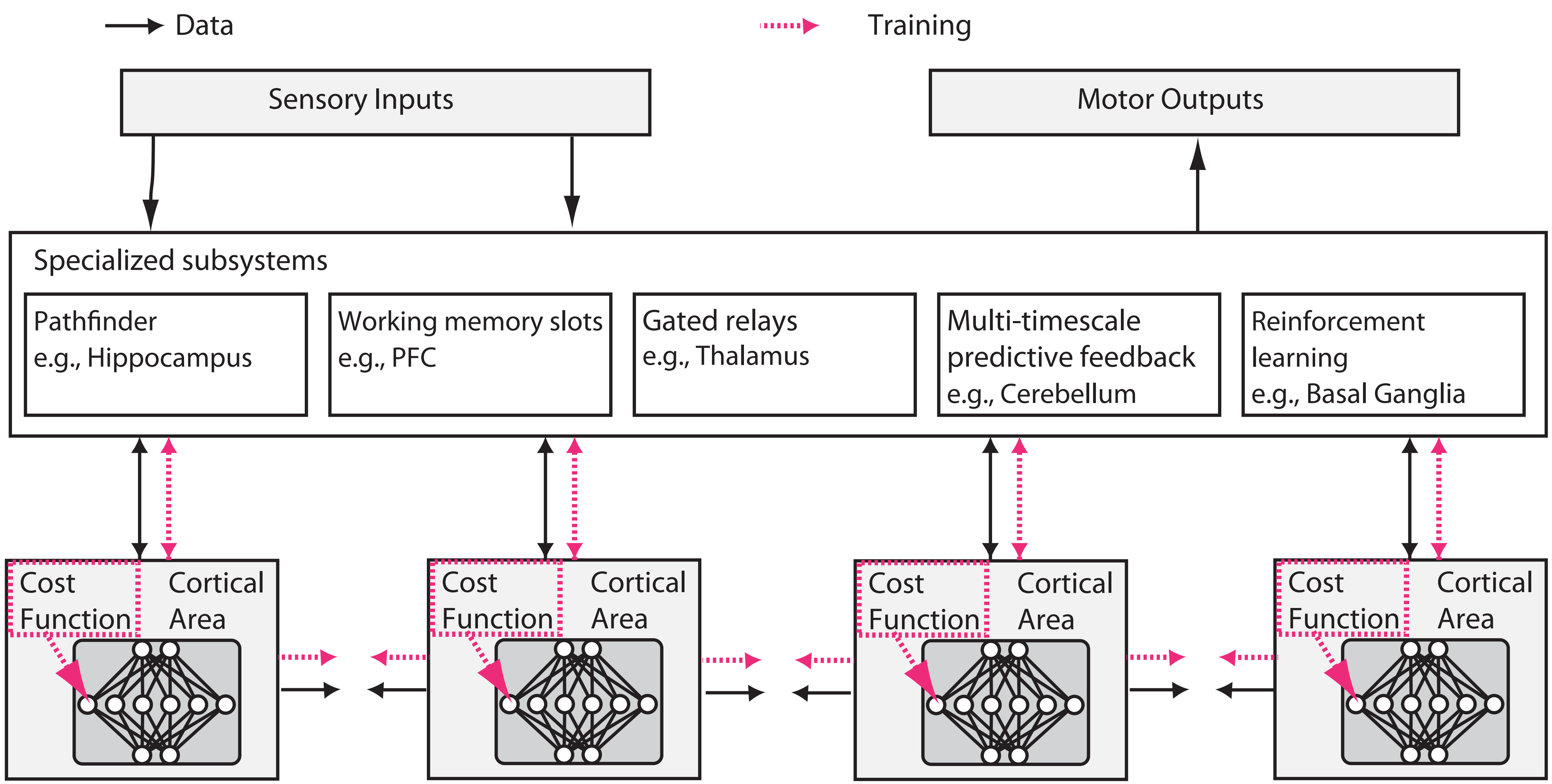
Stewart, Eliasmith et al 2010

Pre-structured architectures in the brain: to make learning efficient?



The neural optimal control hierarchy for motor control

T DeWolf and C Eliasmith


Data
Training
Sensory Inputs
Motor Outputs
Specialized subsystems
Pathfinder
e.g., Hippocampus
Working memory slots
e.g., PFC
Gated relays
e.g., Thalamus
Multi-timescale
predictive feedback
e.g., Cerebellum
Reinforcement
learning
e.g., Basal Ganglia
Cost
Function
Cortical
Area
Cost
Function
Cortical
Area
Cost
Function
Cortical
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Cost
Function
Cortical
Area

Differences with today's deep learning

Information represented via assemblies/attractors

Autoassociative dynamics in the generation of sequences of hippocampal place cells

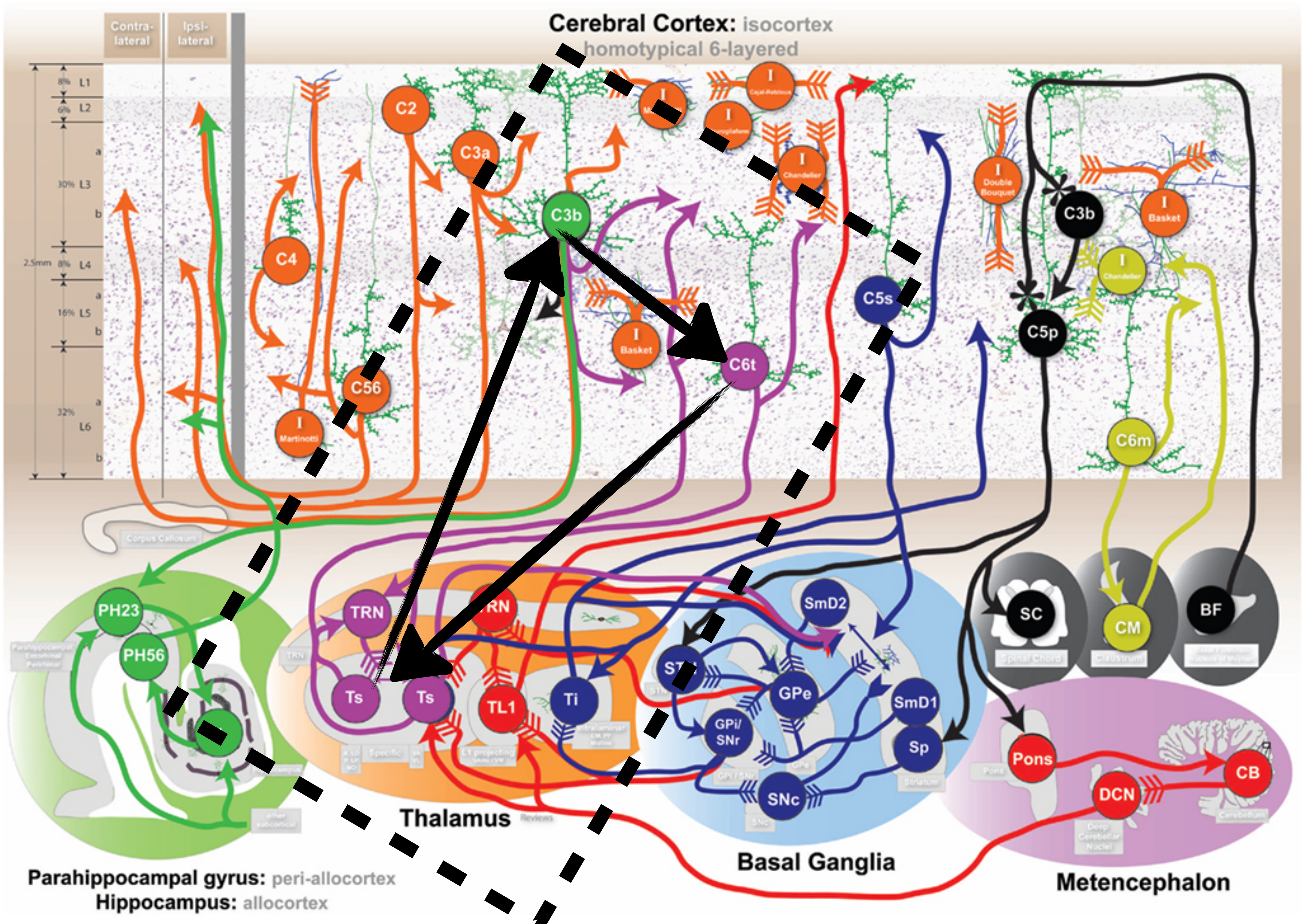
Brad E. Pfeiffer* and David J. Foster†

Neuronal circuits produce self-sustaining sequences of activity patterns, but the precise mechanisms remain unknown. Here we provide evidence for autoassociative dynamics in sequence generation. During sharp-wave ripple (SWR) events, hippocampal neurons express sequenced reactivations, which we show are composed of discrete attractors. Each attractor corresponds to a single location, the representation of which sharpens over the course of several milliseconds, as the reactivation focuses at that location. Subsequently, the reactivation transitions rapidly to a spatially discontiguous location. This alternation between sharpening and transition occurs repeatedly within individual SWRs and is locked to the slow-gamma (25 to 50 hertz) rhythm. These findings support theoretical notions of neural network function and reveal a fundamental discretization in the retrieval of memory in the hippocampus, together with a function for gamma oscillations in the control of attractor dynamics.

See also: "Imprinting and recalling cortical ensembles" by Yuste lab

Differences with today's deep learning

The attractors may be in cortico-thalamo-cortical loops

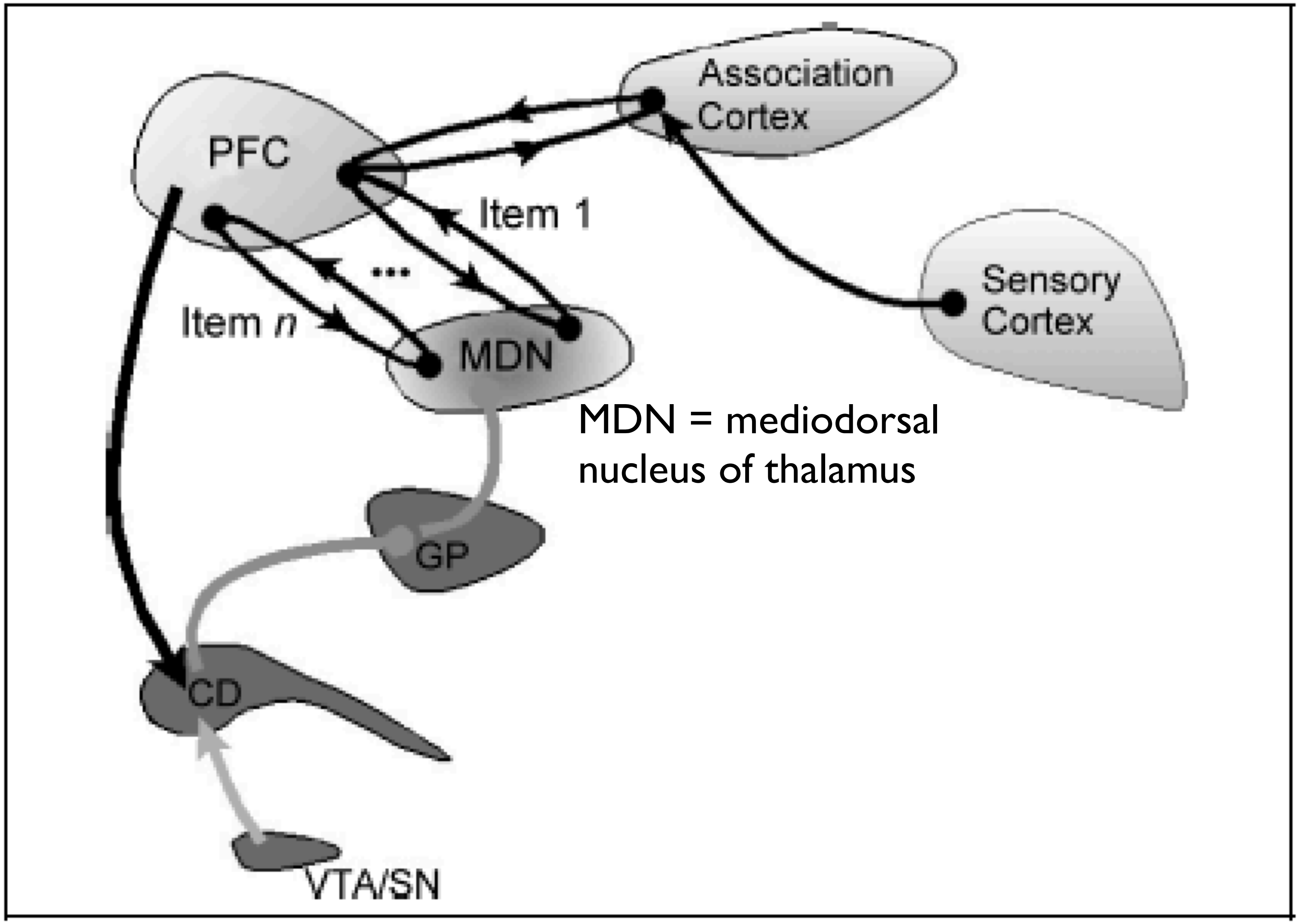


Cognitive consilience: primate non-primary neuroanatomical circuits underlying cognition

Soren Van Hout Solari[1,2]* and Rich Stoner[3]*

Differences with today's deep learning

The attractors may be in cortico-thalamo-cortical loops



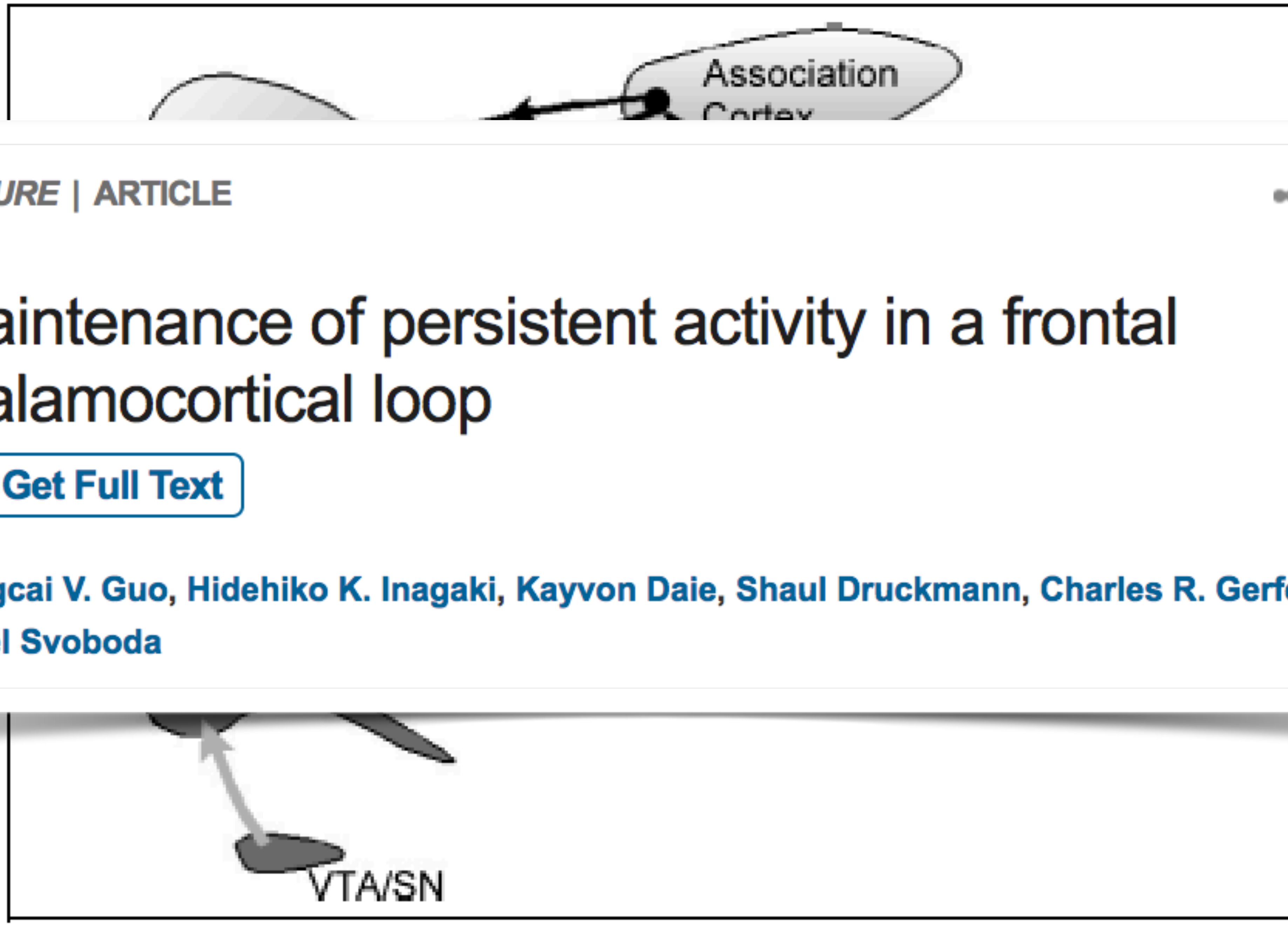
FROST: A Distributed Neurocomputational Model of Working Memory Maintenance

F. Gregory Ashby[1], Shawn W. Ell[2], Vivian V. Valentin[1], and Michael B. Casale[1]

Basal ganglia gated cortico-thalamo-cortical loops in working memory...

Differences with today's deep learning

The attractors may be in cortico-thalamo-cortical loops



NATURE | ARTICLE

Maintenance of persistent activity in a frontal thalamocortical loop

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Zengcai V. Guo, Hidehiko K. Inagaki, Kayvon Daie, Shaul Druckmann, Charles R. Gerfen & Karel Svoboda

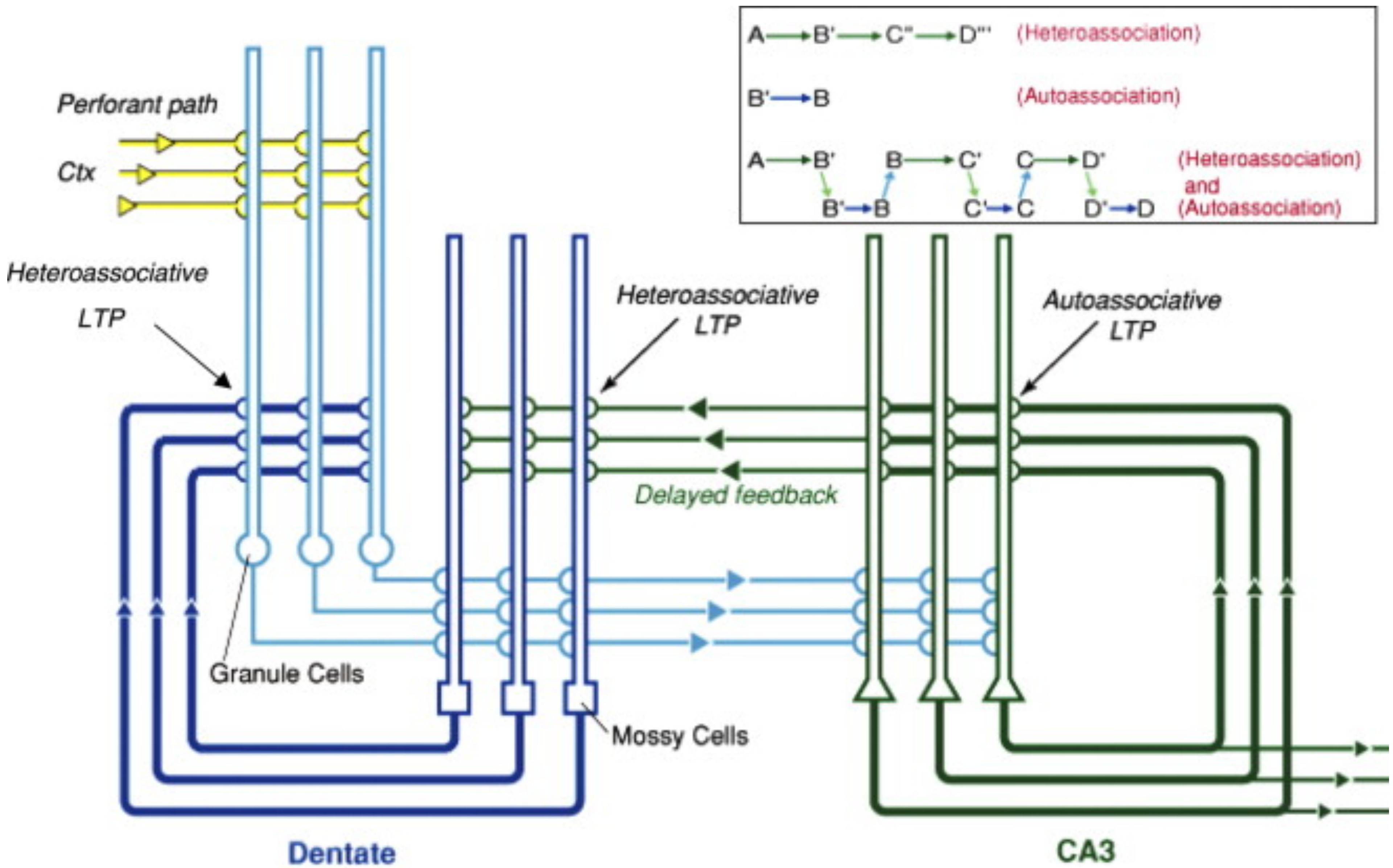
FROST: A Distributed Neurocomputational Model of Working Memory Maintenance

F. Gregory Ashby[1], Shawn W. Ell[2], Vivian V. Valentin[1], and Michael B. Casale[1]

Basal ganglia gated cortico-thalamo-cortical loops in working memory...

Differences with today's deep learning

Auto-associative and hetero-associative memories



Recall of memory sequences by interaction of the dentate and CA3: A revised model of the phase precession

John E. Lisman[a], Lucia M. Talamini[b, 1], Antonino Raffone[c, 2]

Differences with today's deep learning

Coordinating communication via oscillations?

Thalamus sets up synchronous oscillations in donor and recipient cortical areas, and this synchrony gates direct cortico-cortical information transfer between them

(adapted from [6]). Information is transmitted via the cortico–cortical connections to the next cortical region or regions, while the HO thalamic nuclei selectively activate the appropriate downstream cortical area that will be engaged in the next level of processing. Building from

Thalamic pathways underlying prefrontal cortex–medial temporal lobe oscillatory interactions

Nicholas A. Ketz, Ole Jensen, Randall C. O'Reilly

DOI: http://dx.doi.org/10.1016/j.tins.2014.09.007 | CrossMark

Differences with today's deep learning

Coordinating communication via oscillations?

NATURE | LETTER

Thalamic amplification of cortical connectivity sustains attentional control

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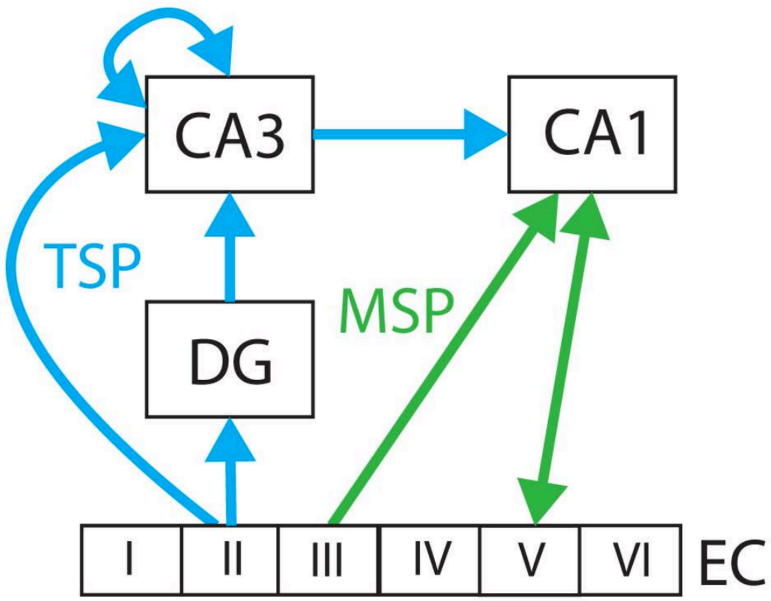
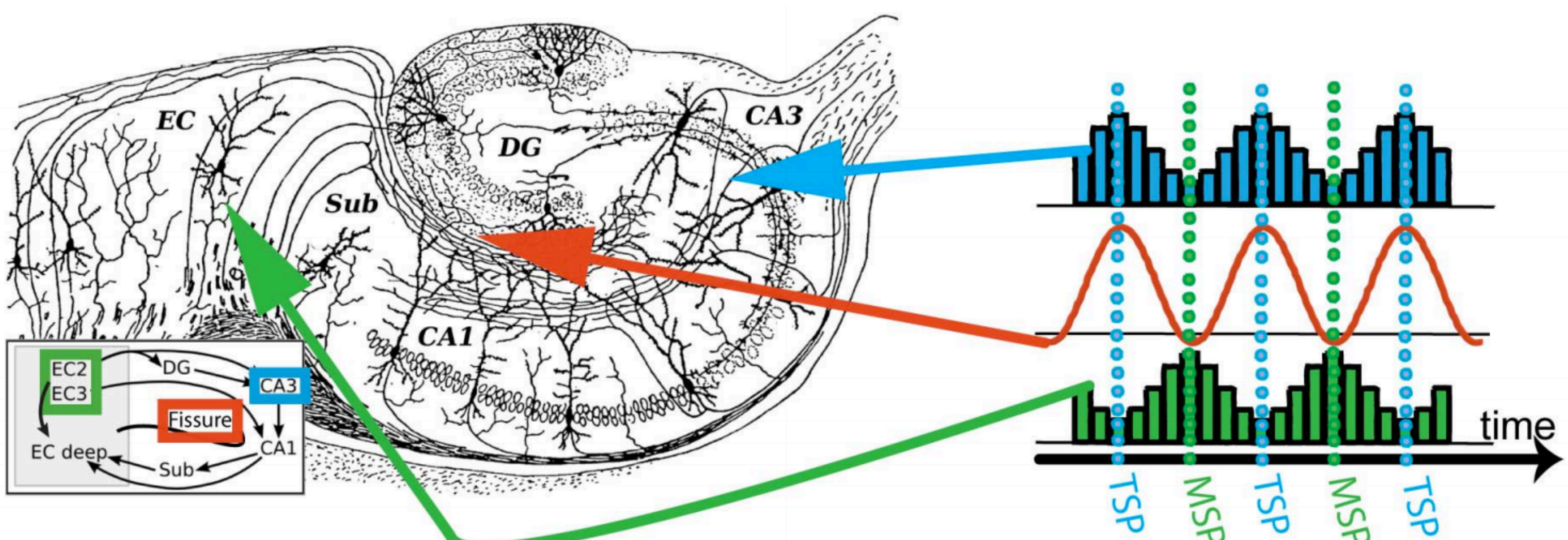
L. Ian Schmitt, Ralf D. Wimmer, Miho Nakajima, Michael Happ, Sima Mofakham & Michael M. Halassa

Differences with today's deep learning

Coordinating learning via oscillations?





Theta Coordinated Error-Driven Learning in the Hippocampus

Nicholas Ketz, Srinimisha G. Morkonda, Randall C. O'Reilly

<u>TAKE HOME MESSAGES</u>

We have no idea if the brain "does backprop", but also no reason to think it <u>cannot</u>

The end of the "representations + transformations" program?

Neural representations are complex

You can find any almost any "tuning"

(e.g., see recent Giacomo/Ganguli grid cell results)

Neural computations are diverse

What if "understanding" should mean identifying:

Architecture

Cost Functions (as a function of area and time)

Means of optimization

…rather than directly modeling how representations
are transformed, i.e.,
rather than listing "atoms of computation"

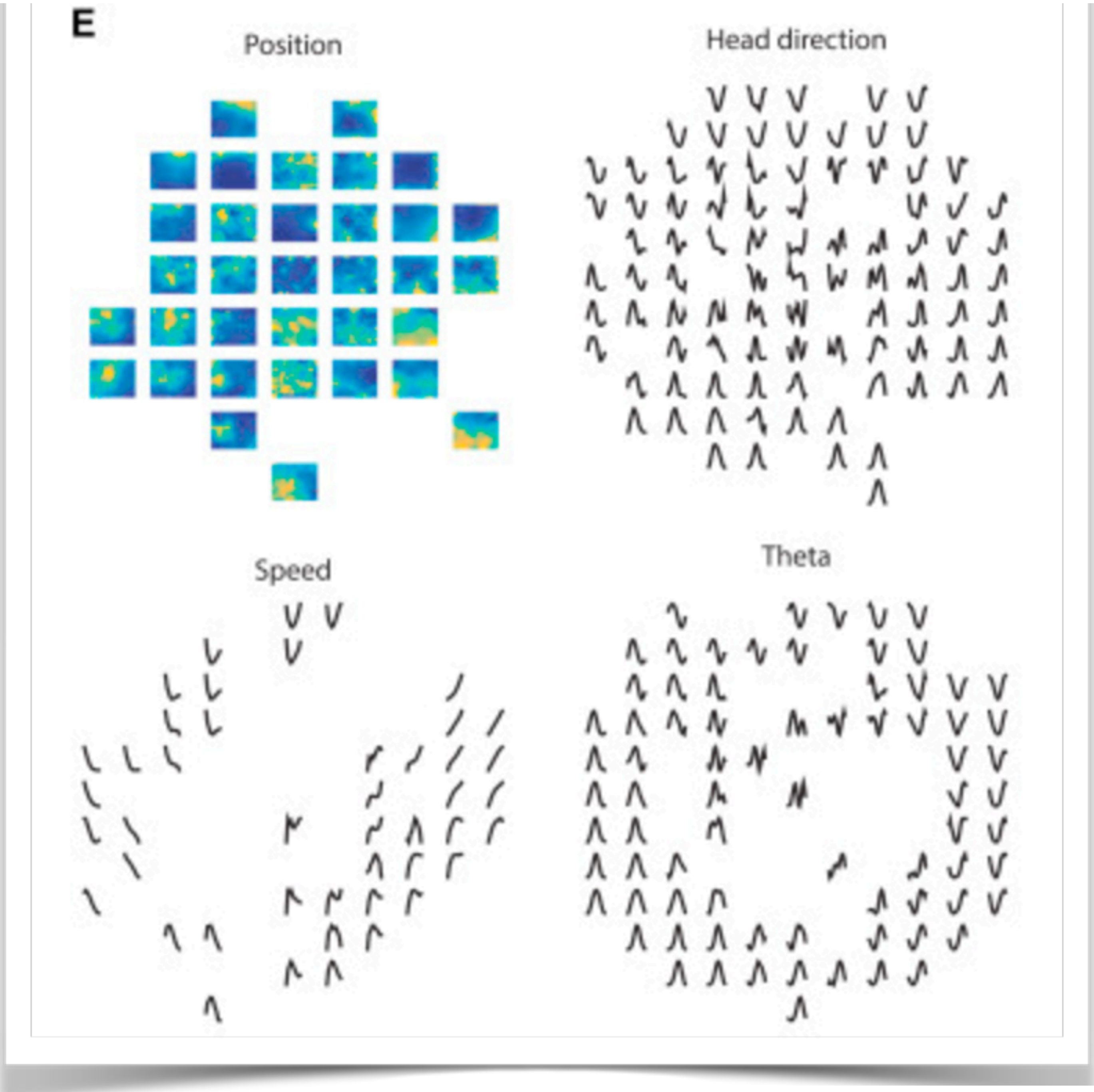
But: <u>need</u> to understand the significance of key elements like
Attractors, Oscillations, Dendritic Computation, Diversity of Neurons/Synapses
and the nature of the the specialized memory systems and control structures

Look to mesoscale anatomy for clues to architecture?

You can find almost any "tuning"

Summary

Medial entorhinal grid cells display strikingly symmetric spatial firing patterns. The clarity of these patterns motivated the use of specific activity pattern shapes to classify entorhinal cell types. While this approach successfully revealed cells that encode boundaries, head direction, and running speed, it left a majority of cells unclassified, and its pre-defined nature may have missed unconventional, yet important coding properties. Here, we apply an unbiased statistical approach to search for cells that encode navigationally relevant variables. This approach successfully classifies the majority of entorhinal cells and reveals unsuspected entorhinal coding principles. First, we find a high degree of mixed selectivity and heterogeneity in superficial entorhinal neurons. Second, we discover a dynamic and remarkably adaptive code for space that enables entorhinal cells to rapidly encode navigational information accurately at high running speeds. Combined, these observations advance our current understanding of the mechanistic origins and functional implications of the entorhinal code for navigation.



A Multiplexed, Heterogeneous, and Adaptive Code for Navigation in Medial Entorhinal Cortex

Kiah Hardcastle, Niru Maheswaranathan, Surya Ganguli, Lisa M. Giocomo[3]

Thank You