Explainable and Reliable AI and Autonomous Adaptive Intelligence:

Deep Learning, Adaptive Resonance, and Models of Perception, Emotion, and Action

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This lecture is based on the following article:

Grossberg, S. (2020). A path towards Explainable AI and Autonomous Adaptive Intelligence: Deep Learning, Adaptive Resonance, and Models of Perception, Emotion, and Action
Frontiers in Neurobotics, June 25, 2020
https://doi.org/10.3389/fnbot.2020.00036 (OPEN ACCESS)

The article summarizes core problems of DEEP LEARNING, such as its untrustworthiness (unexplainable) and unreliability (catastrophic forgetting),

explains how ADAPTIVE RESONANCE overcomes them, indeed overcomes 17 problems of Deep Learning,

and outlines a blueprint for achieving autonomous adaptive intelligence

The article is part of a Frontiers in Neurobotics special issue about EXPLAINABLE AI

Its editors J. L. Olds, J. L. Krichmar, H. Tang, and J. V. Sanchez-Andres write

"Though Deep Learning is the main pillar of current AI techniques and is ubiquitous in basic science and real-world applications, it is also flagged by AI researchers for its black-box problem: *it is easy to fool, and it also cannot explain how it makes a prediction or decision*"

Deep Learning is NOT TRUSTWORTHY

No life or death decision, such as a medical or financial decision, can confidently be made based upon a Deep Learning prediction

FROM BACK PROPAGATION TO DEEP LEARNING

Deep Learning uses the back propagation (BP) algorithm to learn how to predict output vectors in response to input vectors

BP was based upon perceptron learning principles
Rosenblatt (1958, 1987)

It has a complicated history; cf., Schmidhuber (2020)

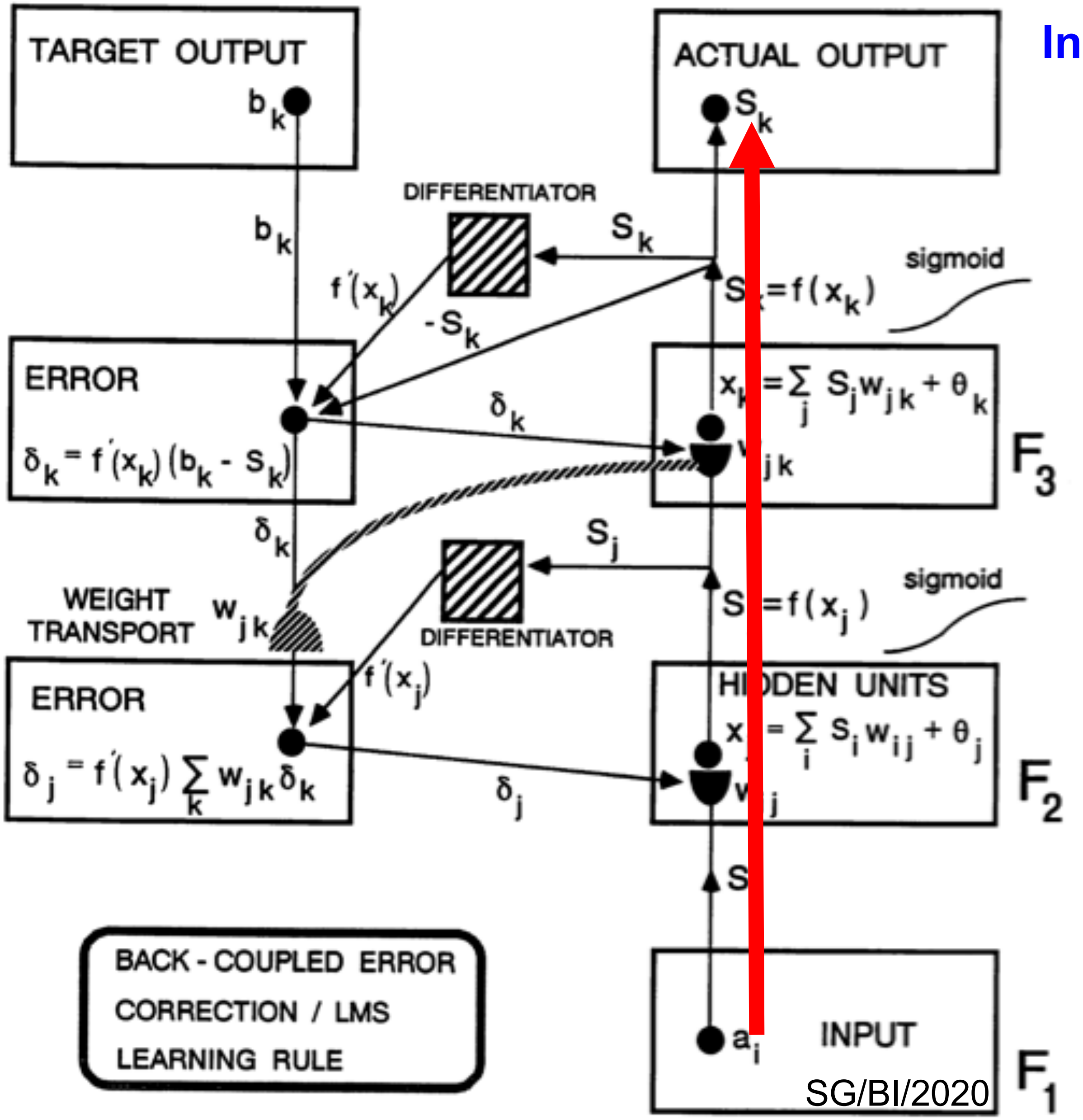
Major contributors include:
Amari (1972), Werbos (1974), Parker (1985)

BP reached its modern form with simulated applications in Werbos (1974)

It was popularized by
Rumelhart, Hinton, and Williams (1986)

BACK PROPAGATION CIRCUIT
figure reprinted from Carpenter (1989)

Information flows FEEDFORWARD



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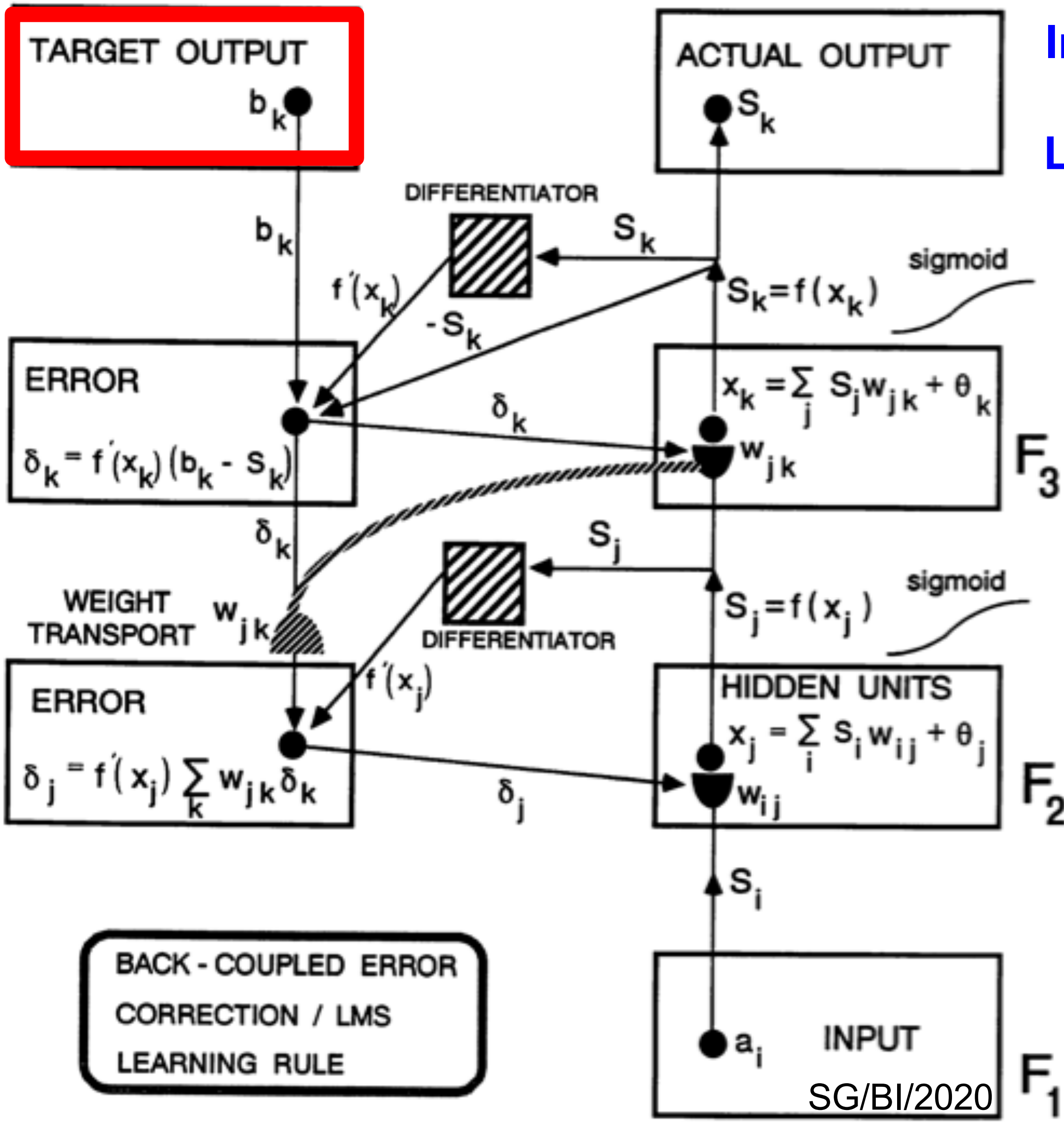

Information flows FEEDFORWARD

Learning is SUPERVISED

An external teacher on each trial

BACK PROPAGATION CIRCUIT

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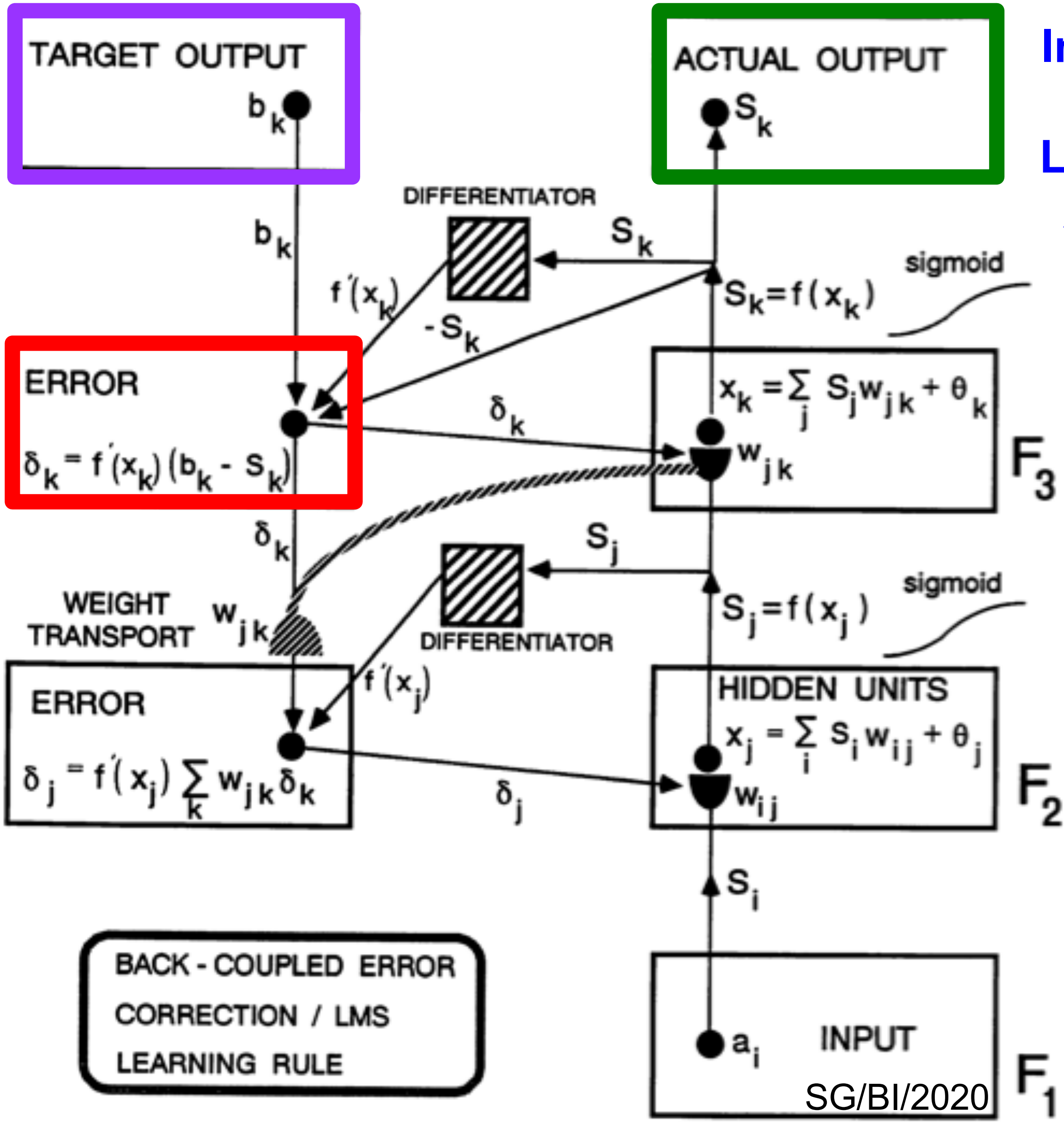

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Teaching signal is the ERROR or MISMATCH between ACTUAL and TARGET outputs

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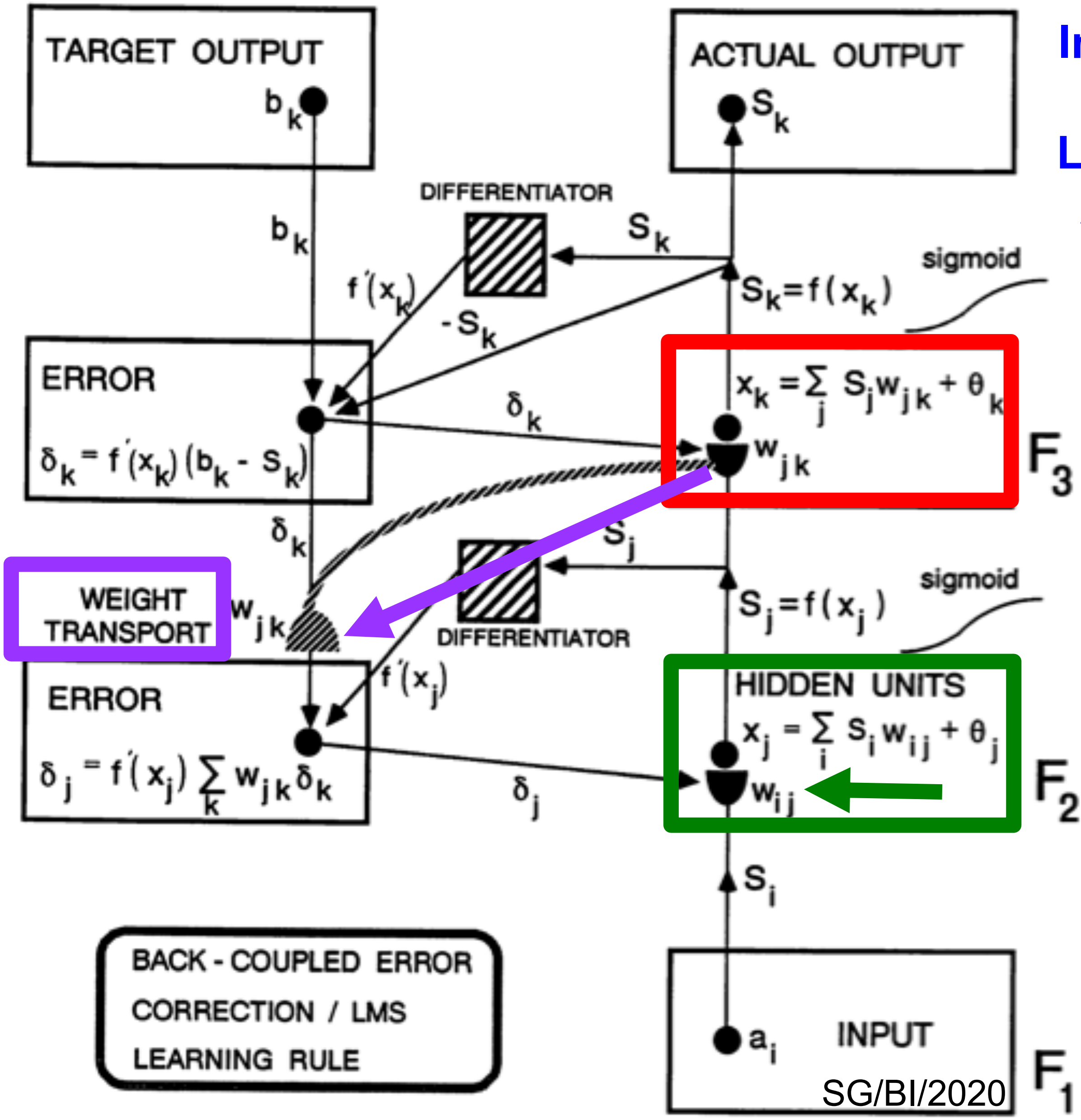

Information flows FEEDFORWARD

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An external teacher on each trial

Teaching signal is the ERROR or MISMATCH between ACTUAL and TARGET outputs

Teaching signal in level F_3 of adaptive weights w_{ij} in level F_2 have no network pathway whereby to reach F_2

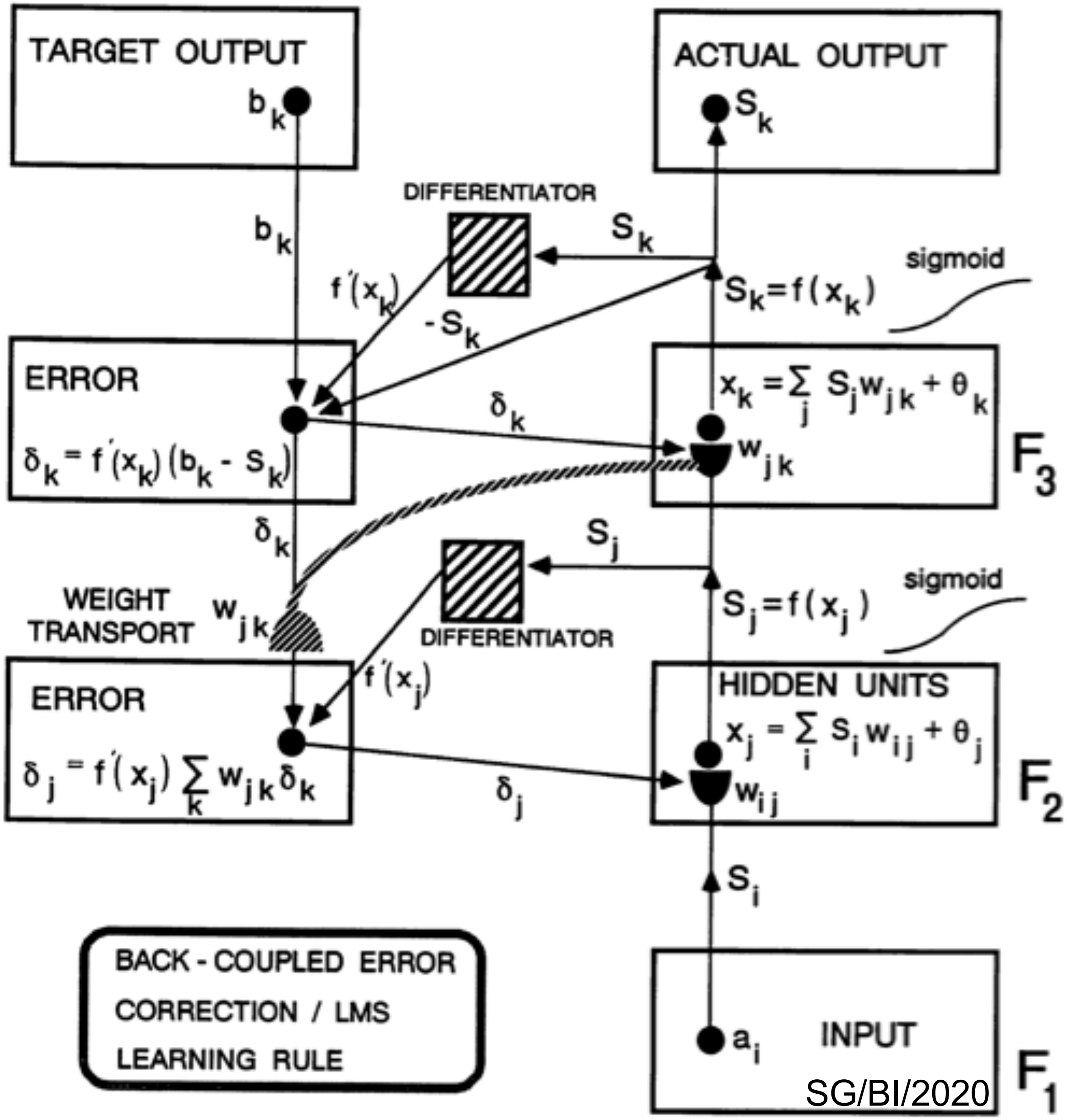
Use WEIGHT TRANSPORT of the teaching signal!

NON-LOCAL!

NON-BIOLOGICAL!

BACK PROPAGATION CIRCUIT

figure reprinted from Carpenter (1989)



SLOW LEARNING

Adaptive weights change just a little to reduce error on each learning trial

REQUIRES MANY TRIALS

(i.e., repetitions of database) to learn, possibly hundreds or thousands of trials

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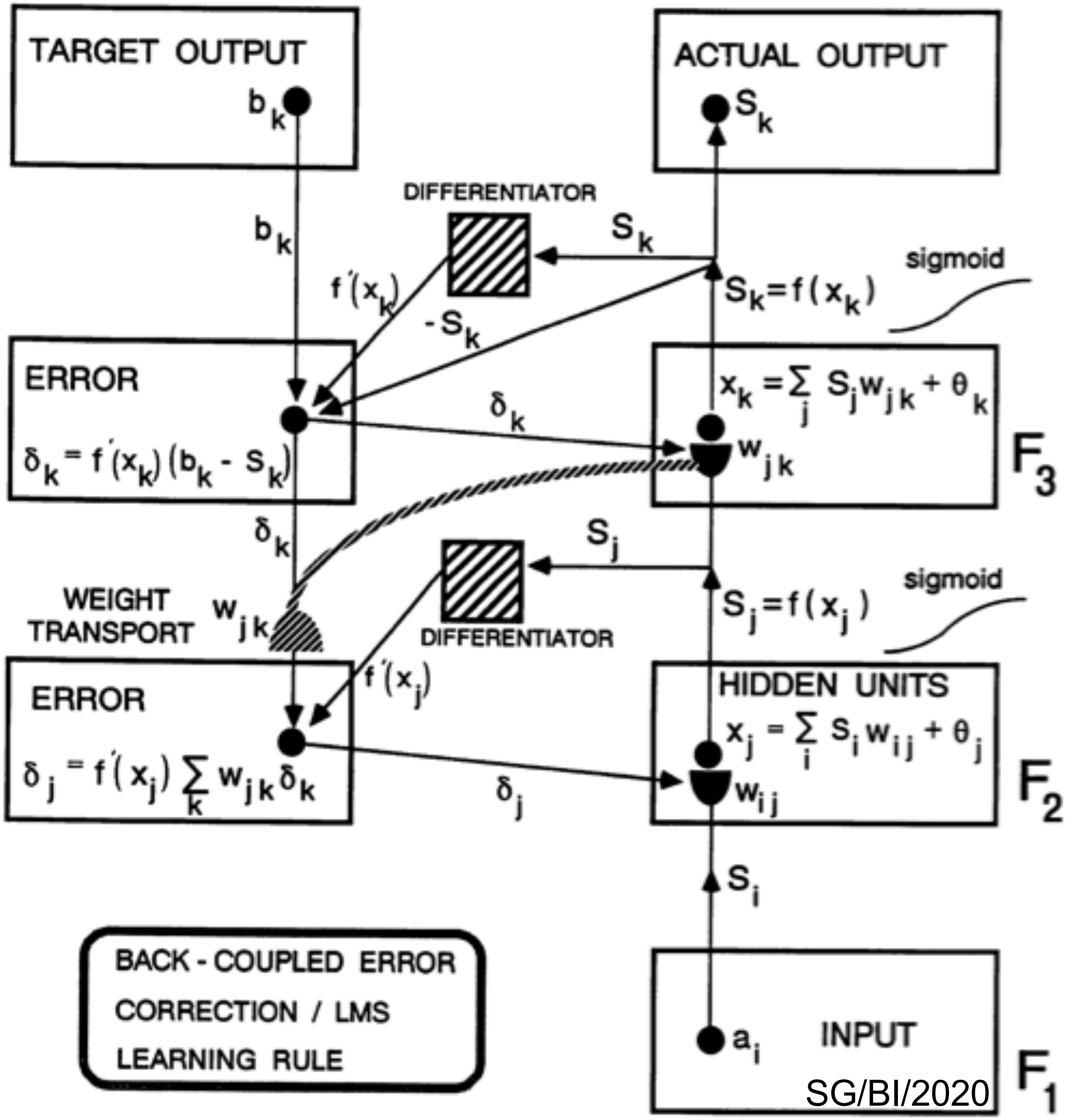
figure reprinted from Carpenter (1989)



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Adaptive weights zero error signals on EACH trial

Cf. learn a face that you see just once, and remember it for a long time

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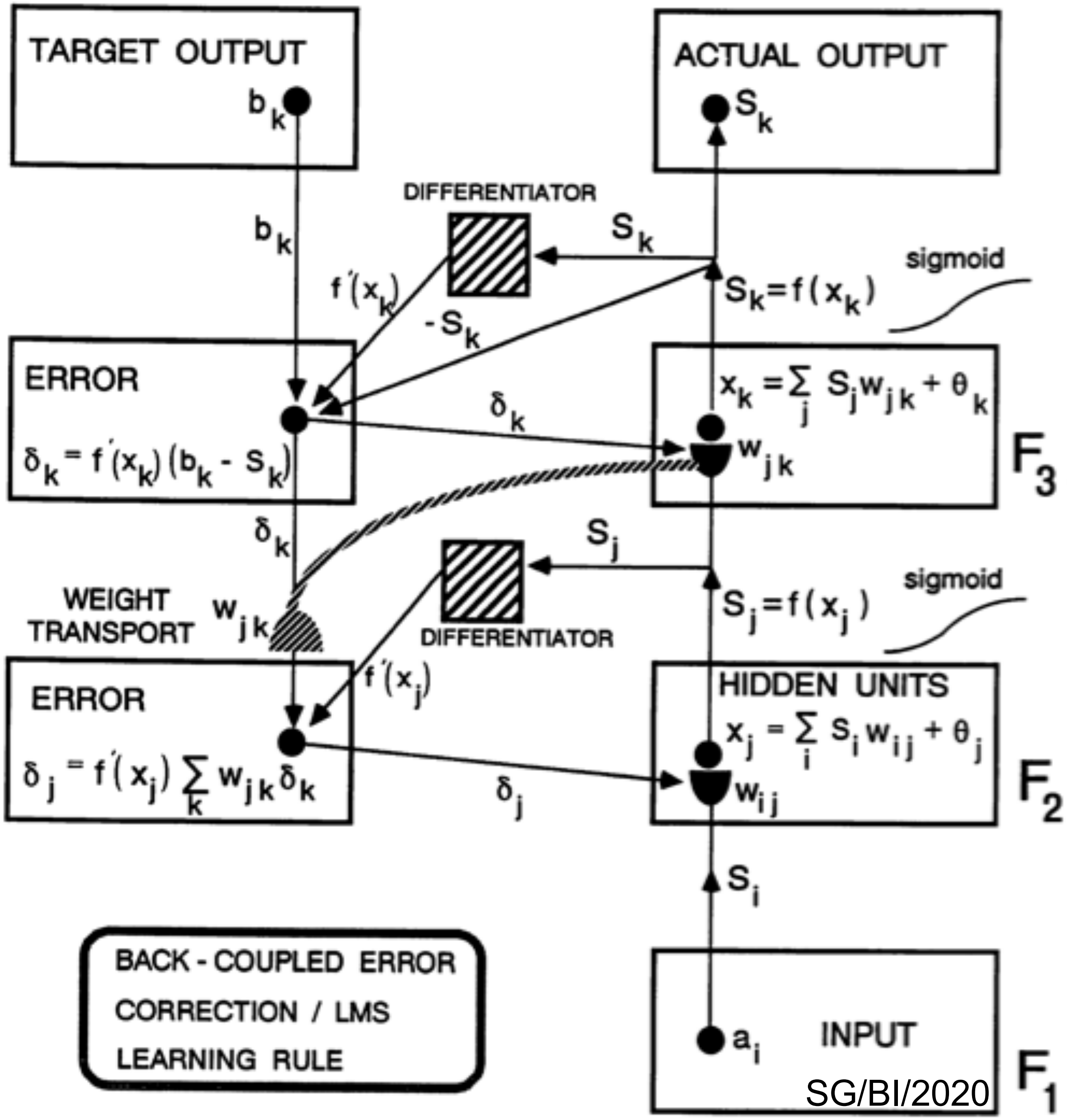

CATASTROPHIC FORGETTING

During any learning trial, an unpredictable part of its learned memory can collapse

McCloskey & Cohen (1989)

Ratcliff (1990), French (1999)

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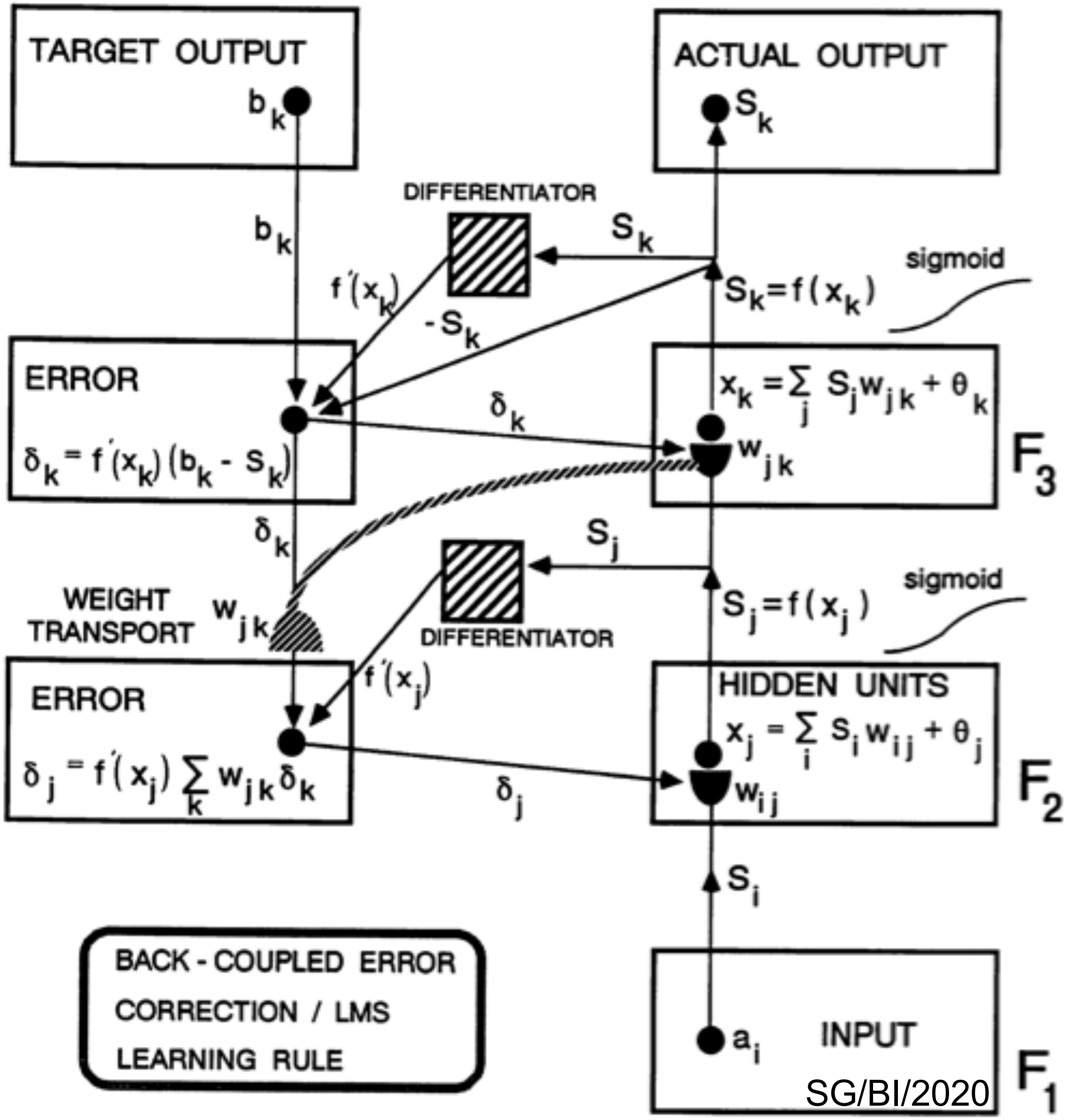

CATASTROPHIC FORGETTING

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Deep Learning is thus neither RELIABLE nor TRUSTWORTHY

BACK PROPAGATION CIRCUIT

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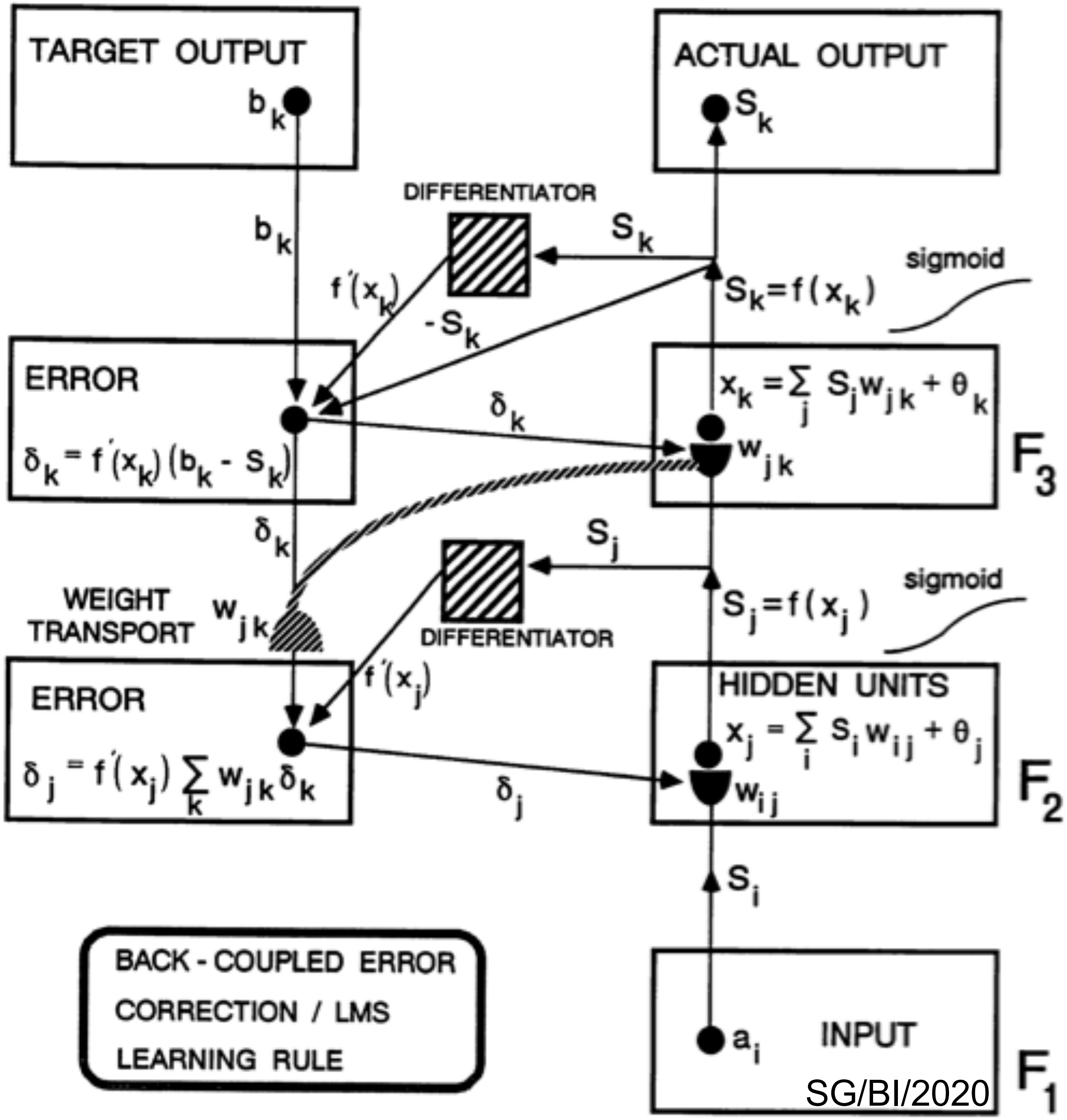

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WHY?

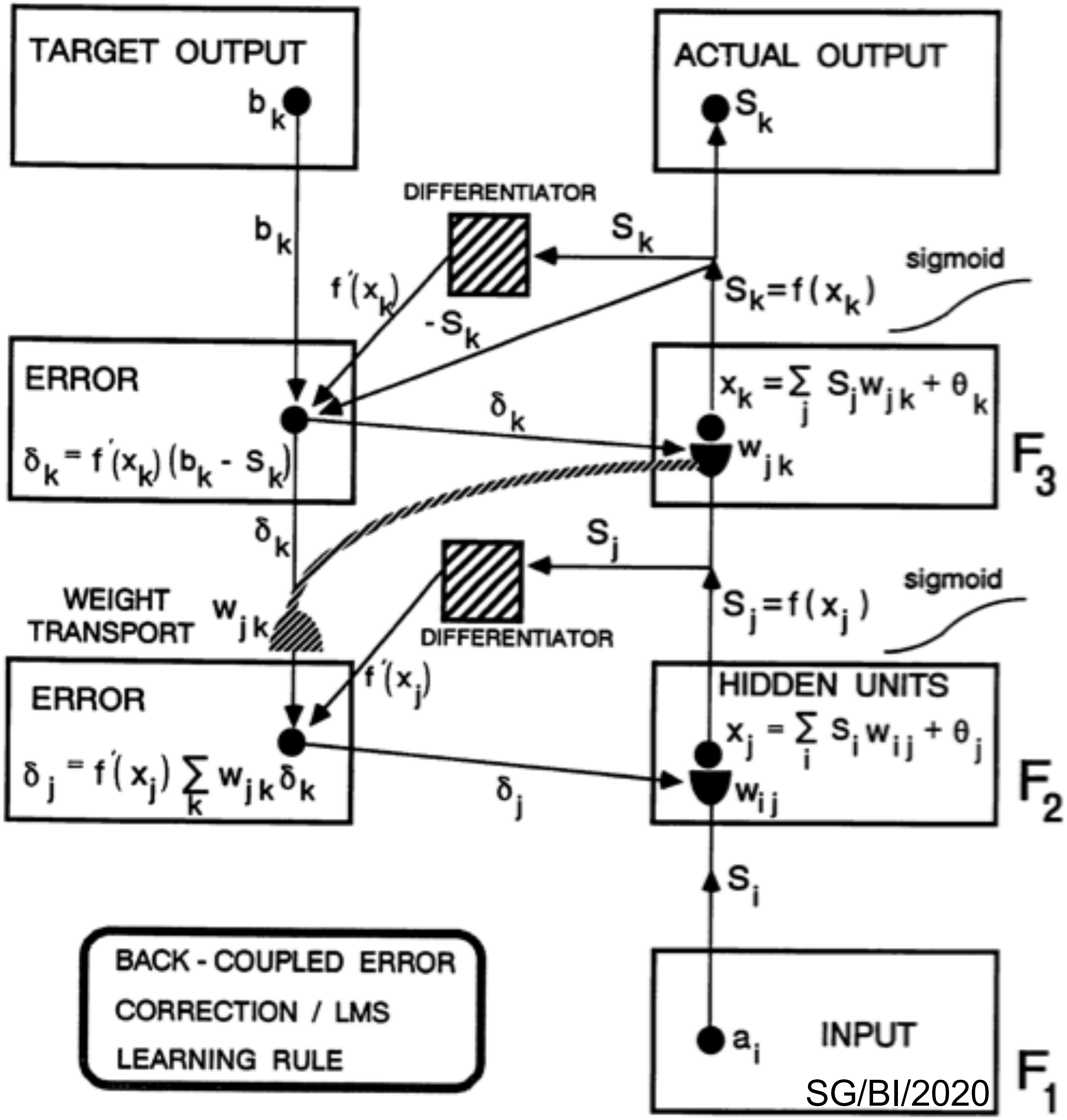
All inputs are processed by a shared set of learned weights

It cannot selectively buffer learned weights that are still predictively useful (no attention)

This problem occurs in ANY learning algorithm whose shared weight updates follow the gradient of the error in response to the current batch of data points, while ignoring past batches

MULTIPLE EFFORTS TO FIX BACK PROPAGATION

figure reprinted from Carpenter (1989)



Selectively slow learning "on the weights important for…supervised learning and reinforcement learning problems …by optimizing…parameters… using Bayes' rule"
Kirkpatrick et al (2017)

Assumes:
omniscient observer who can discover and alter "important weights"

non-local computations e.g., Bayesian computation

Same problems with evolutionary algorithms
Clune et al (2013)

and diffusion-based neuromodulation
Velez & Clune (2017)

These efforts to overcome catastrophic forgetting created additional conceptual and computational problems

I view them as adding
EPICYCLES
to ameliorate a fundamental flaw in the model

Reminiscent of adding epicycles to correct problems in the Ptolemaic model of the solar system

The Copernican model that we now accept did not require epicycles!

Perhaps this is why
Geoffrey Hinton said in
AXIOS (LeVine, 2017)
that he is

"deeply suspicious of back propagation…
I don't think it's how the brain works.
We clearly don't need all the labeled data…
My view is,
throw it all away and start over"

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We do not have to start over!

These problems were solved in the 1970s and 1980s!

17 PROBLEMS OF BACK PROPAGATION OVERCOME BY ADAPTIVE RESONANCE

Grossberg (1988, *Neural Networks*, 1, 17-41)

- Real-time (on-line) learning vs. lab-time (off-line) learning
- Learning in nonstationary unexpected world vs. in stationary controlled world
- Self-organized unsupervised or supervised learning vs. supervised learning
- Dynamically self-stabilize learning to arbitrarily many inputs vs. catastrophic forgetting
- Maintain plasticity forever vs. externally shut off learning when database gets too large
- Effective learning of arbitrary databases vs. statistical restrictions on learnable data
- Learn internal expectations vs. impose external cost functions
- Actively focus attention to selectively learn critical features vs. passive weight change
- Closing vs. opening the feedback loop between fast signaling and slower learning
- Top-down priming and selective processing vs. activation of all memory resources
- Match learning vs. mismatch learning: Avoiding the noise catastrophe
- Fast and slow learning vs. only slow learning: Avoiding the oscillation catastrophe
- Learning guided by hypothesis testing and memory search vs. passive weight change
- Direct access to globally best match vs. local minima
- Asynchronous learning vs. fixed duration learning: A cost of unstable slow learning
- Autonomous vigilance control vs. unchanging sensitivity during learning
- General-purpose self-organizing production system vs. passive adaptive filter

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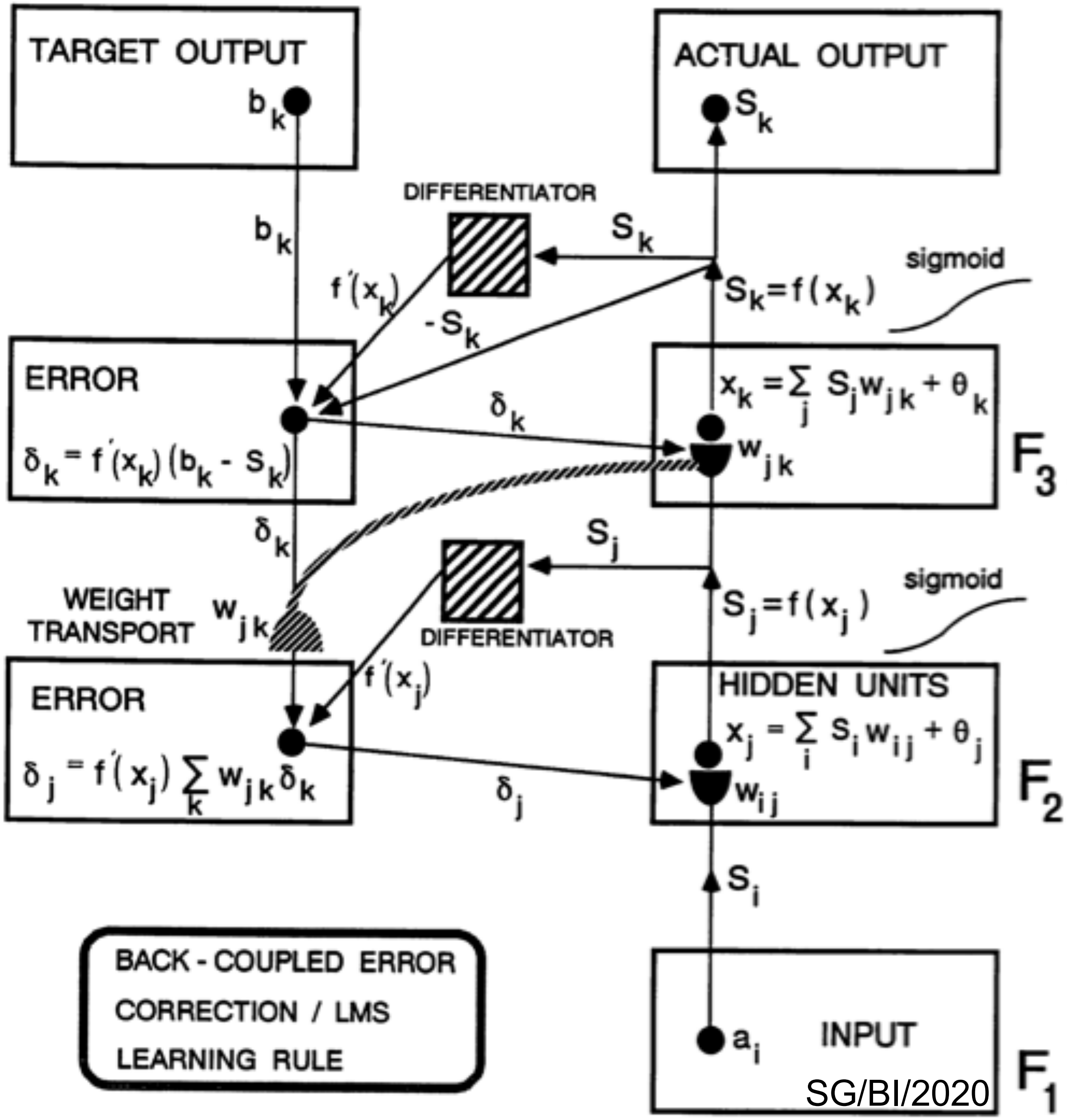

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VERSUS…

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ART can learn to classify an entire database using fast learning on a single learning trial

Carpenter and Grossberg (1987, 1988)

ART OVERCOMES ALL 17 PROBLEMS OF BP

without EPICYCLES!

Moreover...

All the core ART predictions have been supported by subsequent psychological and neurobiological data

ART is a principled biological and technological THEORY

ART has explained data from hundreds of experiments

ART has made scores of predictions that have subsequently received experimental support

All the core ART predictions have been supported by subsequent psychological and neurobiological data

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Why is ART so successful?

ART CAN BE DERIVED FROM A THOUGHT EXPERIMENT ABOUT A UNIVERSAL PROBLEM IN ERROR CORRECTION

Grossberg (1980, *Psychological Review*, 87, 1-51)

The thought experiment asks the question:

How can a coding error be corrected if no individual cell knows that one has occurred?

"The importance of this issue becomes clear when we realize that erroneous cues can accidentally be incorporated into a code when our interactions with the environment are simple and will only become evident when our environmental expectations become more demanding.

Even if our code perfectly matched a given environment, we would certainly make errors as the environment itself fluctuates"

AUTONOMOUS LOCAL LEARNING IN A CHANGING WORLD

ART CAN BE DERIVED FROM A THOUGHT EXPERIMENT ABOUT A UNIVERSAL PROBLEM IN ERROR CORRECTION

Grossberg (1980, *Psychological Review*, 87, 1-51)

AUTONOMOUS LOCAL LEARNING IN A CHANGING WORLD

A purely logical inquiry into error correction
is translated at every step of the thought experiment into processes
learning autonomously in real time with only locally computed quantities

The thought experiment uses familiar environmental facts
about how we learn as its hypotheses
ART circuits naturally emerge

ART circuits may thus, in some form, be embodied in all future autonomous adaptive intelligent devices, whether biological or artificial

ART has, probably for this reason, already been used in many large-scale engineering and technological applications

EARLY ARTMAP BENCHMARK STUDIES

Database benchmark:

MACHINE LEARNING (90-95% correct)

ARTMAP (100% correct on a training set an order of magnitude smaller)

Database benchmarks:

BACKPROPAGATION (10,000 – 20,000 training epochs)

ARTMAP (1-5 epochs)

Medical database:

STATISTICAL METHOD (60% correct)

ARTMAP (96% correct)

Letter recognition database:

GENETIC ALGORITHM (82% correct)

ARTMAP (96% correct)

Used in applications where other algorithms fail

e.g. Boeing CAD Group Technology

Part design reuse and inventory compression

Need fast learning and stable memory to learn and search a huge (16 million 1 million dimensional vectors) and continually growing non-stationary parts inventory

ART WORKS!

Large-scale applications in engineering and technology

techlab.bu.edu

- Boeing parts design retrieval (used to design Boeing 777)
- satellite remote sensing
- radar identification
- robot sensory-motor control and navigation
- machine vision
- 3D object and face recognition
- Macintosh operating system software
- automatic target recognition
- ECG wave recognition
- protein secondary structure identification
- character classification
- musical analysis
- air quality monitoring and weather prediction
- medical imaging and database analysis
- multi-sensor chemical analysis
- strength prediction for concrete mixes
- signature verification
- decision making and intelligent agents
- machine condition monitoring and failure forecasting
- chemical analysis
- electromagnetic and digital circuit design

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protein secondary structure identification
character classification
musical analysis
air quality monitoring and weather prediction
medical imaging and database analysis
multi-sensor chemical analysis
strength prediction for concrete mixes
signature verification
decision making and intelligent agents
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chemical analysis
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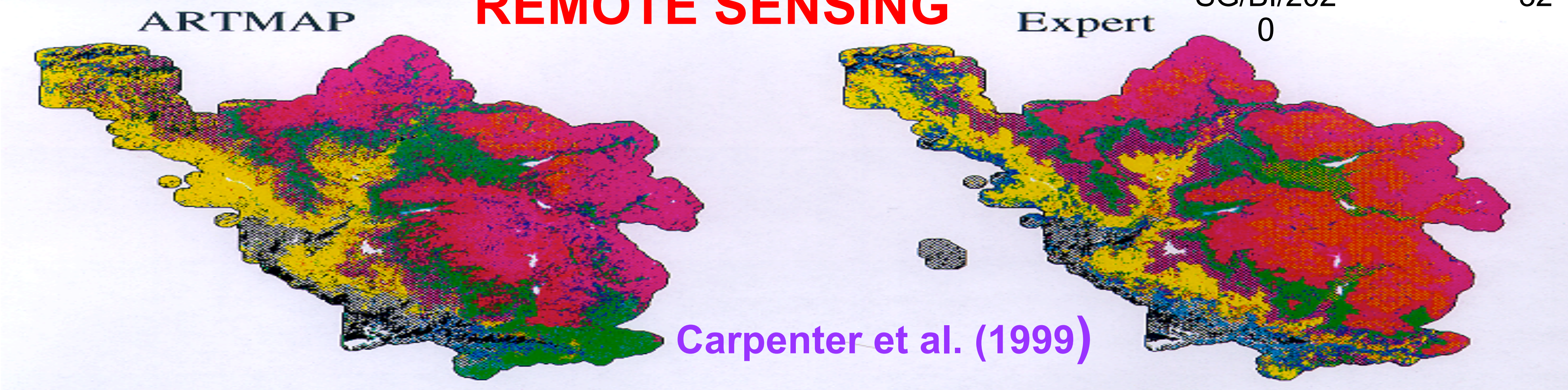
REMOTE SENSING



Carpenter et al. (1999)

17 vegetation classes

AI Expert system – 1 year

- Field identification of natural regions
- Derivation of ad hoc rules for each region, by expert geographers
- Correct 80,000 of 250,000 site labels
- 230*m* (site–level) scale

ARTMAP system – 1 day

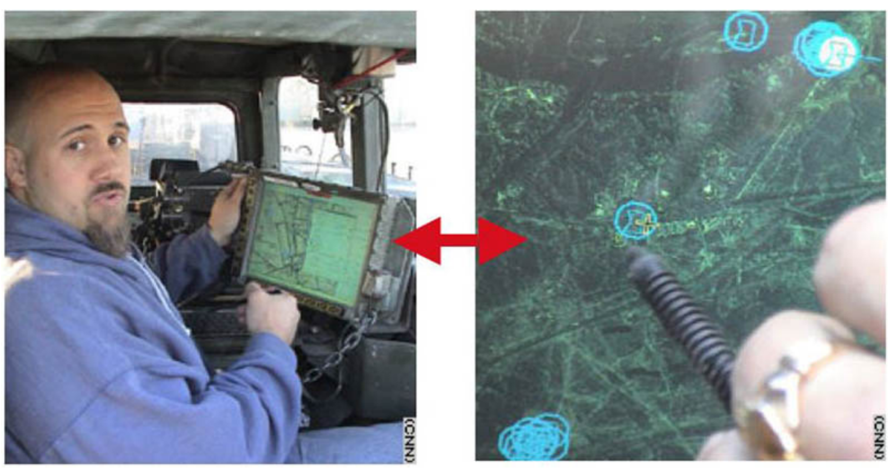
- Rapid, automatic, no natural regions or rules
- Confidence map
- 30*m* (pixel–level) scale: can see roads
- Equal accuracy at test sites

INFORMATION FUSION IN REMOTE SENSING

Carpenter et al. (2004)

Multimodal integration of information from many sources to learn a knowledge structure:

- CONSISTENT
- STABLE
- ROBUST
- LEARNED ONLINE
- SELF-ORGANIZED



SOURCE 1
GOAL 1
SENSOR 1
TIME 1

SOURCE 2
GOAL 2
SENSOR 2
TIME 2

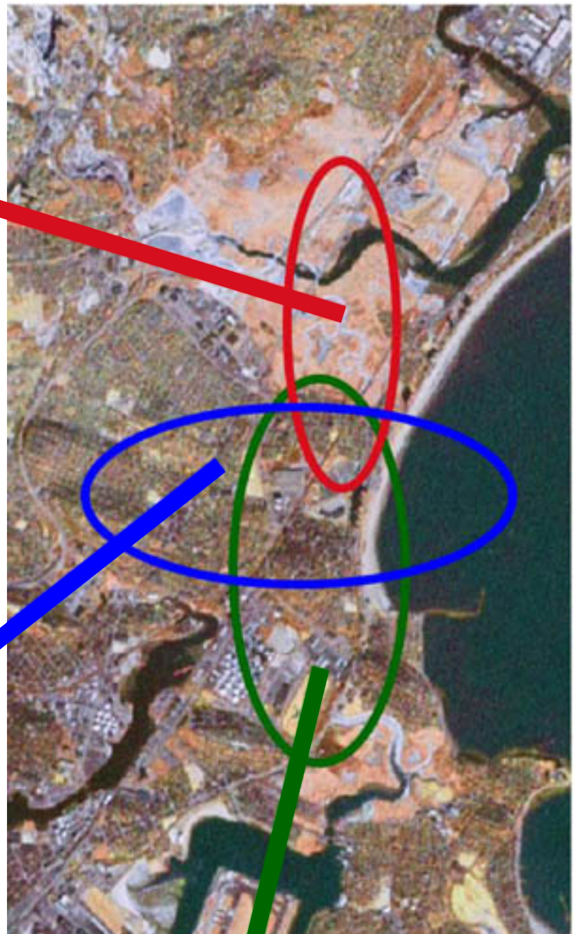
SOURCE 3
GOAL 3
SENSOR 3
TIME 3

Boston testbed

CONSISTENT KNOWLEDGE FROM INCONSISTENT DATA

Automatically learns and stably stores one-to-many mappings

water
open space
built-up



ocean
beach
park
ice
road
river
residential
industrial

man-made
natural

PROBLEM: Integrate multiple sources into a coherent knowledge structure

Solution 1:
HUMAN MAPPING EXPERT:
Slow, expensive, possibly unavailable

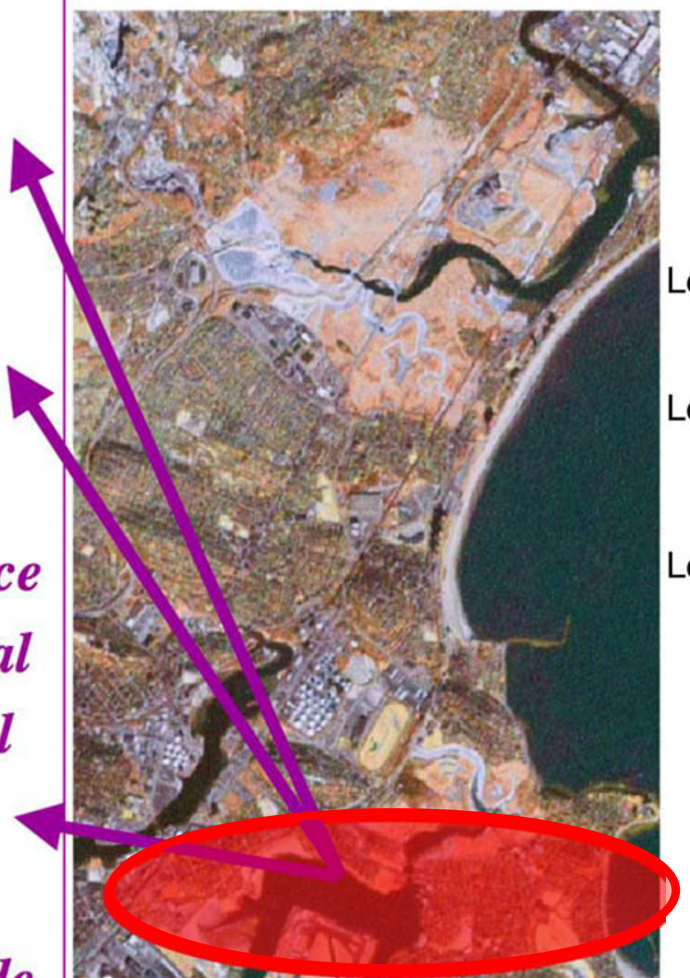
Solution 2:
Distributed ARTMAP MODEL:
Fast, automatic, easy to deploy
NO PRIOR RULES OR DOMAIN KNOWLEDGE

Self-organizing expert system

SELF-ORGANIZES a HIERARCHY of COGNITIVE RULES

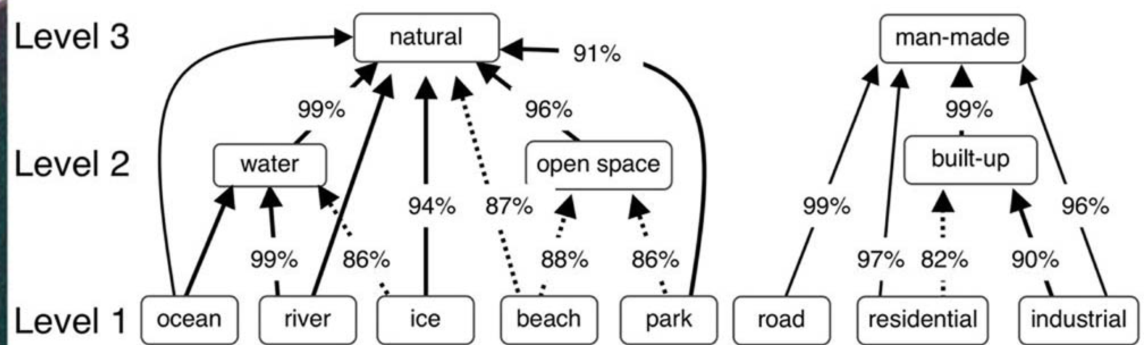
Distributed predictions across test set pixels

ocean
beach
park
ice
road
river
water
open space
residential
industrial
built-up
natural
man-made



Boston testbed

RULE DISCOVERY



Confidence in each rule = 100%, except where noted

CONSISTENT MAPS, LABELED BY LEVEL

ART WORKS!

Large-scale applications in engineering and technology

Some more recent work about ART:

Special issue of *Neural Networks* in December, 2019:

Wunsch, D. C. II. (2019). Admiring the Great Mountain: A Celebration Special Issue in Honor of Stephen Grossberg's 80th Birthday.

arxiv.org/pdf/1910.13351.pdf

da Silva, L. E.. B., Elnabarawy, I., & Wunsch, D. C. II. (2019). A Survey of Adaptive Resonance Theory Neural Network Models for Engineering Applications.

arxiv.org/pdf/1910.13351.pdf

BP is a feedforward adaptive filter

ART is more than a feedforward adaptive filter

ART IS AN EXPLAINABLE SELF-ORGANIZING PRODUCTION SYSTEM IN A NON-STATIONARY WORLD

BP is a feedforward adaptive filter

ART is more than a feedforward adaptive filter

ART IS AN EXPLAINABLE SELF-ORGANIZING PRODUCTION SYSTEM IN A NON-STATIONARY WORLD

It is SELF-ORGANIZING because it can autonomously carry out arbitrary combinations of unsupervised or supervised learning trials with the world as its only teacher

BP is a feedforward adaptive filter

ART is more than a feedforward adaptive filter

ART IS AN EXPLAINABLE SELF-ORGANIZING PRODUCTION SYSTEM IN A NON-STATIONARY WORLD

It is a PRODUCTION SYSTEM because it uses HYPOTHESIS TESTING to discover and learn RULES via a top-down matching process that focuses attention on CRITICAL FEATURE PATTERNS that predict behavioral success while suppressing irrelevant features

BP is a feedforward adaptive filter

ART is more than a feedforward adaptive filter

ART IS AN EXPLAINABLE SELF-ORGANIZING PRODUCTION SYSTEM IN A NON-STATIONARY WORLD

It is EXPLAINABLE using both its activities, or short term memory (STM) traces and adaptive weights, or long term memory (LTM) traces:

Observing the STM TRACES in a critical feature pattern explain what recognition categories code and what features predict goal-oriented actions

The LTM TRACES in fuzzy ARTMAP translate into fuzzy IF-THEN rules that code what features, in what numerical ranges, control predictions

ART MECHANISMS THAT DEFINE IT AS AN EXPLAINABLE SELF-ORGANIZING PRODUCTION SYSTEM

include:

Bottom-up **adaptive filter (feedforward neural network)**

is supplemented by

top-down learned expectations

and

two types of recurrent inhibitory feedback interactions

that help to choose

recognition categories

and

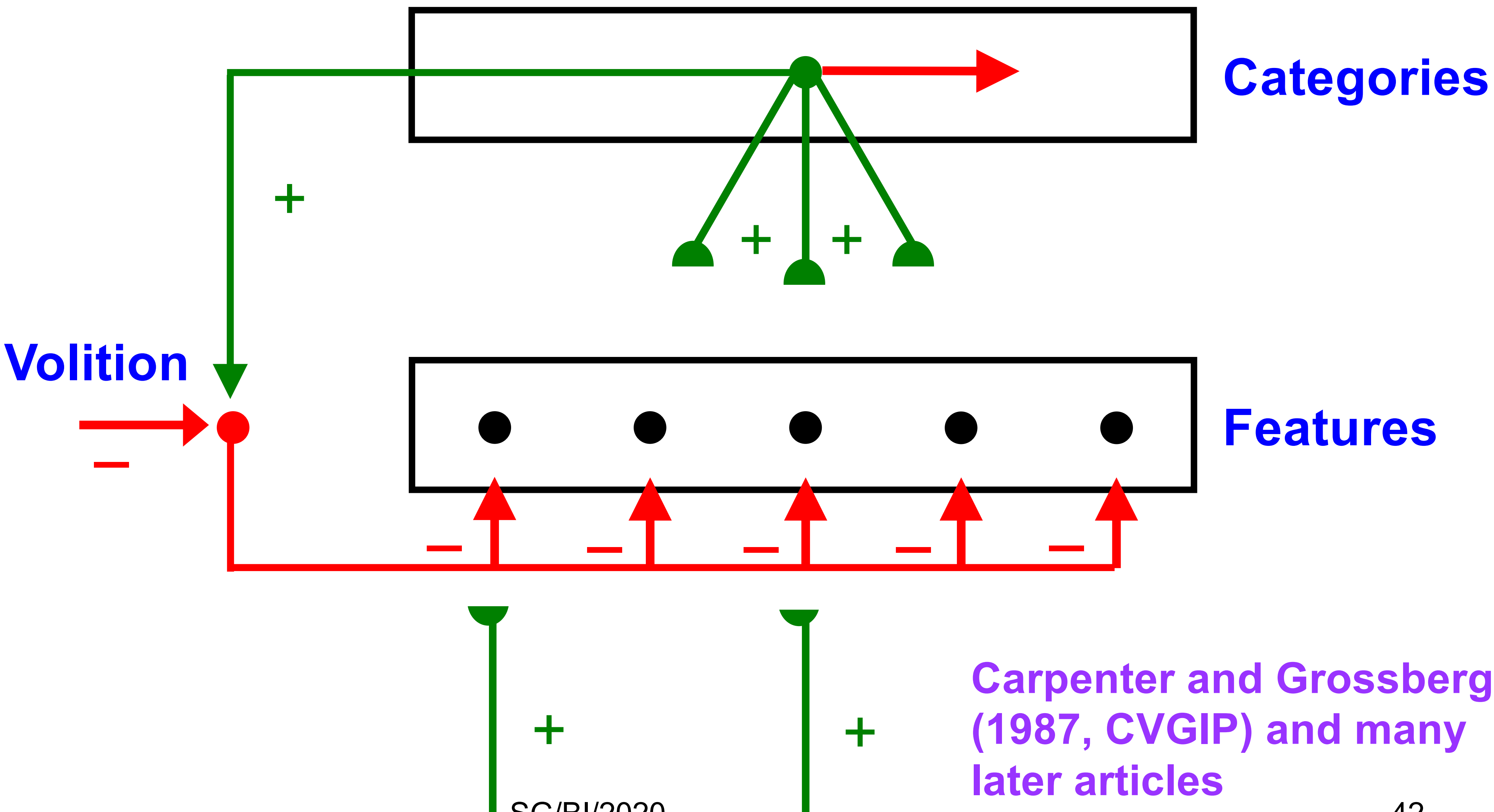
critical feature patterns

Top-down expectations use the ART MATCHING RULE to learn how to FOCUS ATTENTION on CRITICAL FEATURES that control predictive success

ART MATCHING RULE for OBJECT ATTENTION

stabilizes learning (avoids catastrophic forgetting)

Top-down, modulatory on-center, off-surround network



Carpenter and Grossberg (1987, CVGIP) and many later articles

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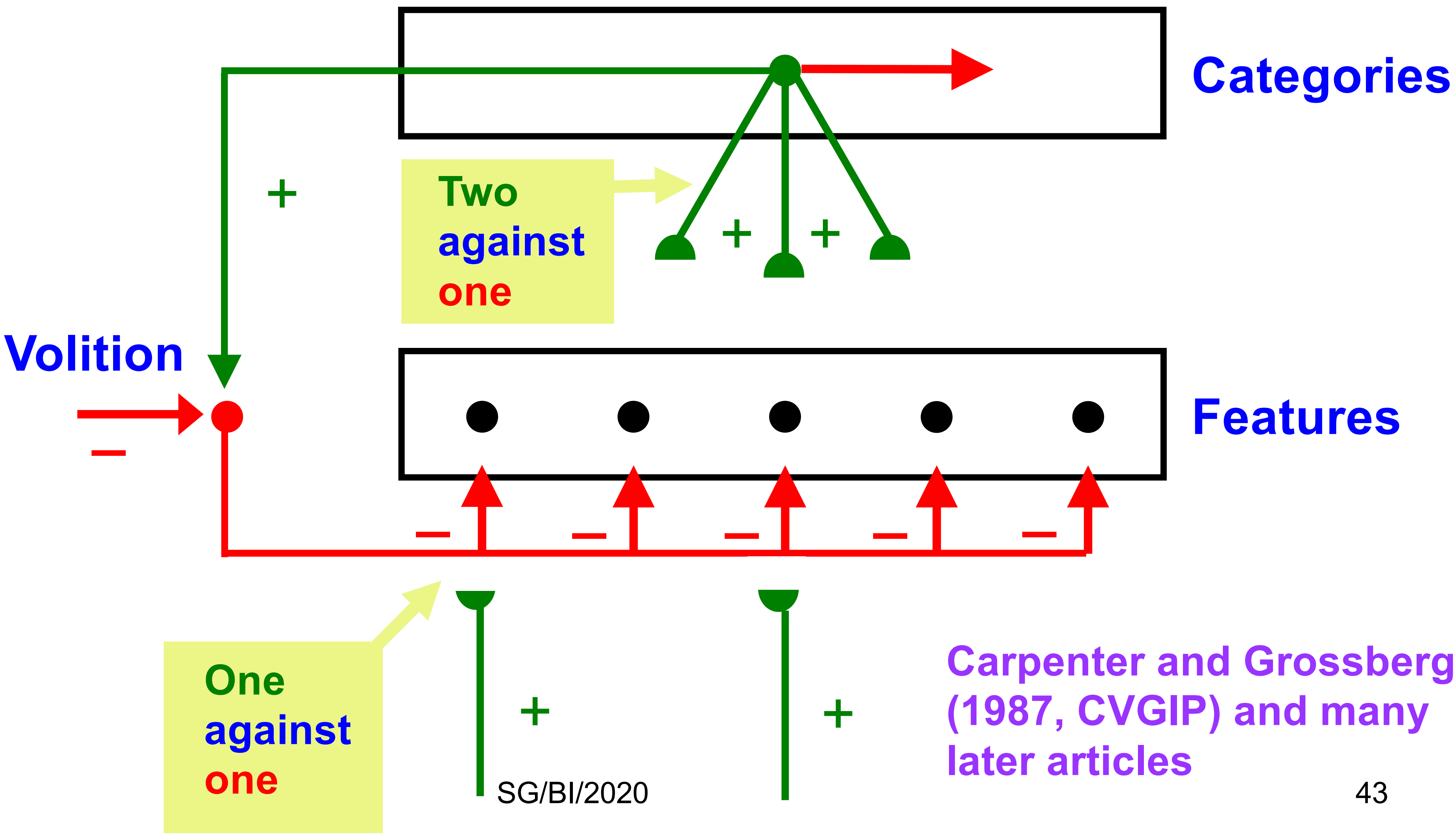

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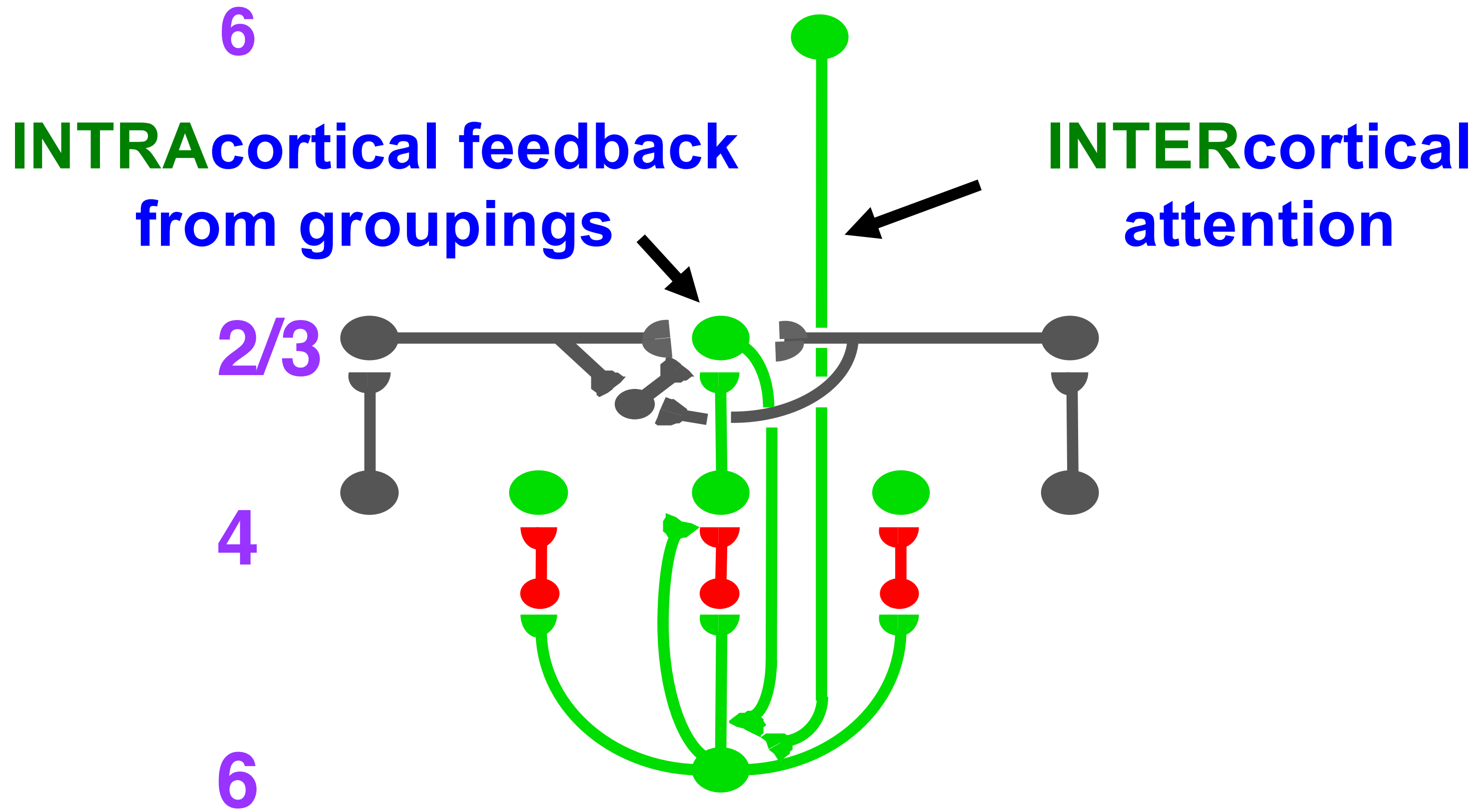
LAMINAR CORTICAL CIRCUIT FOR OBJECT ATTENTION

Grossberg (1999, Spatial Vision)



Attention acts via a
TOP-DOWN
MODULATORY ON-CENTER
OFF-SURROUND NETWORK

LAMINAR CORTICAL CIRCUIT FOR OBJECT ATTENTION

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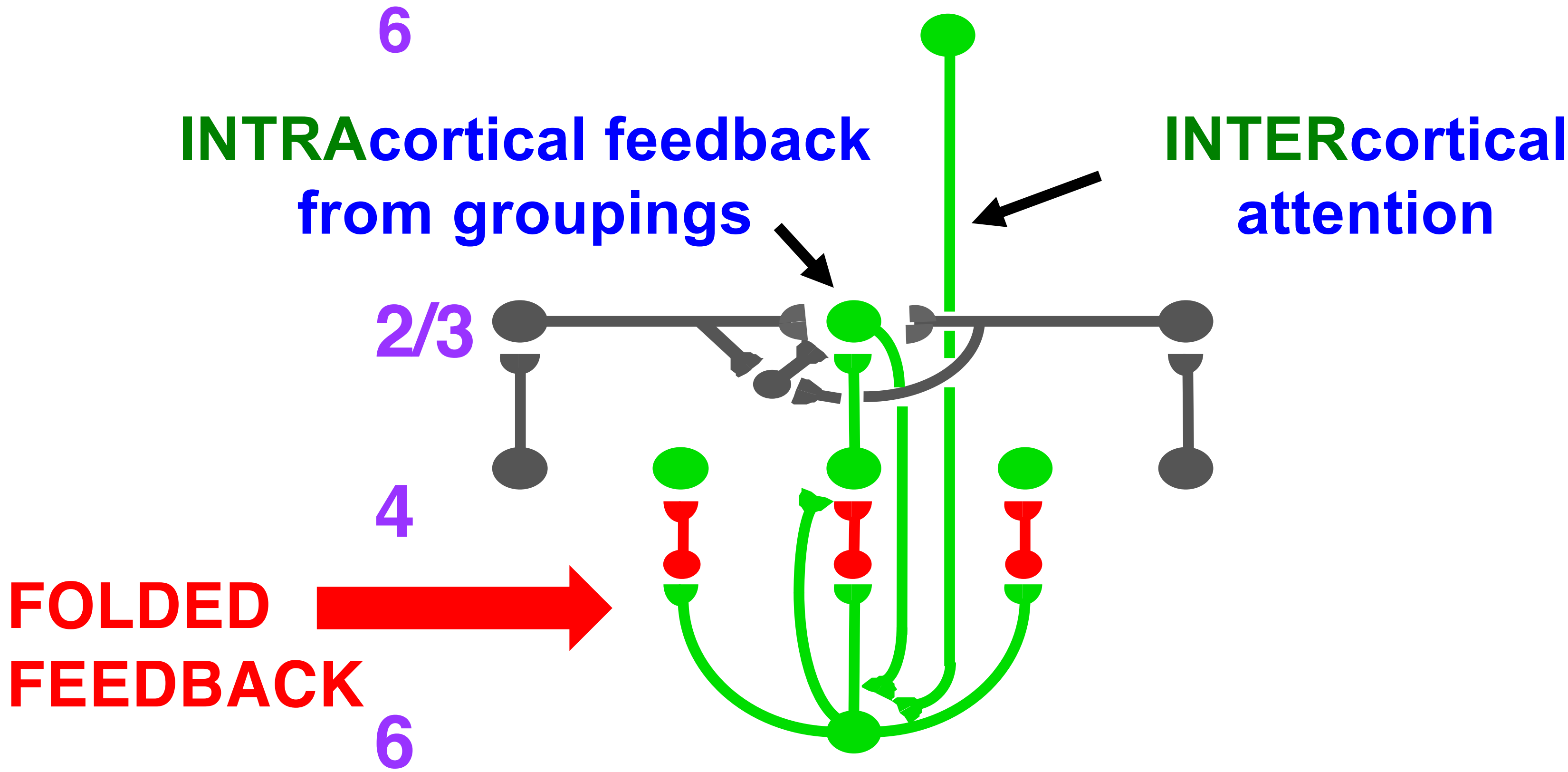

Attention acts via a
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Illustrates NEW PARADIGMS for brain computing

~~INDEPENDENT MODULES~~
~~Computer Metaphor~~

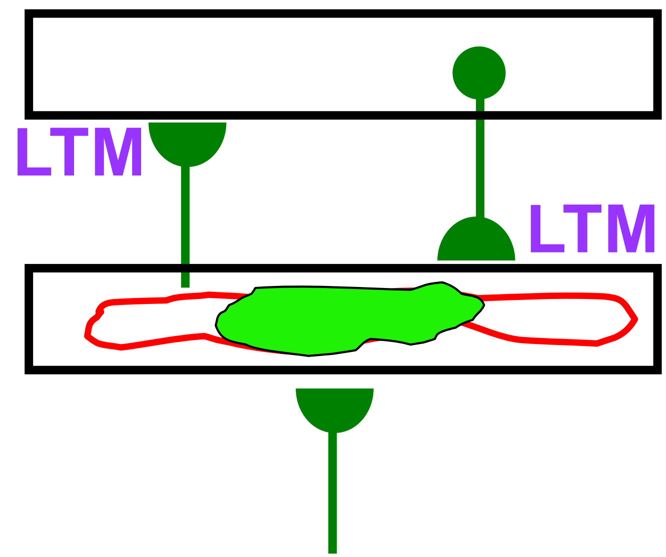
COMPLEMENTARY COMPUTING
What is the nature of brain specialization?

LAMINAR COMPUTING
Why are all neocortical circuits organized in layers?
How do laminar circuits give rise to biological intelligence?

ADAPTIVE RESONANCE

Attended feature clusters reactivate bottom-up pathways

Activated categories reactivate their top-down pathways



Categories
STM

Feature Patterns
STM

Feature-category resonance synchronizes
amplifies
prolongs system response

Resonance triggers learning in bottom-up and top-down adaptive weights: *adaptive* resonance!

“ALL CONSCIOUS STATES ARE RESONANT STATES”

Grossberg (1980)

Surface-shroud resonances support conscious seeing of visual qualia

Feature-category resonances support conscious recognition of visual objects and scenes

Stream-shroud resonances support conscious hearing of auditory qualia

Spectral-pitch-and-timbre resonances support conscious recognition of sources in auditory streams

Item-list resonances support conscious recognition of speech and language

Cognitive-emotional resonances support conscious feelings and recognition of them

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SUPPORT FOR ART PREDICTIONS

ATTENTION HAS AN ON-CENTER OFF-SURROUND

Bullier, Jupe, James, and Girard, 1996
Caputo and Guerra, 1998
Downing, 1988
Mounts, 2000
Reynolds, Chelazzi, and Desimone, 1999
Smith, Singh, and Greenlee, 2000
Somers, Dale, Seiffert, and Tootell, 1999
Sillito, Jones, Gerstein, and West, 1994
Steinman, Steinman, and Lehmkuhne, 1995
Vanduffell, Tootell, and Orban, 2000

"BIASED COMPETITION"

Desimone, 1998
Kastner and Ungerleider, 2001

SUPPORT FOR ART PREDICTIONS

ATTENTION CAN FACILITATE MATCHED BOTTOM-UP SIGNALS

Hupe, James, Girard, and Bullier, 1997
Luck, Chellazi, Hillyard, and Desimone, 1997
Roelfsema, Lamme, and Spekreijse, 1998
Sillito, Jones, Gerstein, and West, 1994
and many more…

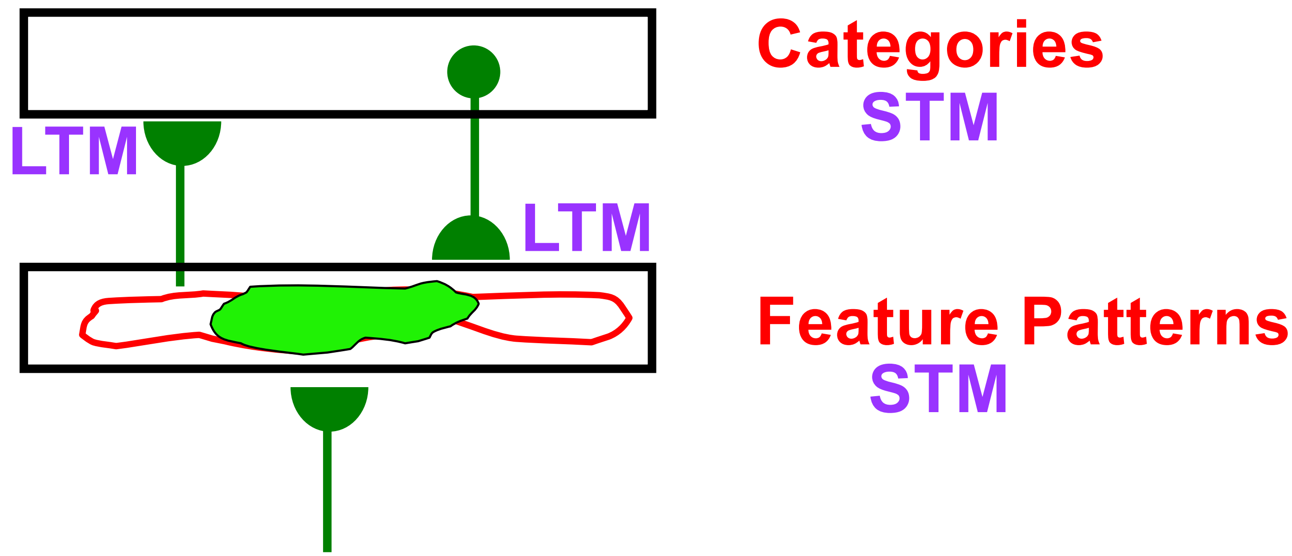
INCONSISTENT WITH MODELS WHERE TOP-DOWN MATCH IS SUPPRESSIVE

Mumford, 1992

Rao and Ballard, 1999

Bayesian Explaining Away

ART IS EXPLAINABLE (TRUSTWORTHY)

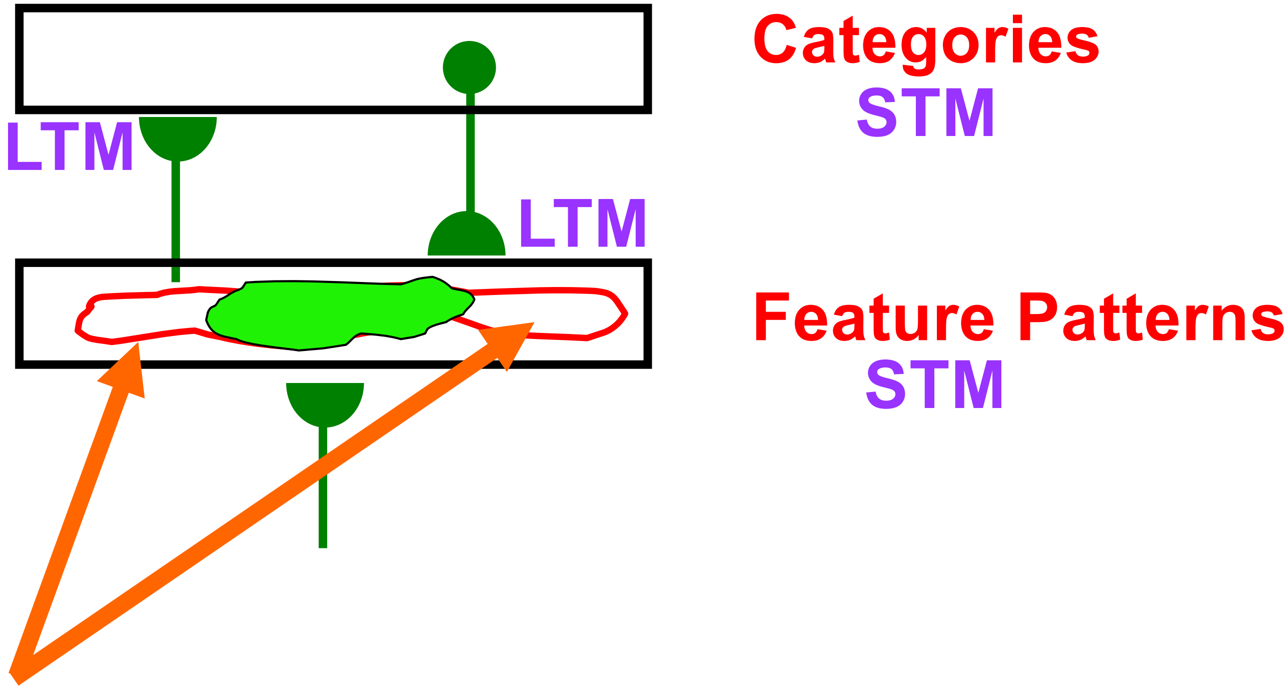


STM: critical feature patterns determine attentional focus that controls information processing

LTM: critical feature patterns determine adaptive weights learned by the BU adaptive filter and TD expectation

Later: fuzzy ARTMAP learns fuzzy IF-THEN rules

ART IS RELIABLE (~~CATASTROPHIC FORGETTING~~)



Outlier features not in critical feature patterns are suppressed

Only predictive features are processed and coded

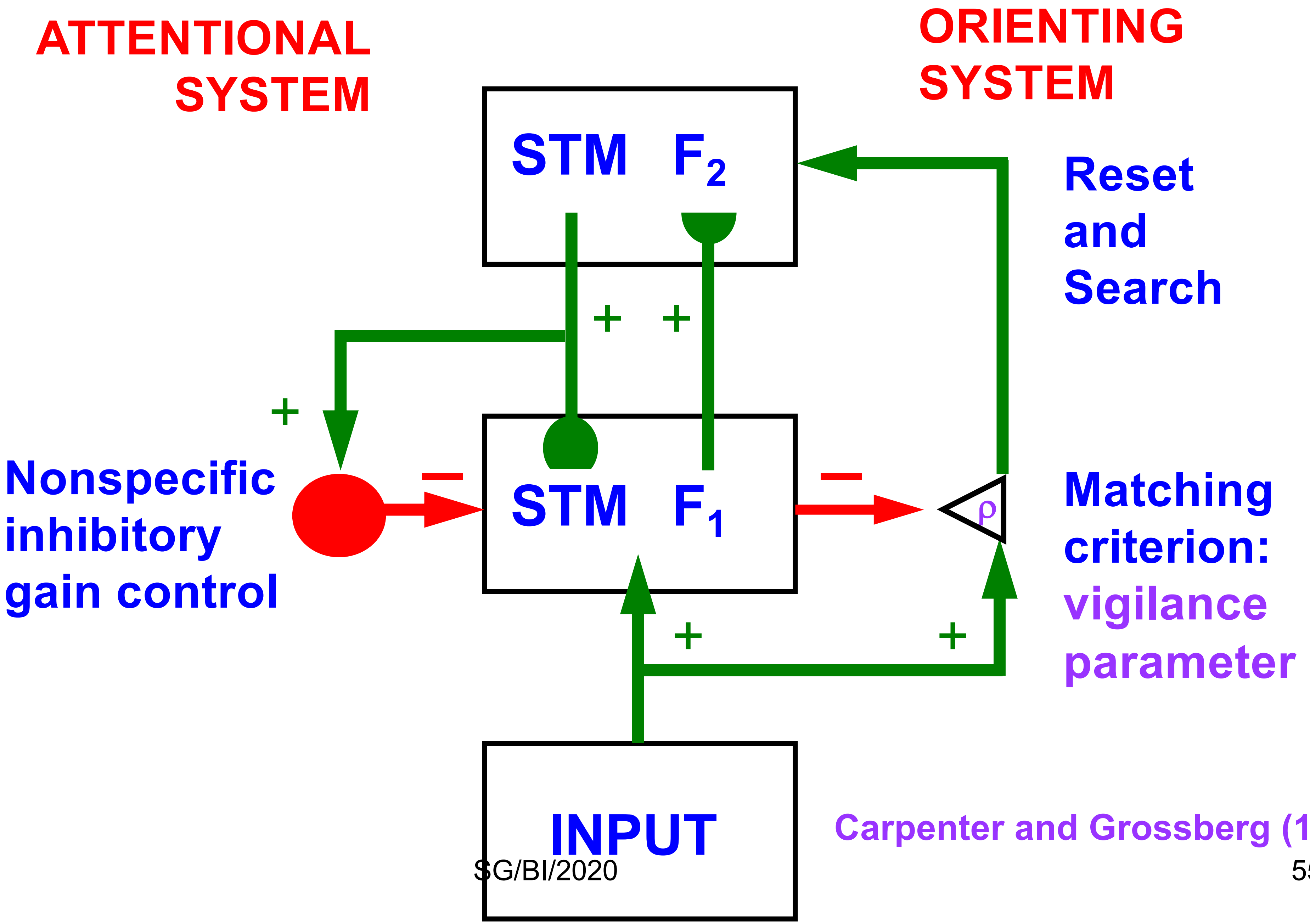
BP is a feedforward adaptive filter

ART is more than a feedforward adaptive filter

ART IS AN EXPLAINABLE SELF-ORGANIZING PRODUCTION SYSTEM IN A NON-STATIONARY WORLD

It is a PRODUCTION SYSTEM because it uses HYPOTHESIS TESTING to discover and learn RULES via a top-down matching process that focuses attention on CRITICAL FEATURE PATTERNS that predict behavioral success while suppressing irrelevant features

ART 1 MODEL



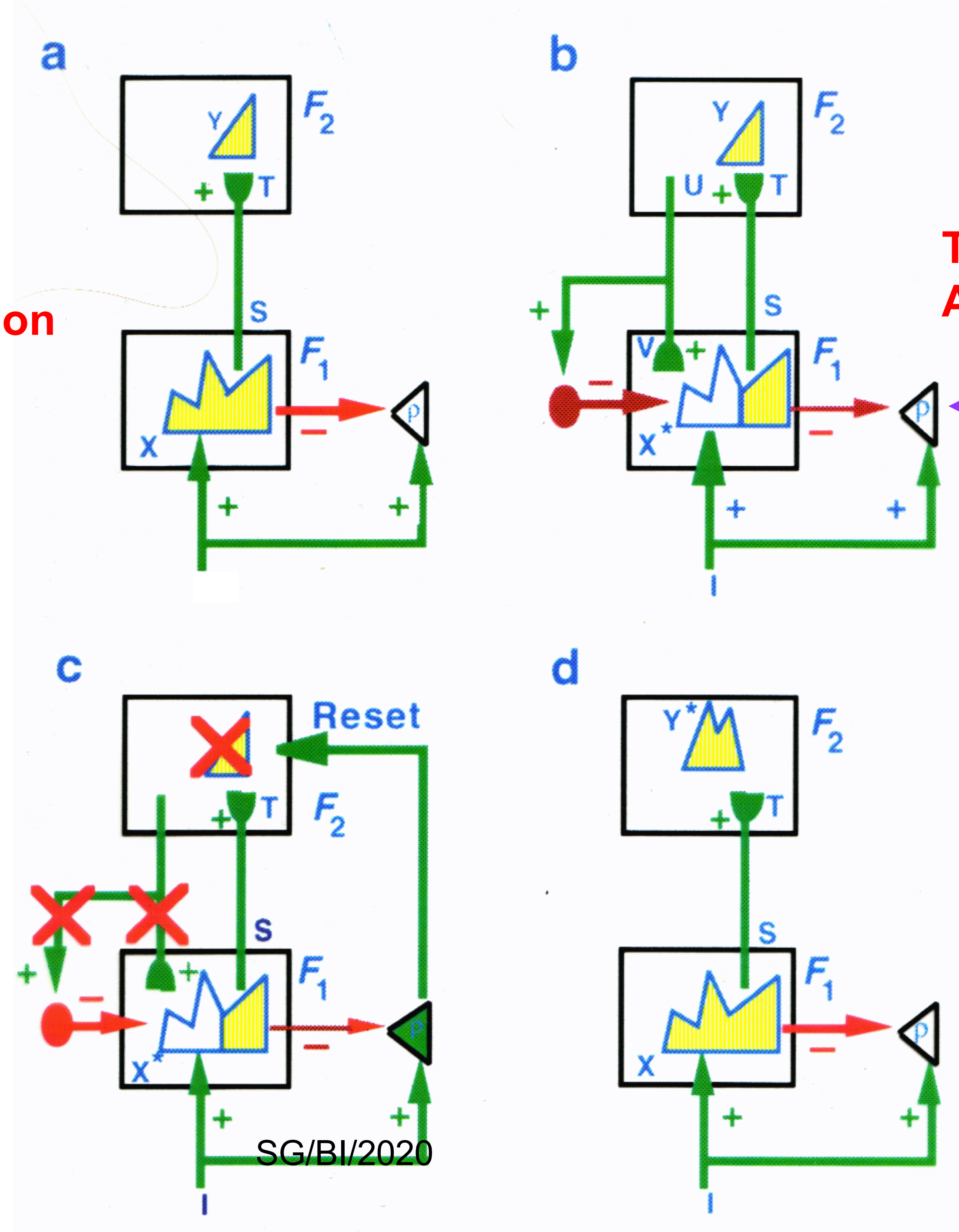
Carpenter and Grossberg (1987)

ART HYPOTHESIS TESTING AND LEARNING CYCLE

Choose category, or symbolic representation

Test hypothesis: ART matching rule

VIGILANCE
How big a mismatch causes reset?



Mismatch Reset: Novelty-Sensitive Arousal Burst

Choose another category

COGNITIVE LEARNING AND MEMORY CONSOLIDATION CYCLE

A dynamic cycle of

RESONANCE

and

RESET

As categories are learned, search automatically disengages

Modulatory novelty potentials subside as this type of memory consolidation ends

Direct access to globally best-matching category

Mathematical proof in: Carpenter & Grossberg, *CVGIP*, 1987

Many supportive psychological and neurobiological data

Explains how we can quickly recognize familiar objects even if, as we get older, we store enormous numbers of memories

ERP SUPPORT FOR HYPOTHESIS TESTING CYCLE

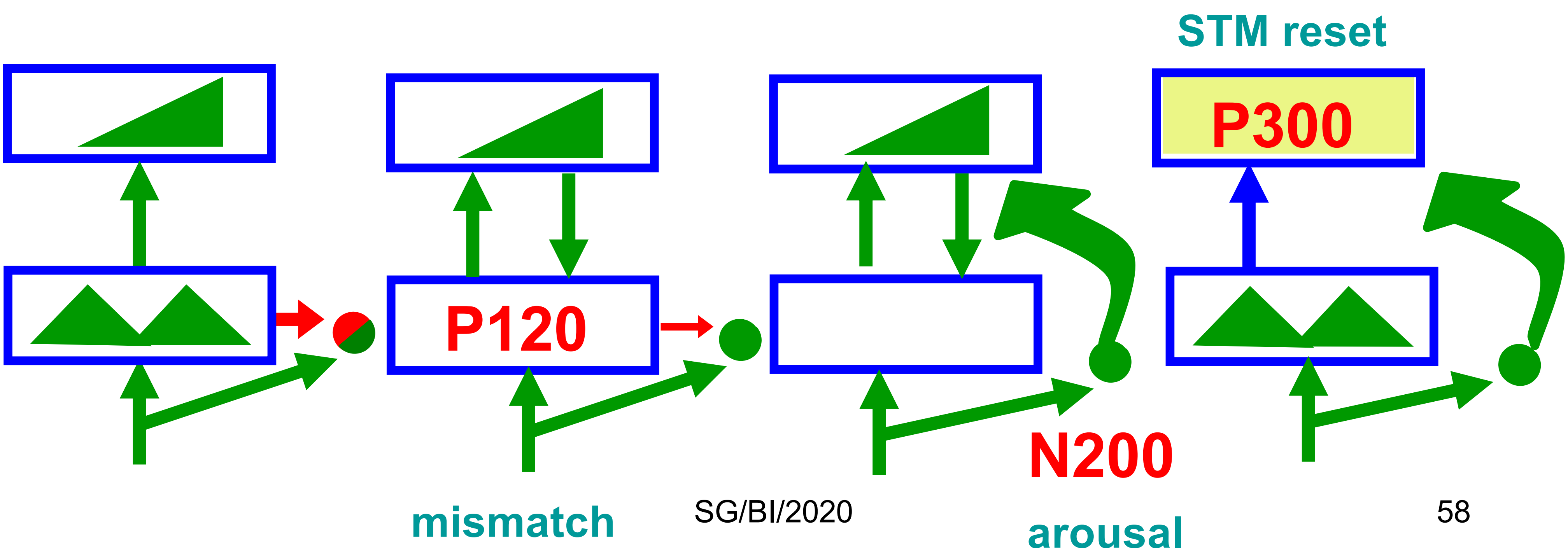
Event-Related Potentials: Human Scalp Potentials

ART predicted correlated sequences of P120-N200-P300

Event Related Potentials during oddball learning

P120 - mismatch; N200 - arousal/novelty; P300 - STM reset

Confirmed in: Banquet and Grossberg, 1987



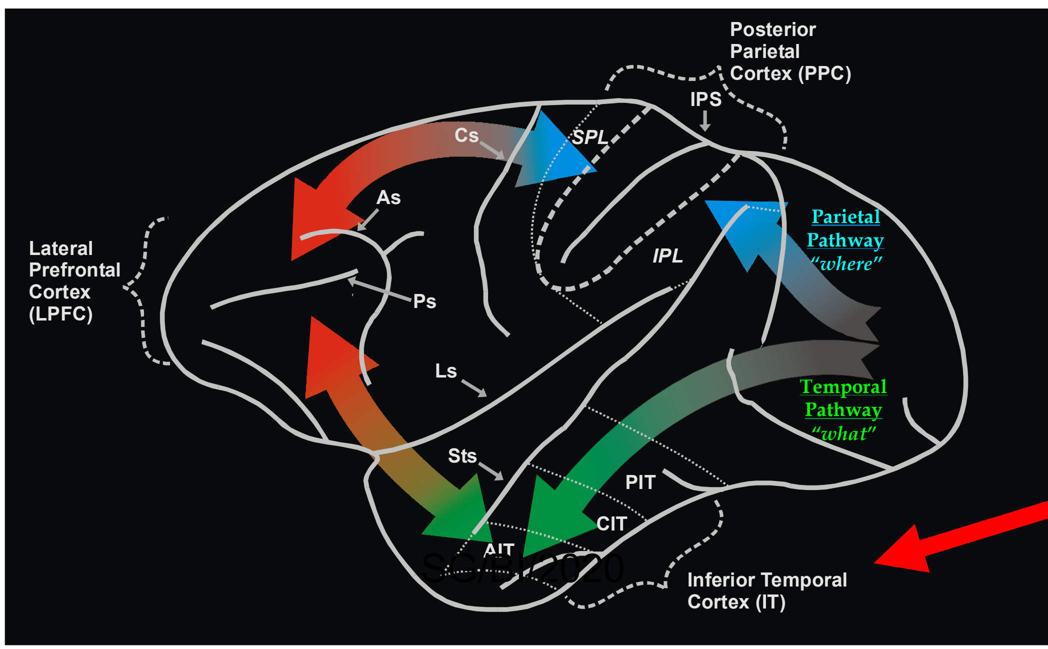
NEUROPHYSIOLOGICAL SUPPORT FOR HYPOTHESIS TESTING CYCLE

Cells in inferotemporal cortex are actively reset during working memory tasks

There is an

"active matching process that was reset between trials."

Miller, Li, Desimone, 1991



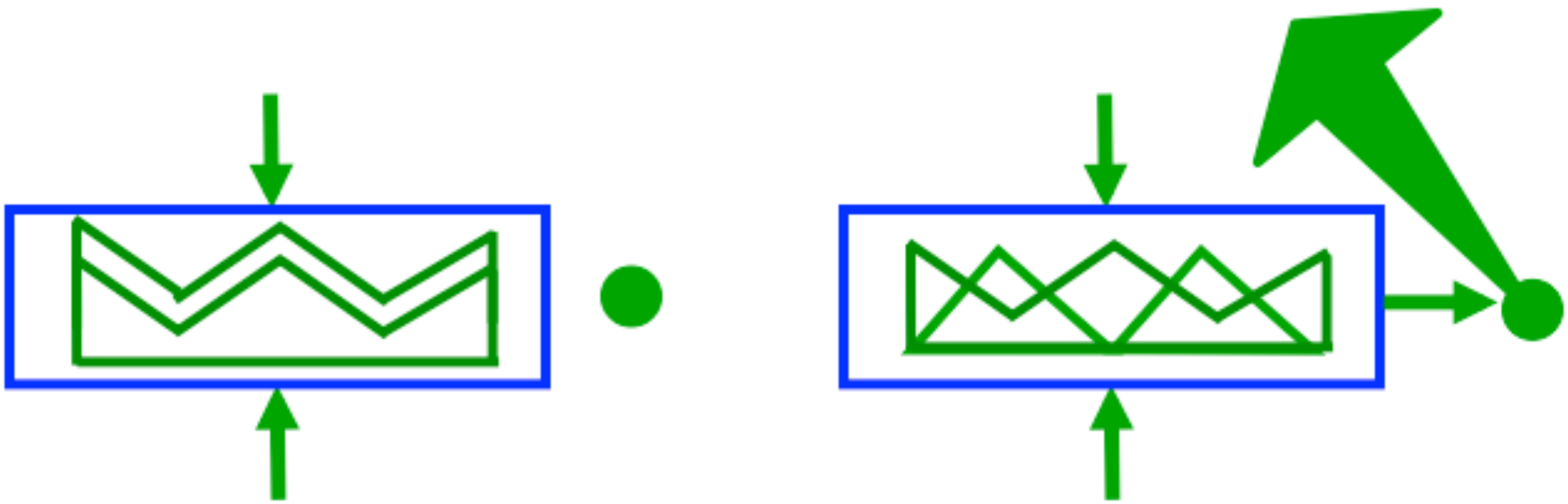
IT cortex

COMPLEMENTARY COMPUTING IN ART

Complementary Match/Mismatch Event-Related Potentials

PN AND N200 ARE COMPLEMENTARY WAVES

MATCH | MISMATCH



PN

Top-Down
Conditionable
Specific
Match

N200

Bottom-Up
Unconditionable
Nonspecific
Mismatch

Illustrates NEW PARADIGMS for brain computing

INDEPENDENT MODULES
Computer Metaphor

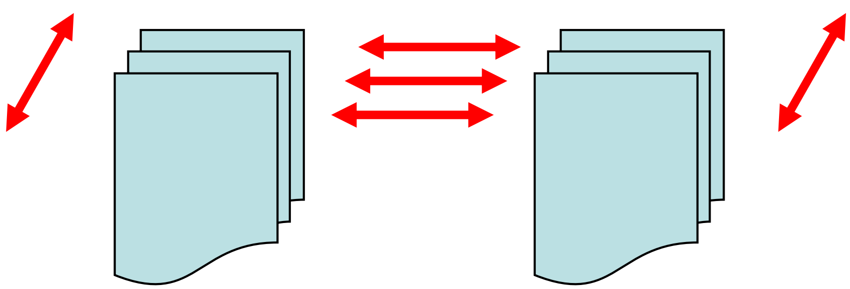
COMPLEMENTARY COMPUTING
What is the nature of brain specialization?

LAMINAR COMPUTING
Why are all neocortical circuits organized in layers?
How do laminar circuits give rise to biological intelligence?

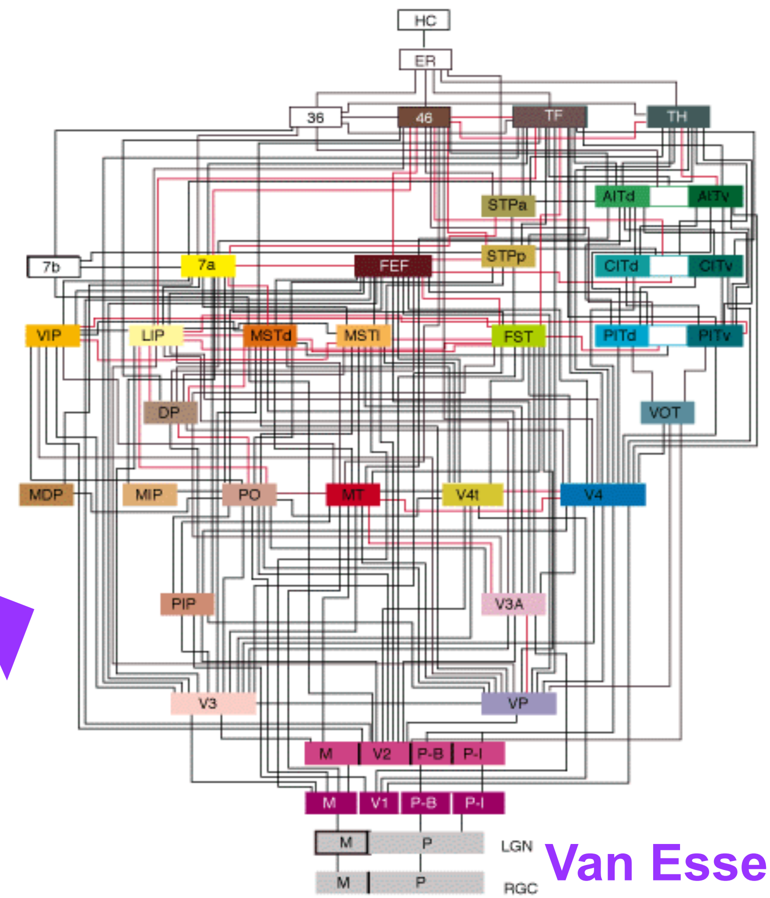
COMPLEMENTARY COMPUTING

New principles of UNCERTAINTY and COMPLEMENTARITY clarify why

Multiple parallel processing streams exist in the brain



Lots of specialization!



Van Essen et al

WHAT ARE COMPLEMENTARY PROPERTIES?

Analogies:

Key fits lock, puzzles pieces fit together

Computing one set of properties at a processing stage prevents that stage from computing a complementary set of properties

Complementary parallel processing streams are BALANCED against one another

INTERACTIONS between streams overcomes their complementary weaknesses and support intelligent and creative behaviors

SOME COMPLEMENTARY PROCESSES

Visual Boundary **Interbob Stream V1-V4**	**Visual Surface** **Blob Stream V1-V4**
Visual Boundary **Interbob Stream V1-V4**	**Visual Motion** **Magno Stream V1-MT**
WHAT Steam **Perception & Recognition** **Inferotemporal and** **Prefrontal areas**	**WHERE Stream** **Space & Action** **Parietal and** **Prefrontal areas**
Object Tracking **MT Interbands and MSTv**	**Optic Flow Navigation** **MT Bands and MSTd**
Motor Target Position **Motor and Parietal Cortex**	**Volitional Speed** **Basal Ganglia**

BP AND DEEP LEARNING DO NOT HAVE

STM activation patterns

STM critical feature patterns

ATTENTION

ANY FAST INFORMATION PROCESSING

LTM top-down learned expectations

HYPOTHESIS TESTING

using interacting STM and LTM traces

No NEURAL ARCHITECTURE

e.g., Complementary Computing

CATASTROPHIC FORGETTING EXAMPLES

Carpenter & Grossberg (1987)

You do not need a large database to show catastrophic forgetting if the ART MATCHING RULE does not hold

Learning lists of JUST FOUR INPUT VECTORS A, B, C, and D can exhibit catastrophic forgetting if they are repeated cyclically in the order:

ABCAD ABCAD ABCAD

and are related to each other in the following way:

CODE INSTABILITY INPUT SEQUENCES

$$D \subset C \subset A$$

$$B \subset A$$

$$B \cap C = \varnothing$$

$$|D| < |B| < |C|$$

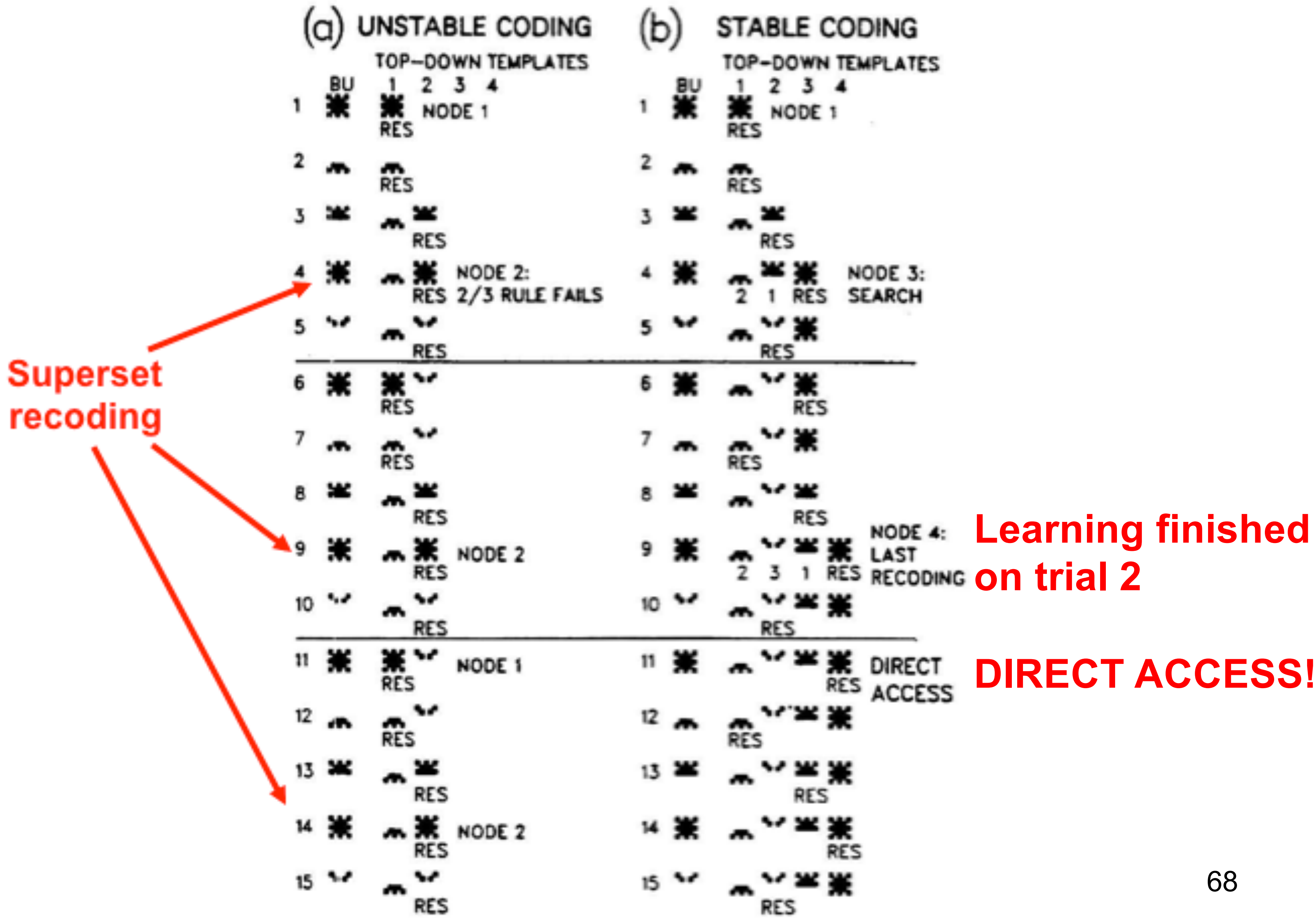
where $|E|$ is the number of features in the set E

Any set of input vectors that satisfy the above conditions will lead to unstable coding if they are periodically presented in the order

$$ABCAD$$

and the top-down ART Matching Rule is shut off

STABLE AND UNSTABLE LEARNING



ART HYPOTHESIS TESTING AND LEARNING CYCLE

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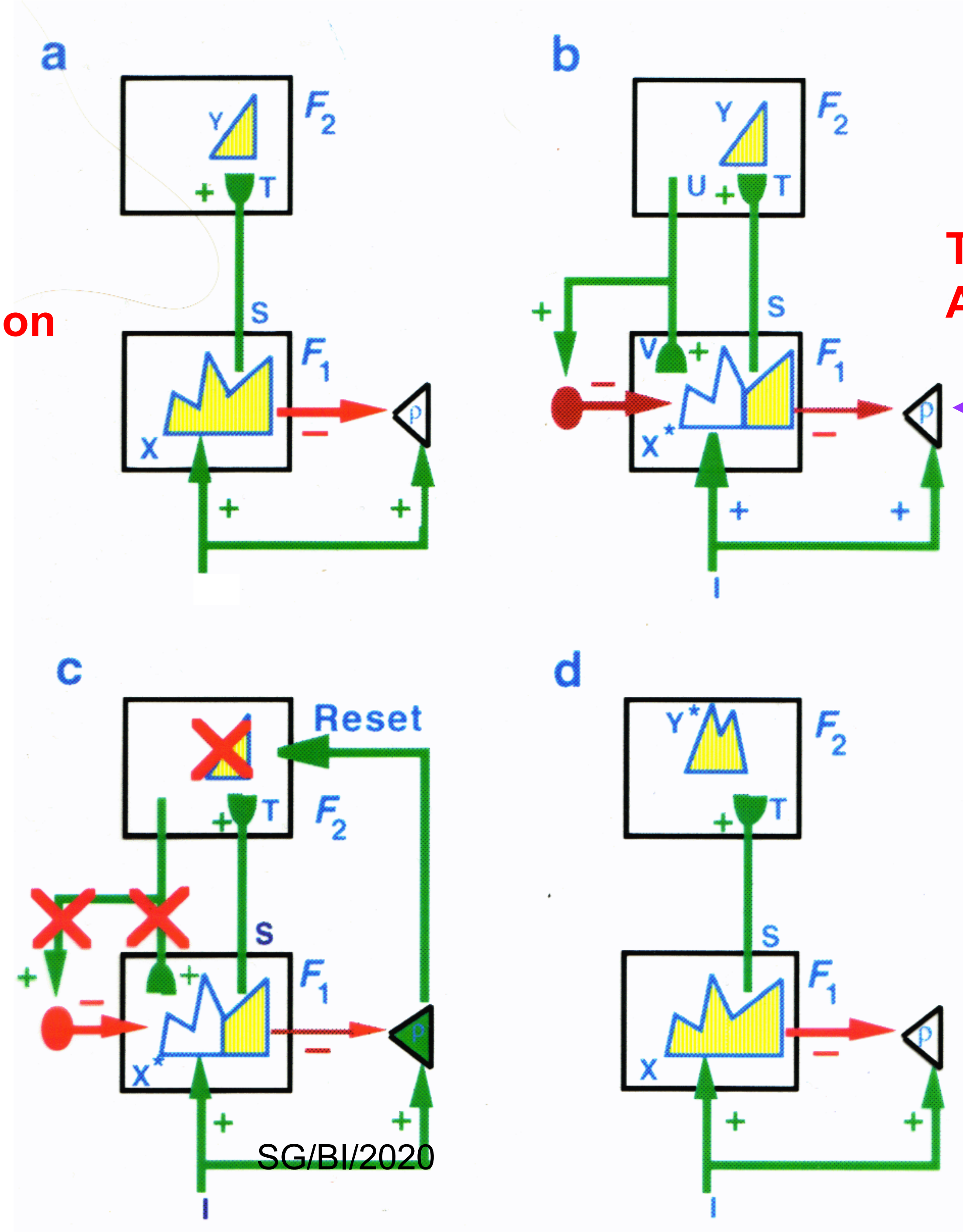


VIGILANCE
How big a mismatch causes reset?

Mismatch Reset: Novelty-Sensitive Arousal Burst

Choose another category

VIGILANCE
determines what features are learned in the CRITICAL FEATURE PATTERN

It clarifies how our brains learn CONCRETE knowledge for some tasks and ABSTRACT knowledge for others

High Vigilance – Narrow Categories; CONCRETE
Mom's face

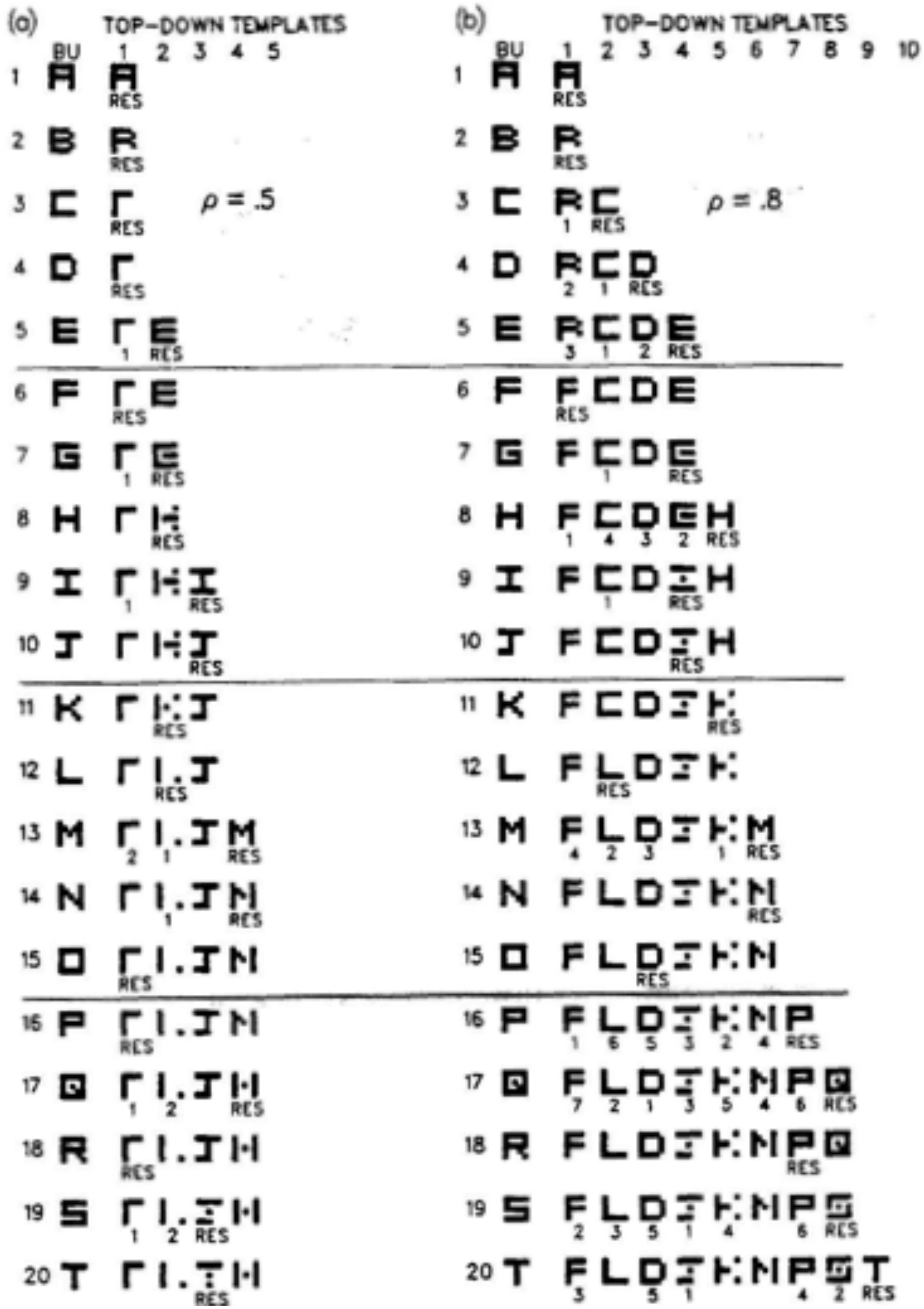
Low Vigilance – Broad Categories; ABSTRACT
A face

Critical feature patterns are explainable at every level of vigilance!

CLASSIFYING ALPHABET AT TWO VIGILANCE LEVELS

Vigilance .5

Fewer, and more abstract, categories



Vigilance .8

More, and more concrete, categories

VIGILANCE DATA IN INFEROTEMPORAL CORTEX

RECEPTIVE FIELD SELECTIVITY MUST BE LEARNED

Some cells respond selectively to particular views of particular faces

Other cells respond to broader features of an animal's environment

Desimone, Gross, Perrett, …

EASY vs. DIFFICULT DISCRIMINATIONS: VIGILANCE!

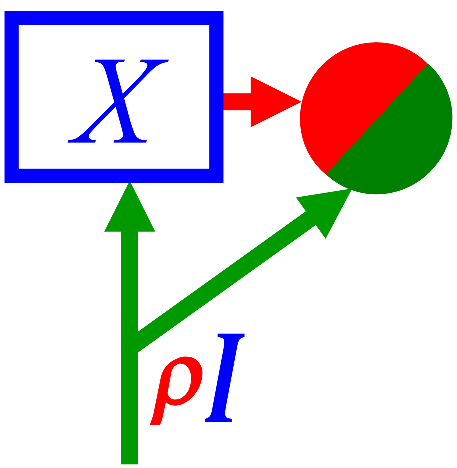
"In the difficult condition the animals adopted a stricter internal criterion for discriminating matching from non-matching stimuli… The animal's internal representations of the stimuli were better separated … increased effort appeared to cause enhancement of the responses and sharpened selectivity for attended stimuli…"

Spitzer, Desimone, and Moran, 1988

VIGILANCE CONTROL

$$\rho|I| - |X| \le 0 \qquad \rho \le \frac{|X|}{|I|}$$ **resonate and learn**

$$\rho|I| - |X| > 0 \qquad \rho > \frac{|X|}{|I|}$$ **reset and search**



ρ is a sensitivity or gain parameter

VIGILANCE CONTROL

$$\rho|I| - |X| \leq 0 \qquad \rho \leq \frac{|X|}{|I|}$$ **resonate and learn**

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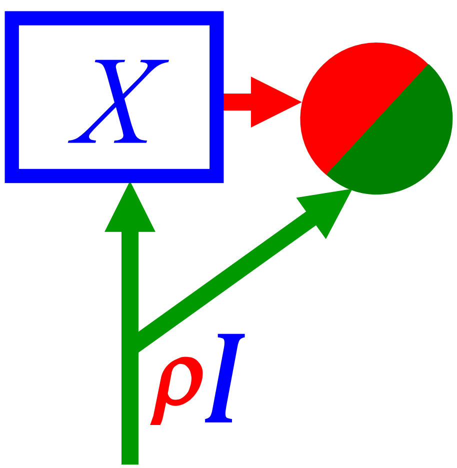


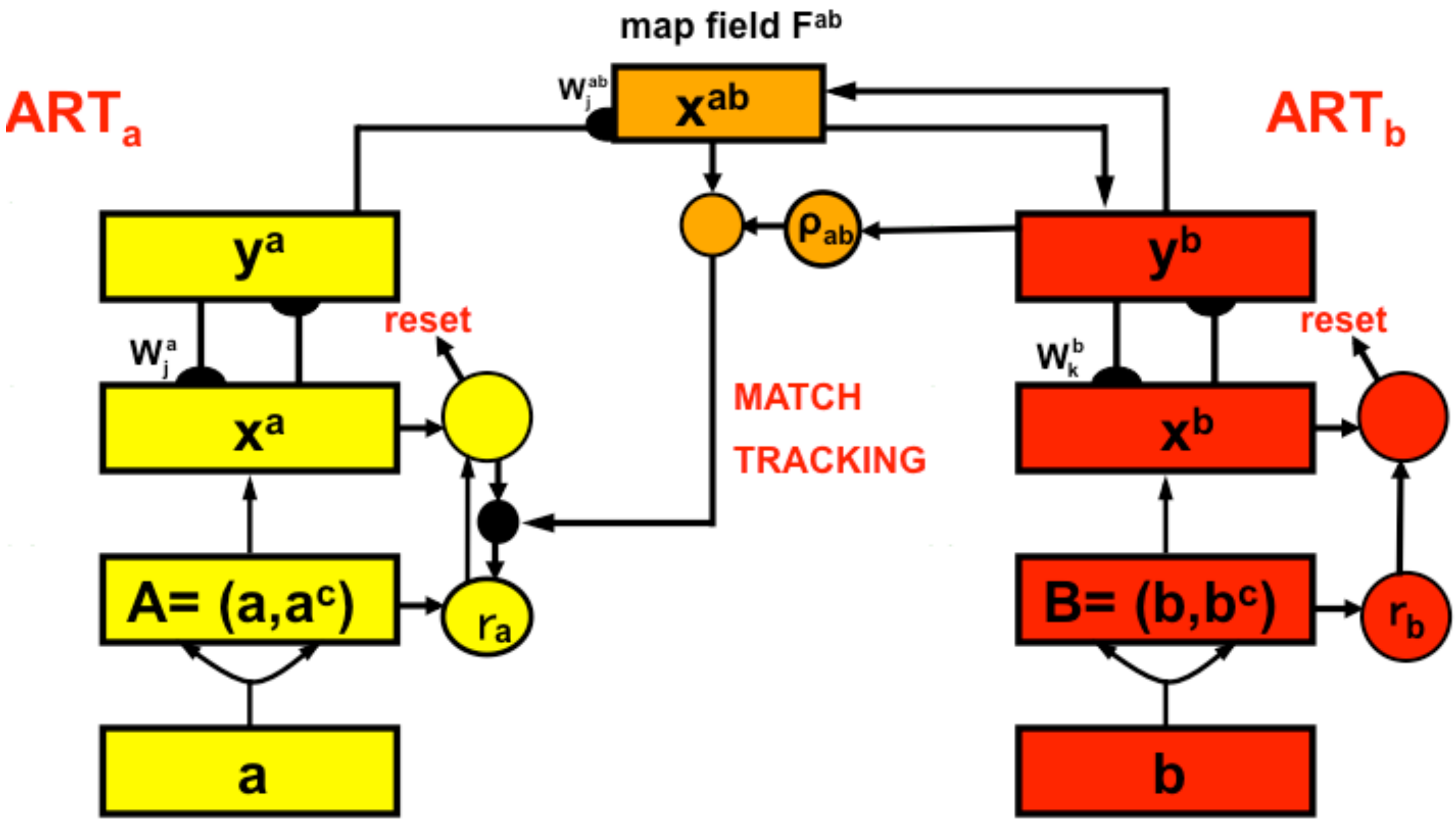
ρ is a sensitivity or gain parameter

How to change vigilance based on predictive success?

FROM UNSUPERVISED TO SUPERVISED ART MODELS

Extend UNSUPERVISED ART to SUPERVISED or UNSUPERVISED ARTMAP

FUZZY ARTMAP

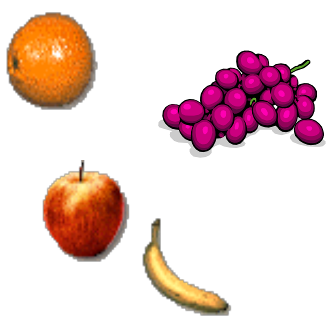


MATCH TRACKING realizes Minimax Learning Principle:

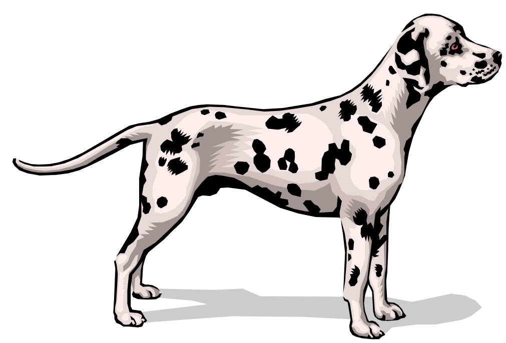
Vigilance increases just above the match ratio of prototype / exemplar, thereby triggering search

LEARN MANY-TO-ONE and ONE-TO-MANY MAPS

Many-to-One	One-to-Many
Compression, Naming	**Expert Knowledge**
(a_1,b)	(a,b_1)
(a_2,b)	(a,b_2)
(a_3,b)	(a,b_3)
(a_4,b)	(a,b_4)

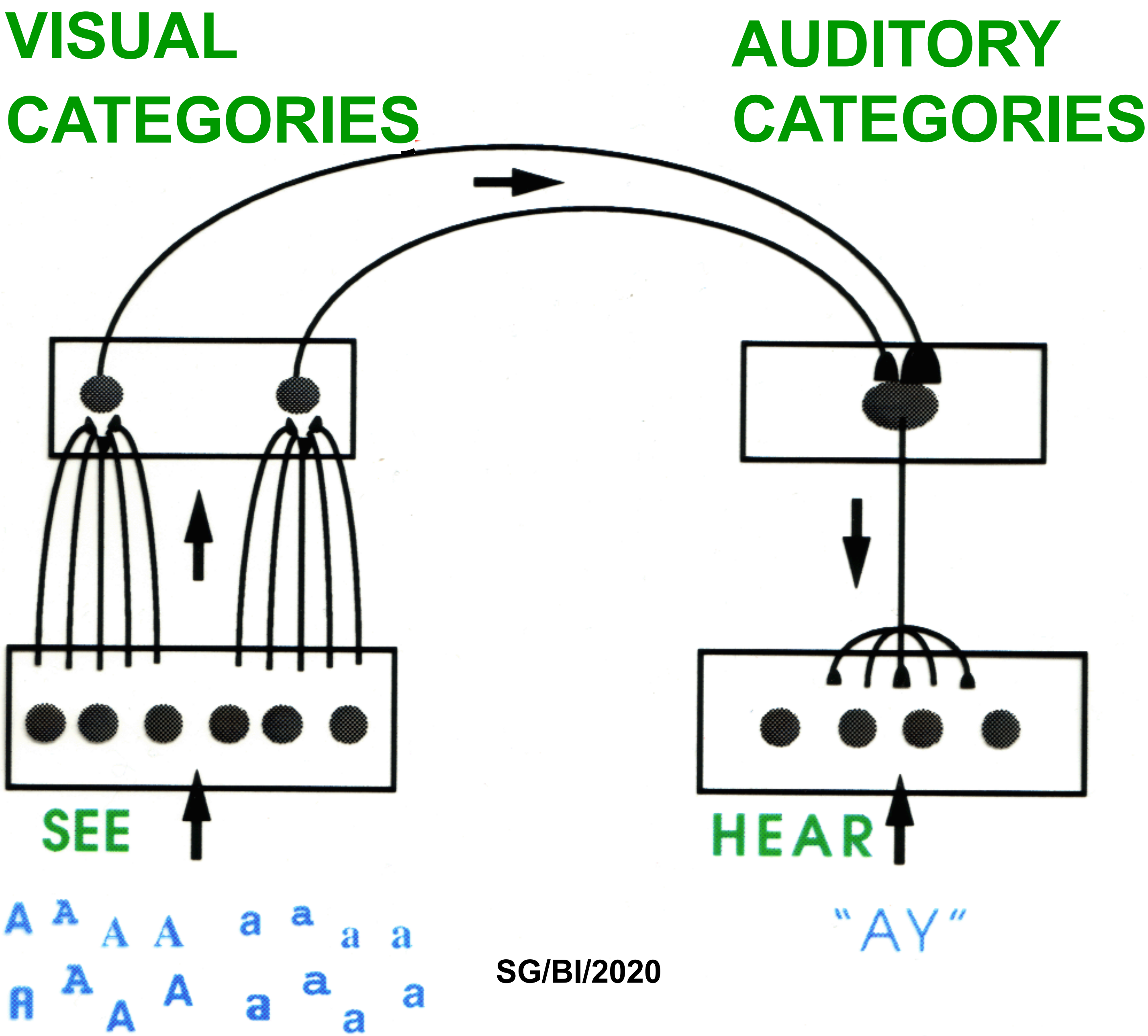


Fruit

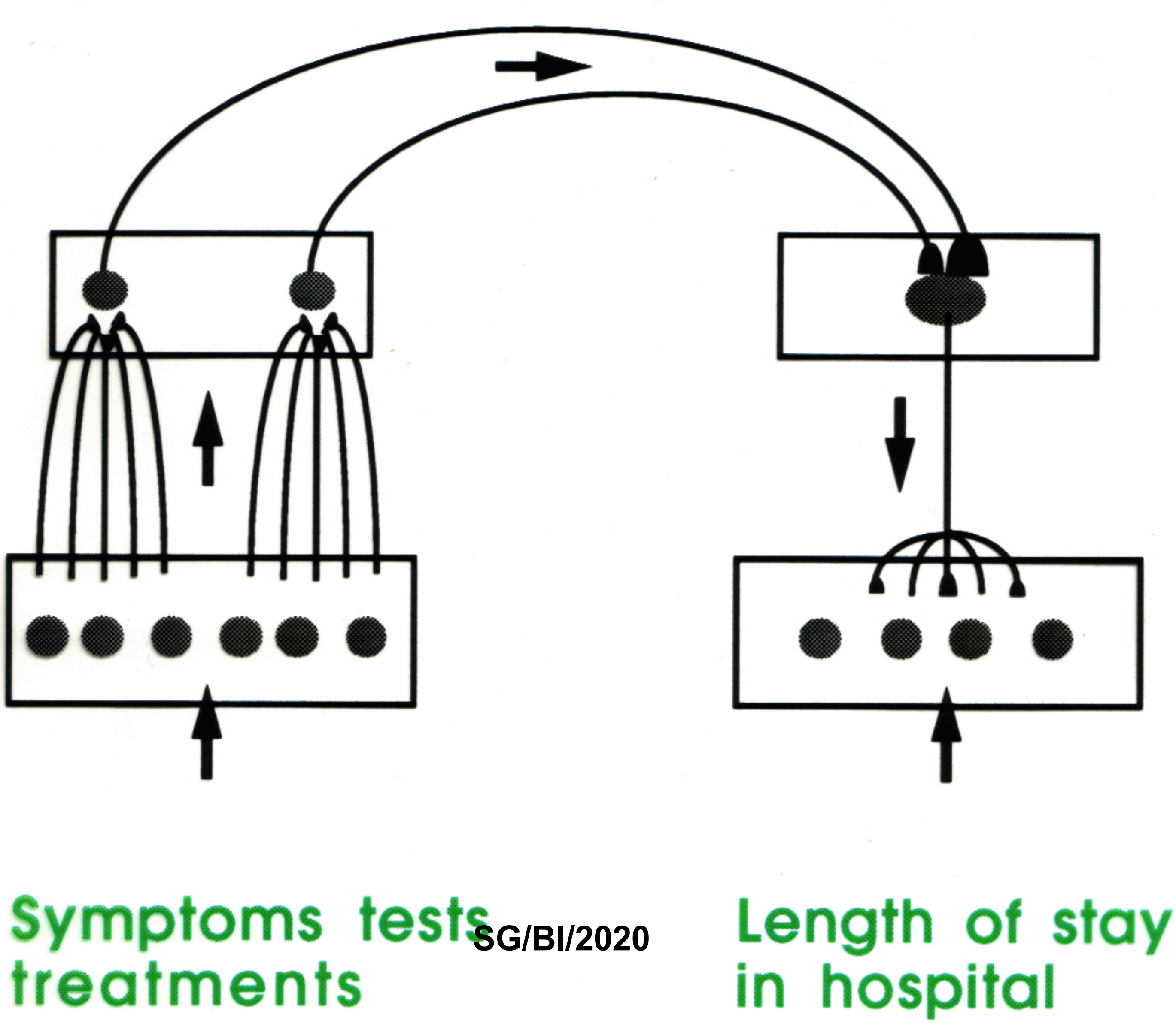


Animal
Mammal
Pet
Dog
Dalmatian
Fireman's
Mascot
"Rover"

MANY-TO-ONE MAP
Two Stages of Compression

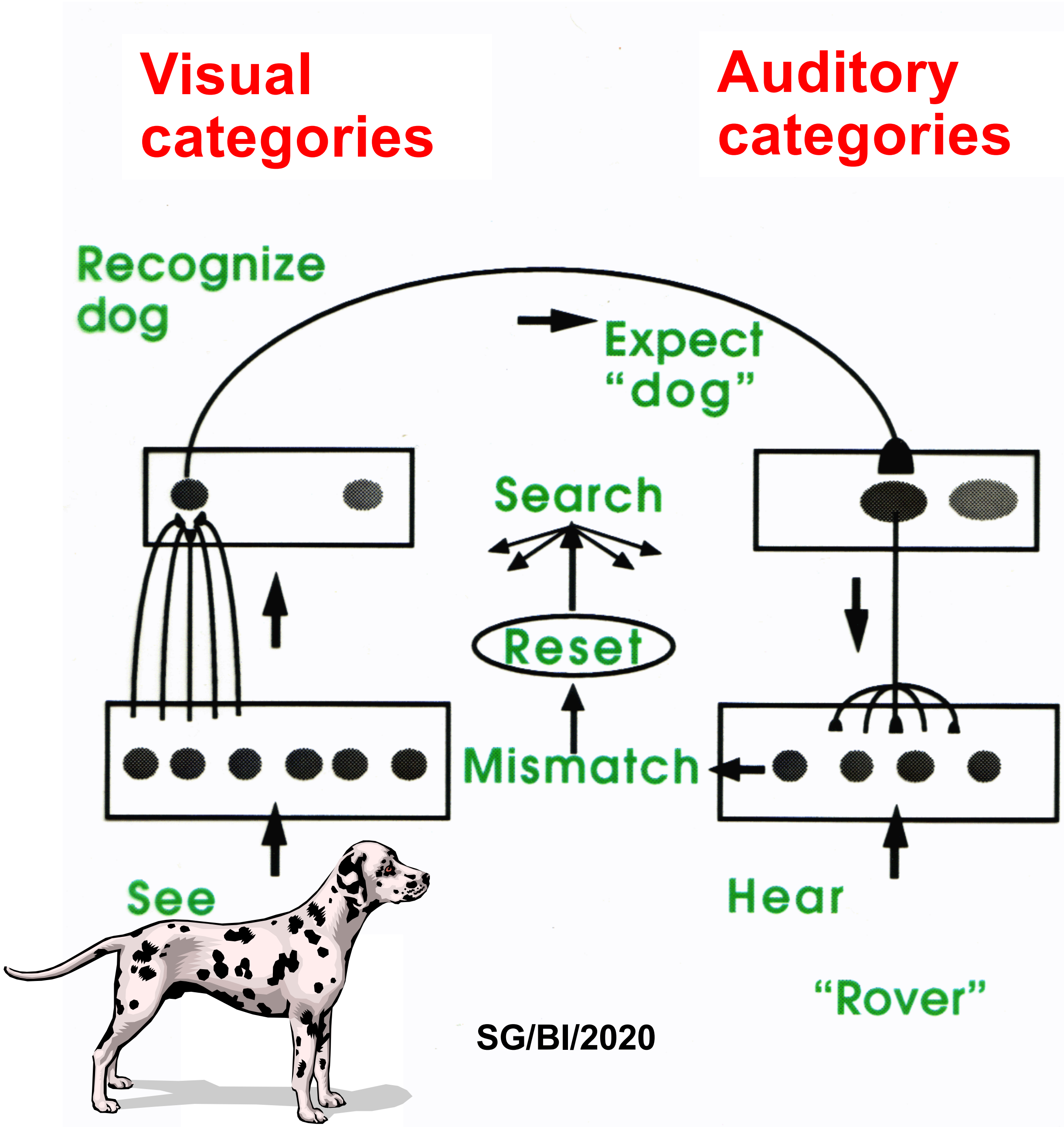


MANY-TO-ONE MAP
Two Stages of Compression
Medical Database Prediction



ONE-TO-MANY MAP

Expert Knowledge



MINIMAX LEARNING PRINCIPLE

How to conjointly

minimize predictive error

and

maximize generalization

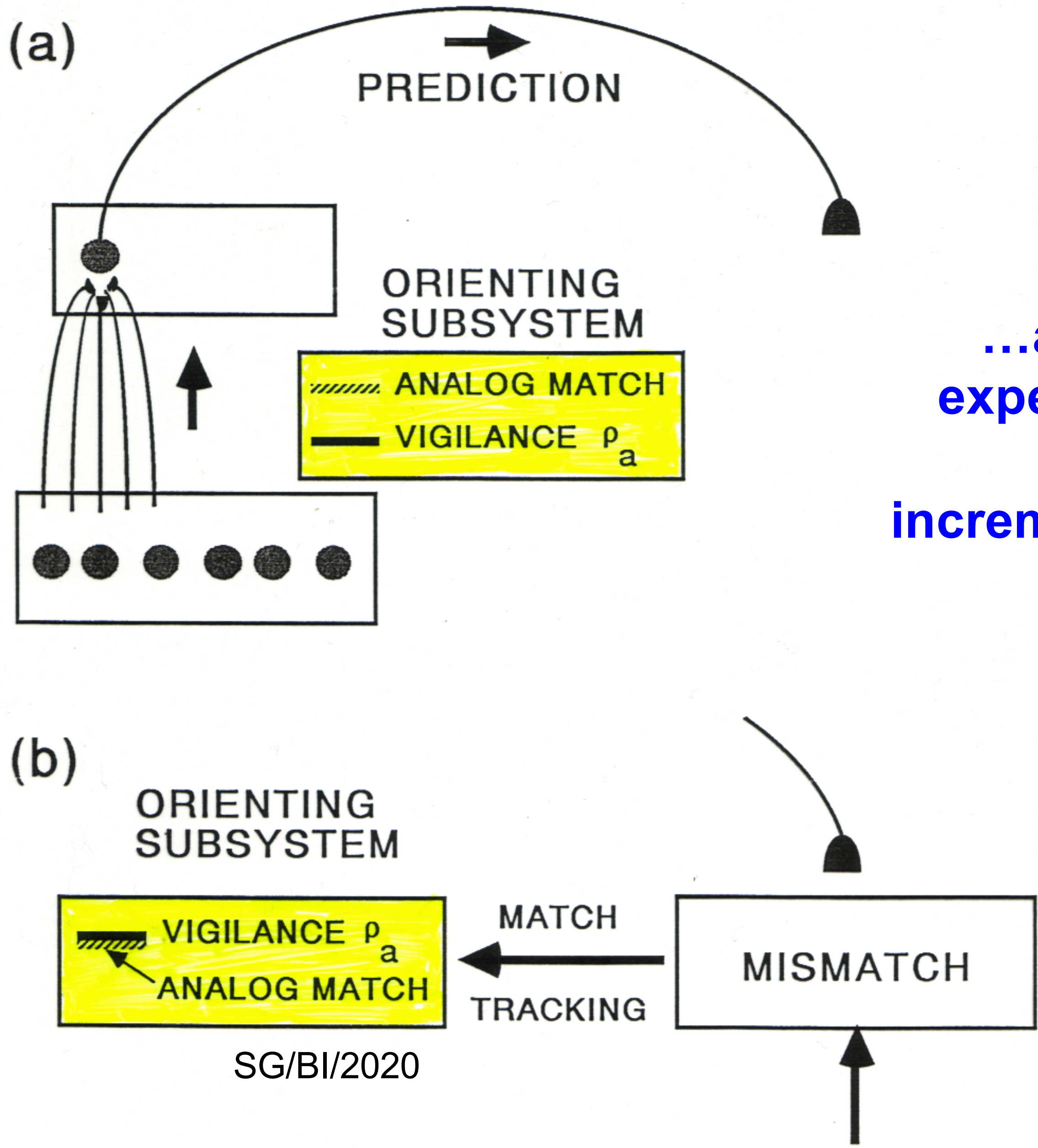
using error feedback

in an incremental fast learning context

in response to nonstationary data?

MATCH TRACKING realizes MINIMAX LEARNING PRINCIPLE

Given a predictive error, vigilance increases just enough to trigger search and thus sacrifices the minimum generalization to correct the error



…and enables expert knowledge to be incrementally learned

Are ART mechanisms like vigilance control realized within LAMINAR cortical and thalamic circuits?
YES!

SMART model
Synchronous Matching ART

Grossberg and Versace, 2008

MAIN QUESTIONS:

How are multiple levels of brain organization

spikes
local field potentials
inter-areal synchronous oscillations
spike-timing dependent plasticity

coordinated to

regulate stable category learning and attention

during cognitive information processing via

laminar cortical circuits

specific and nonspecific thalamic nuclei?

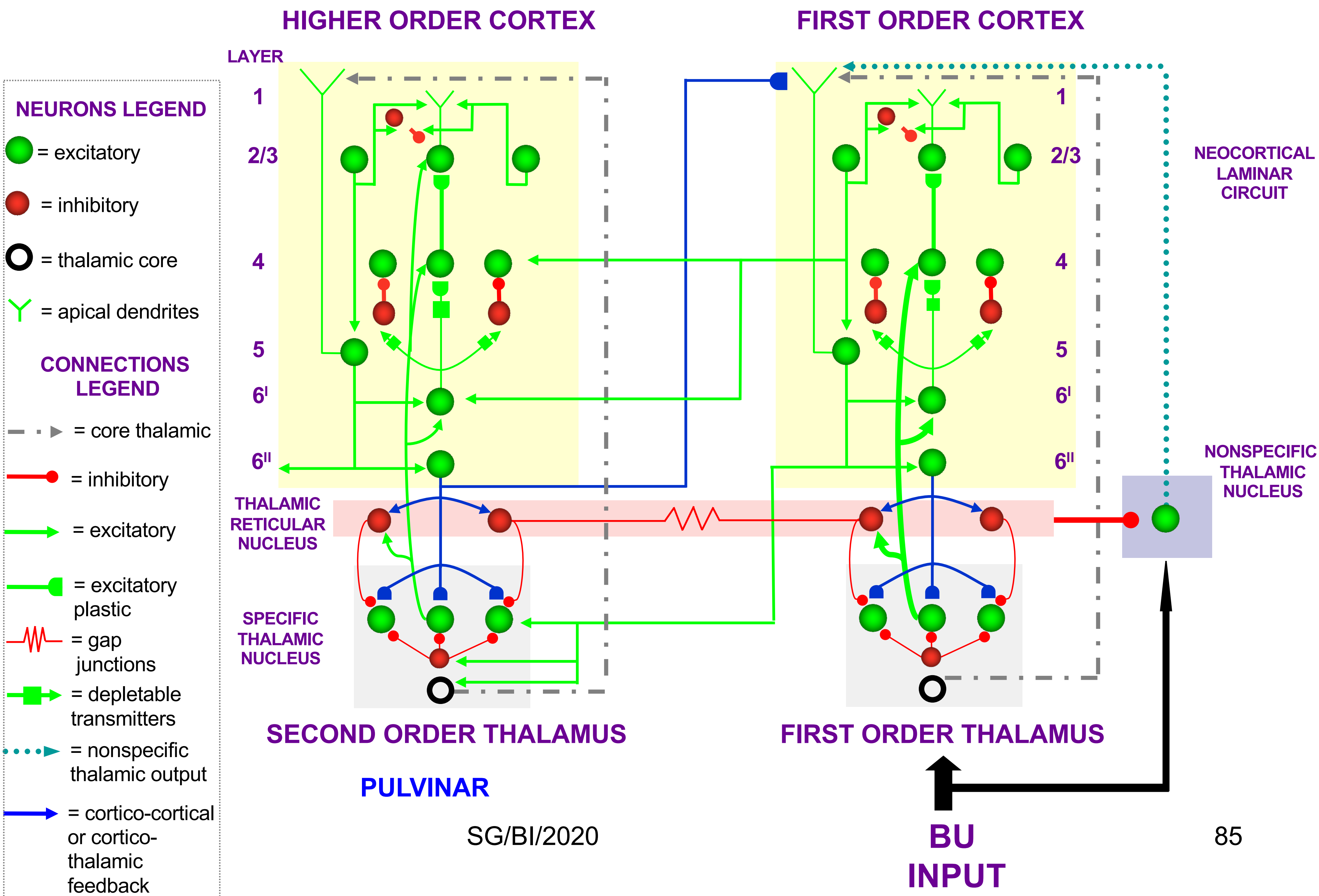
Illustrates NEW PARADIGMS for brain computing

INDEPENDENT MODULES
Computer Metaphor

COMPLEMENTARY COMPUTING
What is the nature of brain specialization?

LAMINAR COMPUTING
Why are all neocortical circuits organized in layers?
How do laminar circuits give rise to biological intelligence?

SMART: MODEL MACROCIRCUIT



SG/BI/2020

THE MODEL FUNCTIONALLY EXPLAINS LOTS OF ANATOMICAL DATA

Connections	Type	Functional interpretation	References
thalamic core A → 4 A	D	Primary thalamic relay cells drive layer 4.	Blasdel and Lund (1983)
thalamic core A → 6^{I} A	D	Primary thalamic relay cells prime layer 4 via the 6 → 4 modulatory circuit.	Blasdel and Lund (1983) for LGN → 6; Callaway (1998) LGN input to 6 is weak and Layer 5 projections to 6 **[Note 1]**
thalamic core A → RE A	D	Recurrent inhibition to primary and secondary thalamic relay cells.	Sherman and Guillery (2001); Jones (2002)
RE A → thalamic core A	I	Off-surround to primary and secondary thalamic relay cells, synchronization of thalamic relay cells.	Cox *et al.* (1997); Pinault and Deschenes (1998); Sherman and Guillery (2001)
RE A → RE A	I	Normalization of inhibition.	Jones (2002); Sohal and Huguenard (2003)
RE A (B) → RE B(A)	GJ	Synchronize RE and thalamic relay cells.	Landisman *et al.* (2002)
RE A → nonspecific thalamic A	I	Inhibition of nonspecific thalamic cells, participates in the reset mechanism.	Kolmac and Mitrofanis (1997); Van der Werf *et al.* (2002)
nonspecific thalamic A → 5 A	M	To 5 through apical dendrites in 1, participates in the reset mechanism.	Van der Werf *et al.* (2002)
4 A → 4 inh. A	D	Lateral inhibition in layer 4.	Markram *et al.* (2004)
4 inh. A → 4 A	I	Lateral inhibition in layer 4.	Markram *et al.* (2004)
4 inh. A → 4 inh. A	I	Normalization of inhibition in layer 4.	Ahmed *et al.* (1997); Markram *et al.* (2004)
4 A → 2/3 A	D	Feedforward driving output from 4 to 2/3.	Fitzpatrick *at al.* (1985); Callaway and Wiser (1996)
2/3 A → 2/3 A	D	Recurrent connections (grouping) in 2/3.	Bosking *et al.* (1997); Schmidt *et al.* (1997); Grossberg and Raizada (2003)
2/3 A → 2/3 inh. A	D	Avoid outward spreading (bipole) in 2/3.	McGuire *et al.* (1991); Grossberg and Raizada (2003)
2/3 inh. A → 2/3 inh. A	I	Normalization of inhibition.	Tamas *et al.* (1998); Grossberg and Raizada(2003)
2/3 A → 4 B	D	Feedforward output from Area A to Area B.	Van Essen *et al.* (1986)
2/3 A → 6^{II} B	D	Feedforward output from Area A to Area B.	Van Essen *et al.* (1986)
2/3 A → 5 A	D	Conveys layer 2/3 output to layer 5.	Callaway and Wiser (1996)
2/3 A → 6^{II} A	D	Conveys layer 2/3 output to layer 6^{II}.	Callaway (1998)

THE MODEL FUNCTIONALLY EXPLAINS LOTS OF ANATOMICAL DATA

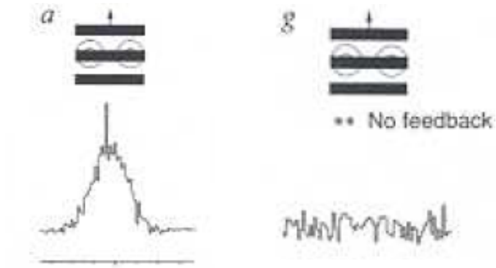
Connections	Type	Functional interpretation	References
5 A → thalamic core B	D	Feedforward connections from Area A to Area B through secondary thalamic relay neurons.	Rockland (1999); Sherman and Guillery (2001)
5 A → 6^{I} A	D	Delivers feedback to the 6 → 4 circuit from higher cortical areas, sensed at the apical dendrites of 5 branching in 1.	Callaway (1998); Callaway and Wiser (1996), class B" cells **[Note 2]**
6^{I} A → 4 A	M	On-center to 4. Mediated by habituative gates.	Stratford *et al.* (1996); Callaway (1998); Grossberg and Raizada (2003)
6^{I} A → 4 int. A	D	Off-surround to 4.	McGuire *et al.* (1984); Ahmed *et al.*, (1997); Callaway (1998)
6^{II} A → thalamic Core A	M	On-center to primary thalamic relay cells.	Sillito *et al.* (1994); Callaway (1998);
6^{II} A → RE A	D	Off-surround to primary thalamic relay cells mediated by thalamic RE.	Guillery and Harting (2003); Sherman and Guillery (2001)
6^{II} B → 2/3, 2/3 inh., 5 A	M	Intercortical feedback from 6^{II} area B to 1 area A, where it synapses on 2/3 excitatory and inhibitory neurons, as well as 5 apical dendrites branching in 1	Rockland and Virga (1989); Rockland (1994); Salin and Bullier (1995)

Abbreviations: **inh.** = inhibitory neurons; **RE** = reticular nucleus**;** **A** = primary (thalamic, cortical) loop; **B** = secondary (thalamic, cortical) loop; **D** = driving excitatory connections; **M** = modulatory connections; **I** = inhibitory connections; **GJ** = gap junctions; **int.** = inhibitory interneuron. **[Note 1]:** Callaway (1998) subdivides Layer 6 neurons in 3 classes: *Class I:* provide feedback to 4C, receive input from LGN, and project back to LGN; *Class IIa:* dendrites in 6, axons from 2/3, project back to 2/3 with modulatory connections; *Class IIb:* dendrites in 5, project exclusively to deep layers (5 & 6) and claustrum. In the model, these populations are clustered in 2 classes, layer 6I and 6II, which provide feedback to thalamic relay cells and layer 4, respectively. **[Note 2]:** Callaway (1998) subdivides Layer 5 neurons in 3 classes: *Class A:* dendrites in 5, axons from 2/3, project back to 2/3 with modulatory connections; *Class B:* dendrites in 5, axons from 2/3, project laterally to 5 and PULVINAR; *Class C:* dendrites in 1, project to superior colliculus. In the model, these differences are ignored, and it is assumed that the model layer 5 neuron receives input from 2/3 (Classes A and B), as well modulatory input from the nonspecific thalamic nuclei (Class C, apical dendrites in layer 1), and provide output to 6^{I} and second-order thalamic nuclei. The inner, recurrent loop with 2/3 has also been ignored.

BRAIN OSCILLATIONS DURING MATCH/MISMATCH

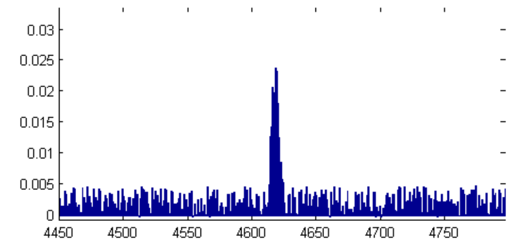
DATA

FB ON **FB OFF**



SIMULATION

FB ON



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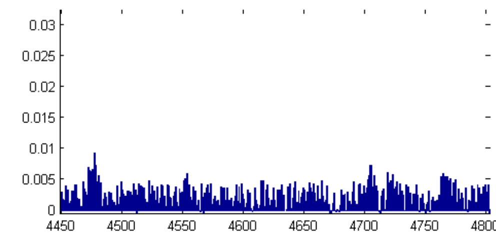
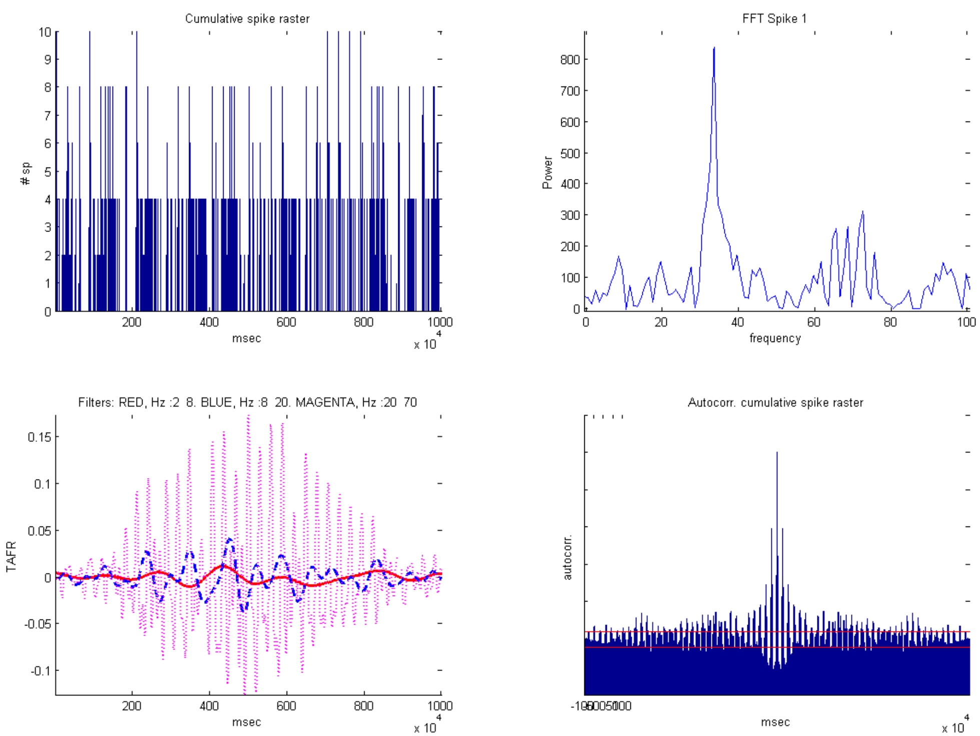
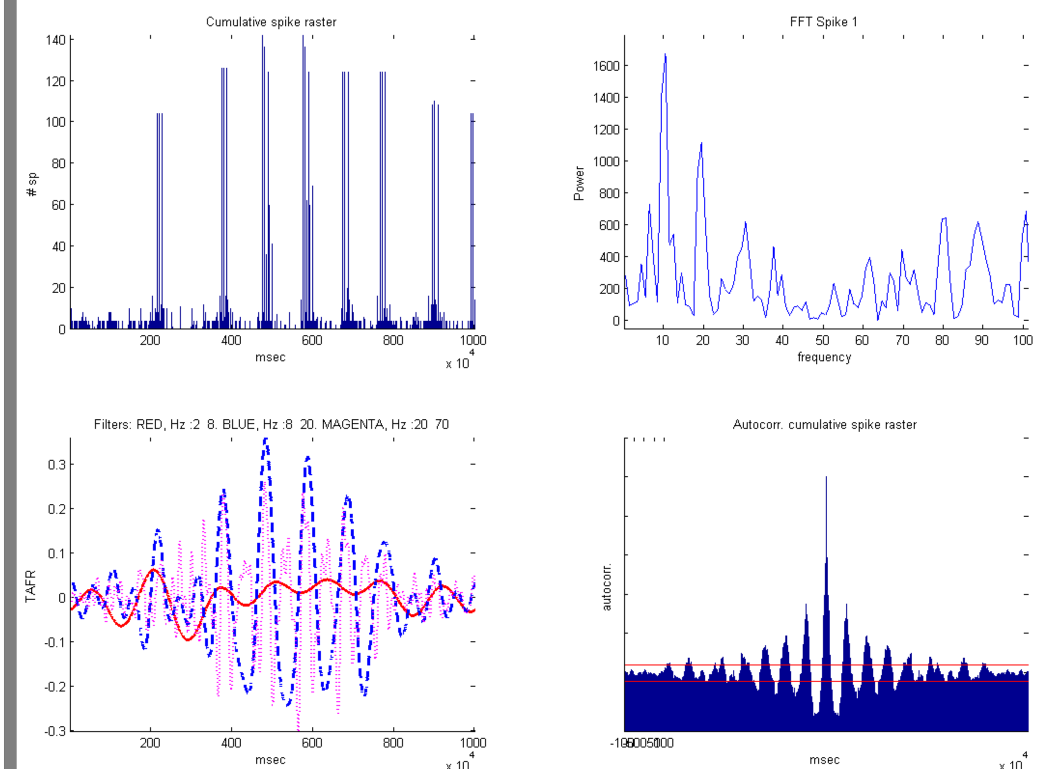


(a) TD CORTICOTHALAMIC FEEDBACK increases SYNCHRONY Sillito *et al.*, 1994



(b) MATCH
Increases γ oscillations

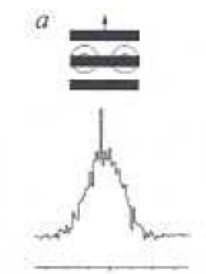


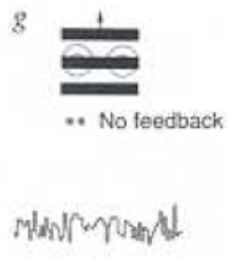
(c) MISMATCH
increases θ, β oscillations

BRAIN OSCILLATIONS DURING MATCH/MISMATCH

DATA

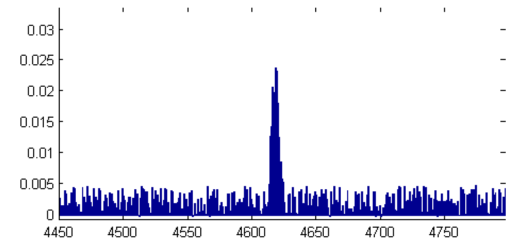
FB ON FB OFF

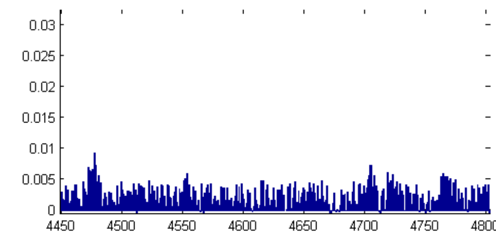




SIMULATION

FB ON FB OFF





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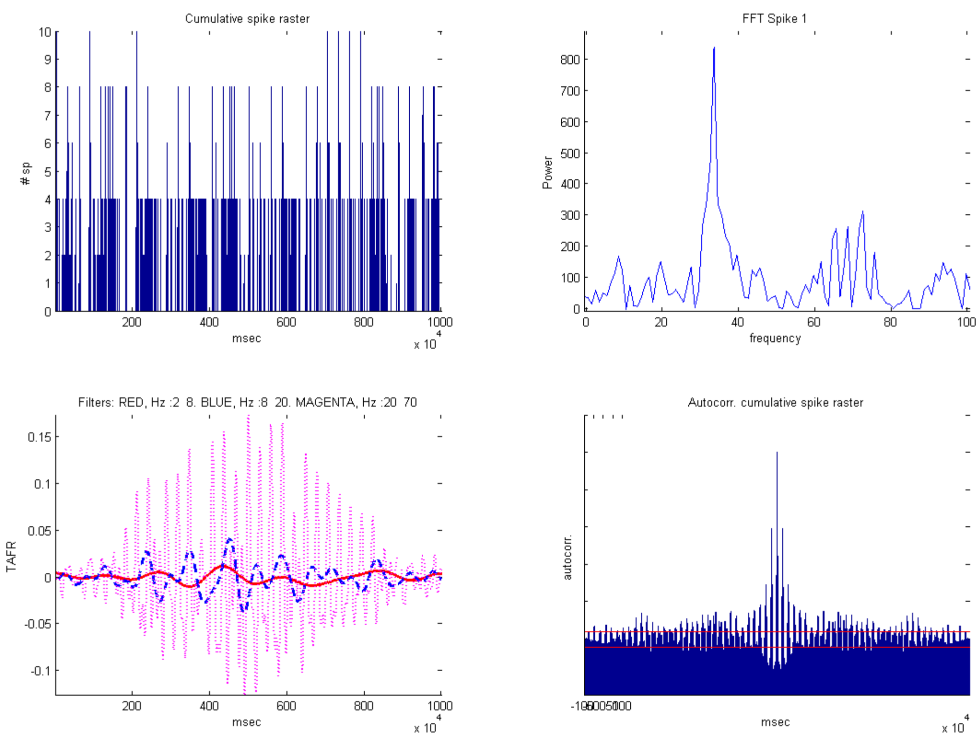
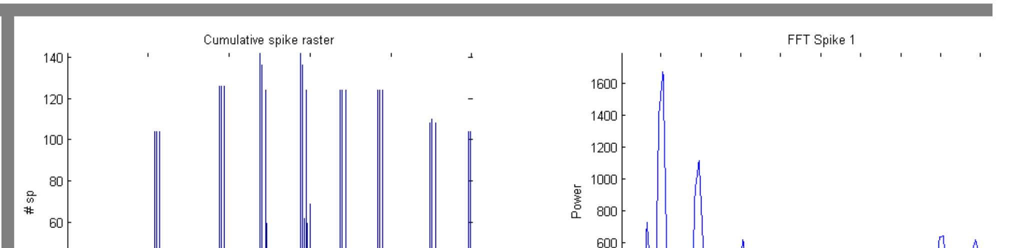
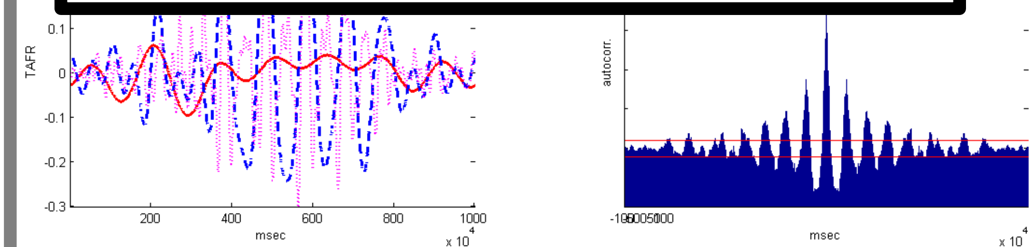




V1 Buffalo et al., 2011
van Kerkoerle et al., 2014
V4 Buschman and Miller, 2009
Hippocampus Berke et al., 2009



(b) MATCH
Increases γ oscillations

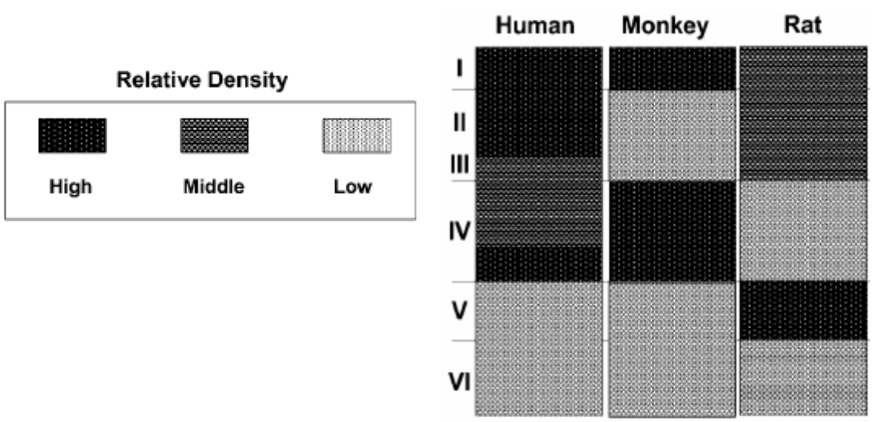
(c) MISMATCH
increases *θ*, *β* oscillations

VIGILANCE CONTROL: MISMATCH-MEDIATED ACETYLCHOLINE RELEASE

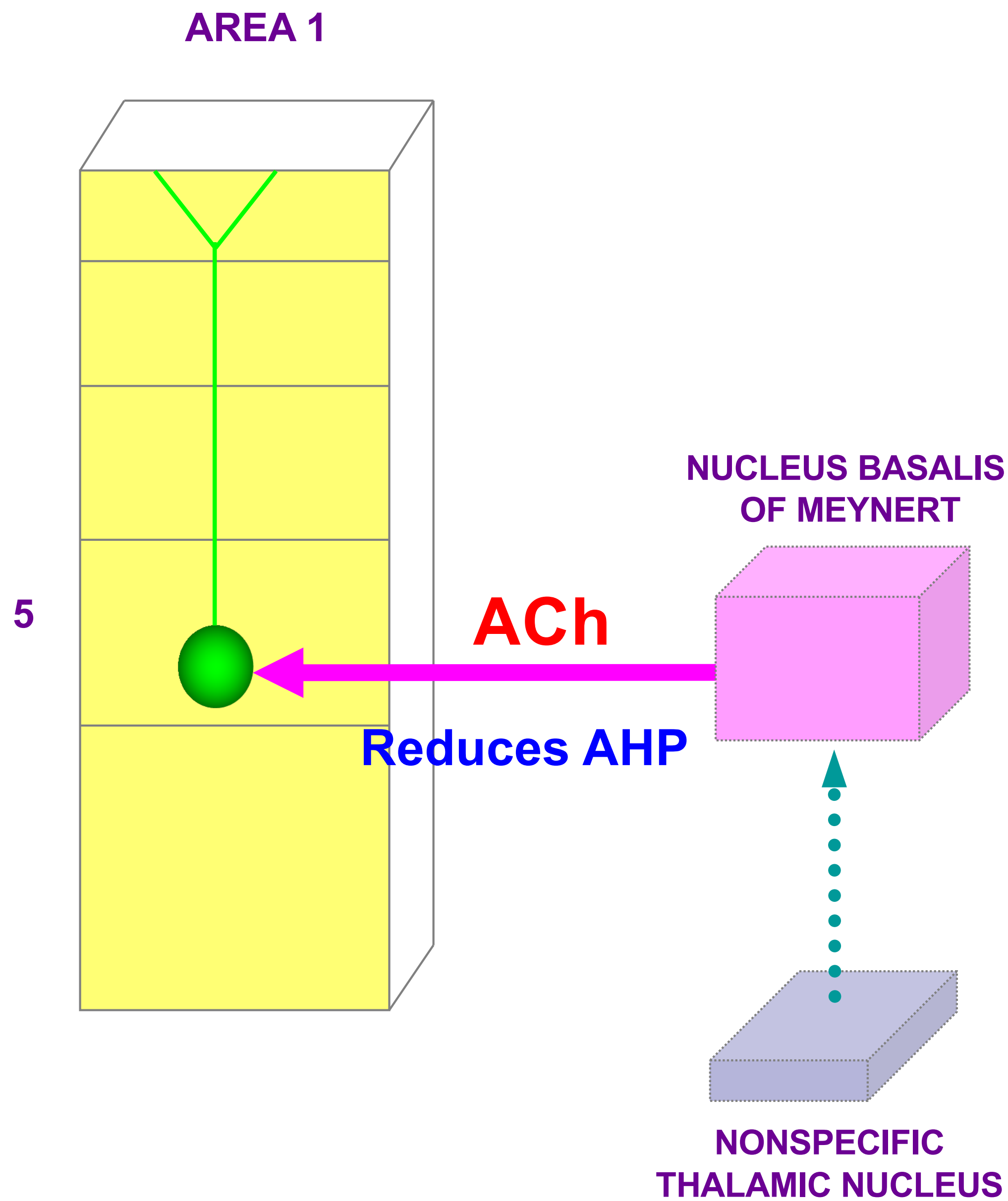
Acetylcholine (Ach) regulation by NONSPECIFIC THALAMIC NUCLEI via NUCLEUS BASALIS OF MEYNERT reduces AHP in layer 5

Ach thereby facilitates RESET (compare ART VIGILANCE control)

HIGH Vigilance ~ Sharp Code
LOW Vigilance ~ Coarse Code



CHOLINERGIC DENSITY AXONS IN V1 AND HOMOLOGS
Gu (2003)



COGNITIVE LEARNING AND MEMORY CONSOLIDATION CYCLE

A dynamic cycle of

RESONANCE

and

RESET

As categories are learned, search automatically disengages

Modulatory novelty potentials subside as

this type of memory consolidation ends

Direct access to globally best-matching category

Mathematical proof in: Carpenter & Grossberg, *CVGIP*, 1987

Many supportive psychological and neurobiological data

Explains how we can quickly recognize familiar objects

even if, as we get older, we store enormous numbers of memories

Catastrophic forgetting occurs if top-down expectations fail

What goes wrong if the ORIENTING SYSTEM fails?

AMNESIA OCCURS!

DYNAMIC PHASE OF MEMORY CONSOLIDATION

While input exemplar still drives

memory search

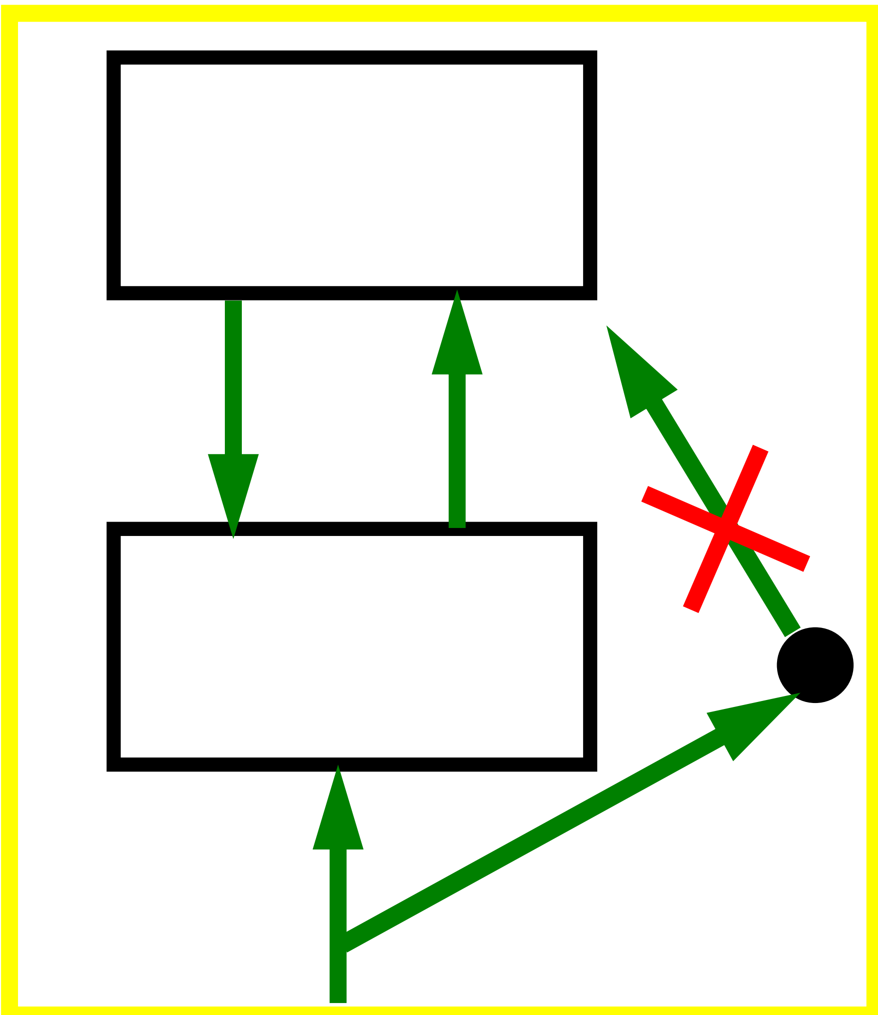
before direct access occurs

An emergent property of the entire circuit

A FORMAL AMNESIC SYNDROME

Due to damaged medial temporal brain structures – Hippocampus

ORIENTING SYSTEM!



1. **Unlimited anterograde amnesia**
   Cannot search for new categories

2. **Limited retrograde amnesia**
   Direct access

3. **Failure of consolidation**
   Squire & Cohen, 1994

4. **Defective novelty reactions**
   Perseveration
   O' Keefe & Nadel, 1978

5. **Memory consolidation and novelty detection**
   Mediated by same structures
   Zola-Morgan & Squire, 1990

A FORMAL AMNESIC SYNDROME

5. **Normal priming**

   Baddeley & Warrington (1970)

   Mattis & Kovner (1984)

6. **Learning of first item dominates**

   Gray (1982)

7. **Impaired ability to attend to relevent dimensions of stimuli**

   Butters & Cermak (1975); Pribram (1986)

HIPPOCAMPECTOMIZED MONKEYS

Fornix transection "impairs ability to change an established habit…impaired learning when one habit is to be formed in one set of circumstances and a different habit in a different set of circumstances that is similar to the first…"

Gaffan (1985)

Memory consolidation and novelty detection mediated by same neural structures

Zola-Morgan & Squire (1990)

Reduction in novelty-related hippocampal potentials as learning proceeds in rats

Deadwyler, West, & Lynch (1979)

Deadwyler, West, & Robinson (1981)

VIGILANCE control during MEDIAL TEMPORAL AMNESIA

Knowlton and Squire (1993) assume that two memory systems are needed to explain their amnesia data

Nosofsky and Zaki (1998) showed that a single exemplar model with a low SENSITIVITY parameter can quantitatively fit their data

Low SENSITIVITY plays a role similar to low VIGILANCE in ART

His exemplar model implicitly needs BU and TD feedback between exemplars and a category PROTOTYPE

VIGILANCE DATA IN INFEROTEMPORAL CORTEX

RECEPTIVE FIELD SELECTIVITY MUST BE LEARNED

- Some cells respond selectively to particular views of particular faces
- Other cells respond to broader features of an animal's environment

Desimone, Gross, Perrett, …

EASY vs. DIFFICULT DISCRIMINATIONS: VIGILANCE!

"In the difficult condition the animals adopted a stricter internal criterion for discriminating matching from non-matching stimuli… The animal's internal representations of the stimuli were better separated … increased effort appeared to cause enhancement of the responses and sharpened selectivity for attended stimuli…"

Spitzer, Desimone, and Moran, 1988

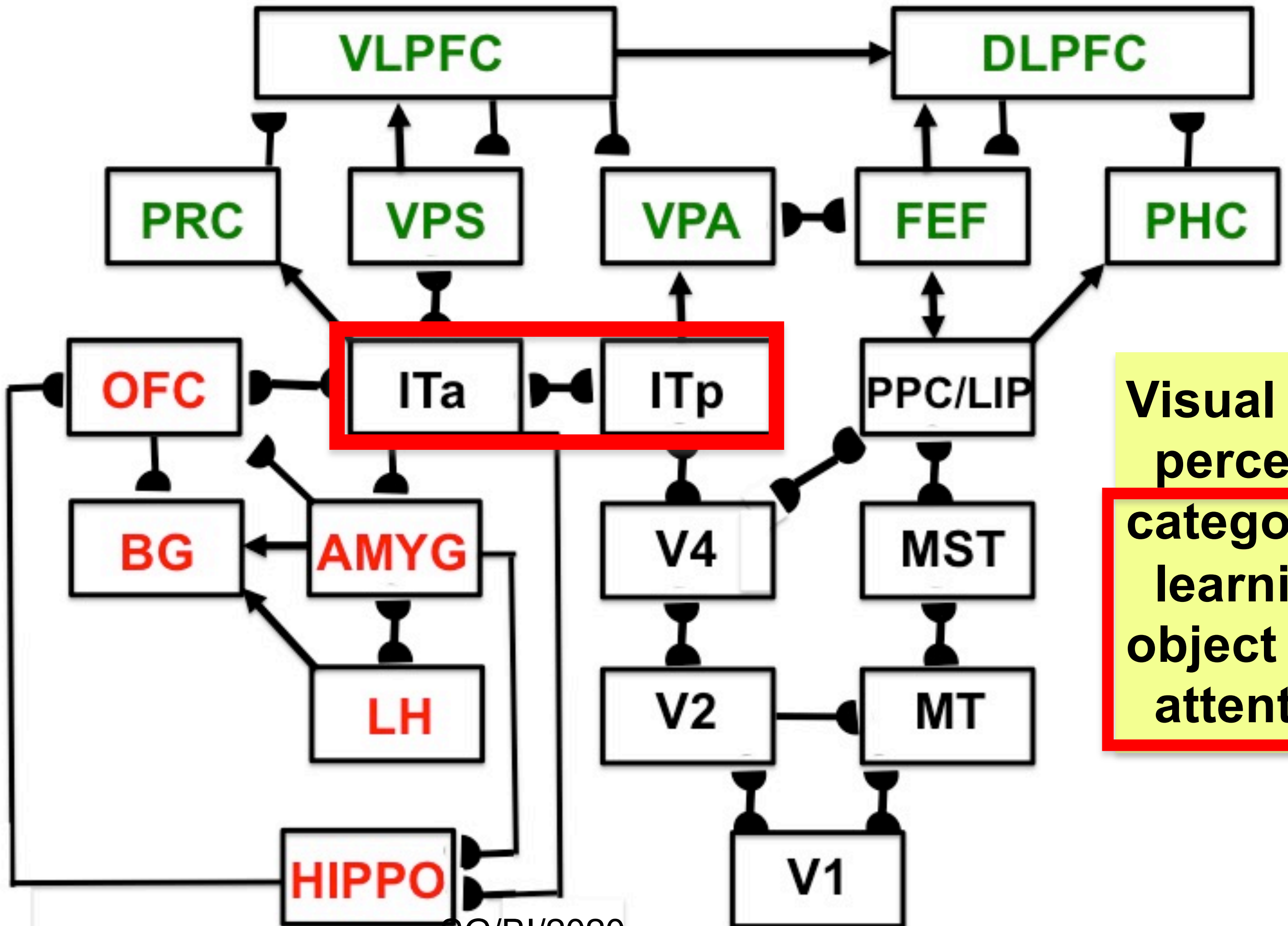
Predictive ART, or pART, architecture macrocircuit

How prefrontal cortex learns to control all higher-order intelligence

Grossberg (2018; see sites.bu.edu/steveg)

Working memory, learned plans, prediction, optimized action

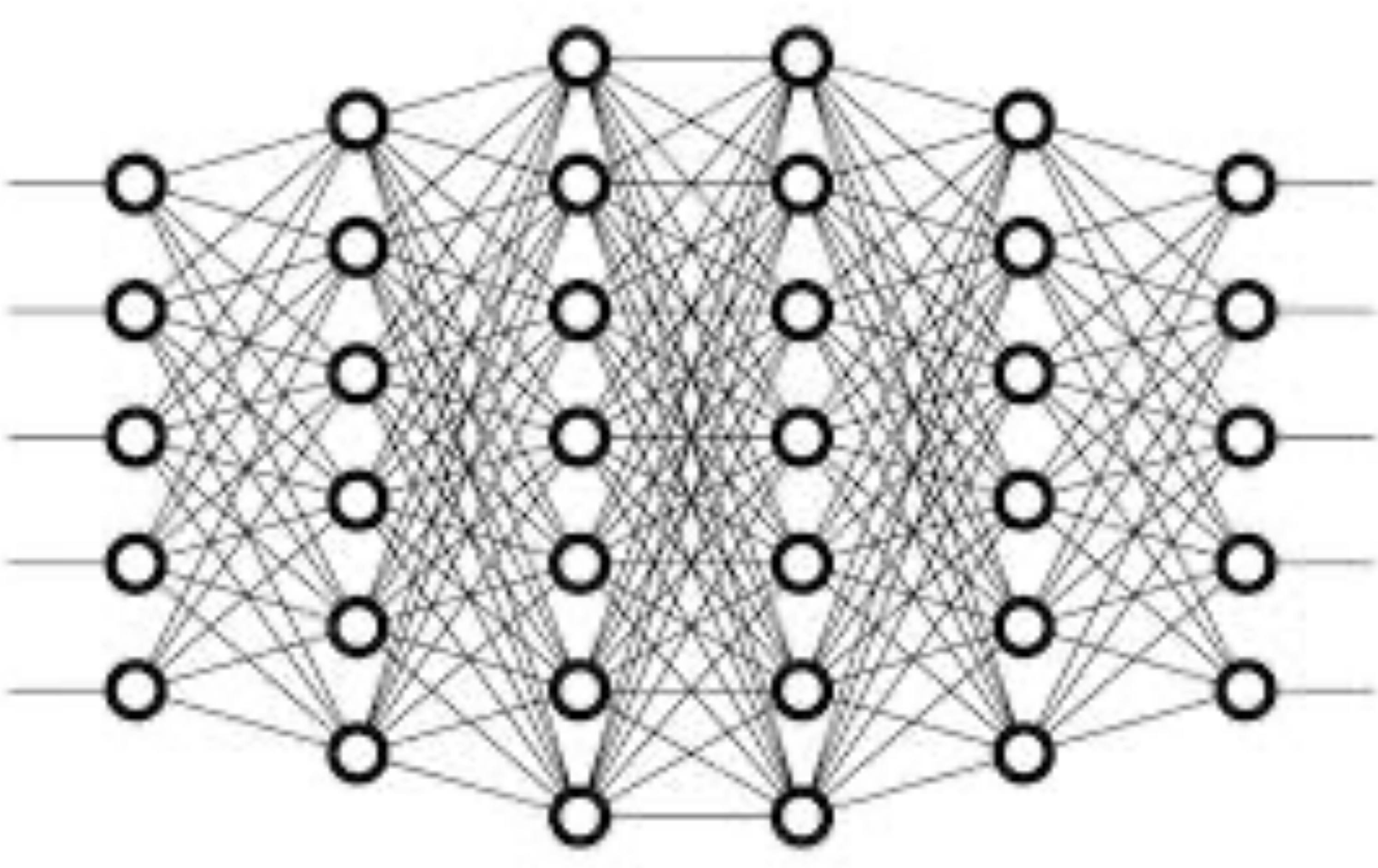
Reinforcement learning, emotion, motivation, adaptively-timed learning,



Visual perception, category learning, object attention

EACH BRAIN REGION IN NATURE AND IN pART CARRIES OUT A DIFFERENT FUNCTION

CONTRAST THE HOMOGENEOUS ORGANIZATION OF A TYPICAL DEEP LEARNING NETWORK



EXPLAINABLE VISUAL PERCEPTS

The functional units of BIOLOGICAL VISION are

COMPLETED DEPTH-SELECTIVE BOUNDARIES

which gate

FILLING-IN OF DEPTH-SELECTIVE SURFACES

BOUNDARIES and SURFACES are
COMPUTATIONALLY COMPLEMENTARY

EXPLAINABLE VISUAL PERCEPTS

The functional units of BIOLOGICAL VISION are

COMPLETED DEPTH-SELECTIVE BOUNDARIES

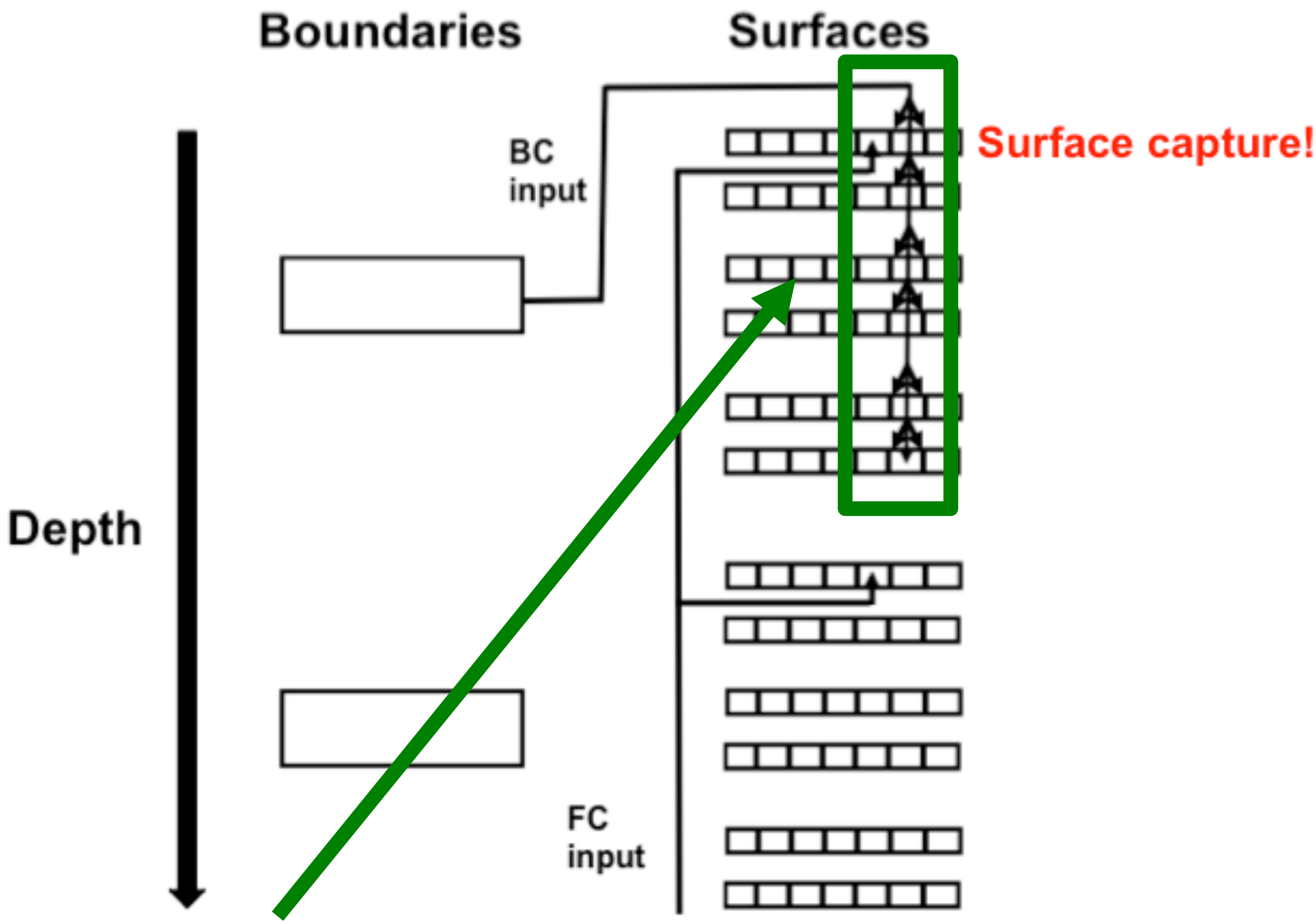
which gate

FILLING-IN OF DEPTH-SELECTIVE SURFACES

BOUNDARIES and SURFACES are COMPUTATIONALLY COMPLEMENTARY

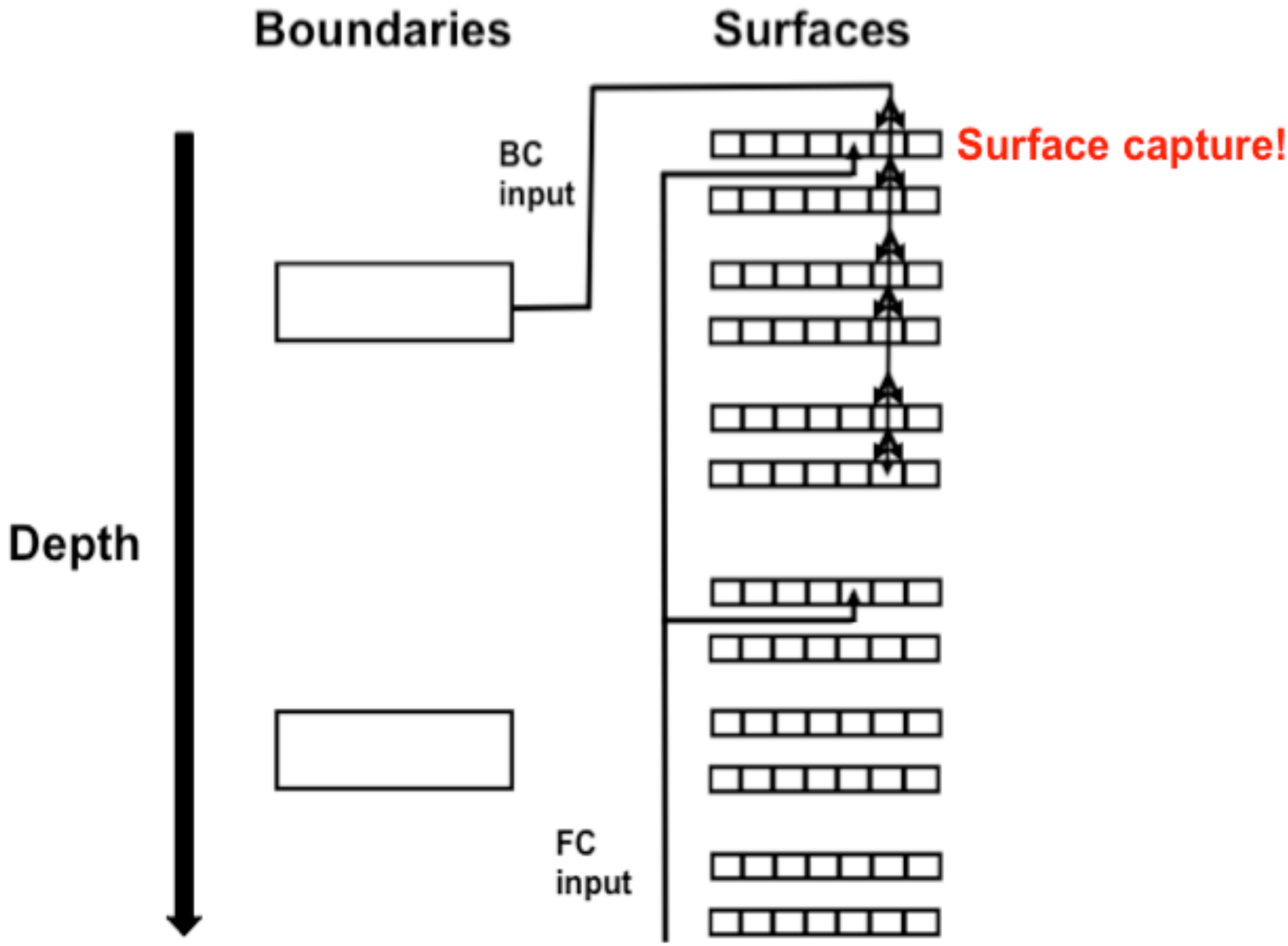
3D VISION AND FIGURE-GROUND SEPARATION

Multiple-scale, depth-selective boundary webs



Spatially abutting and colinear Boundary Contours (BC) and Feature Contours (FC) can trigger depth-selective filling-in of the FC color in the Filling-In-Domain that is surrounded by its BC

BOTH BOUNDARIES AND SURFACES ARE EXPLAINABLE



Boundaries and surfaces are explainable by
observing their depth-selective spatially distributed representations

EXPLAINABLE VISUAL PERCEPTS

The functional units of BIOLOGICAL VISION are

COMPLETED DEPTH-SELECTIVE BOUNDARIES

which gate

FILLING-IN OF DEPTH-SELECTIVE SURFACES

BOUNDARIES and SURFACES are COMPUTATIONALLY COMPLEMENTARY

Illustrates NEW PARADIGMS for brain computing

INDEPENDENT MODULES
Computer Metaphor

COMPLEMENTARY COMPUTING
What is the nature of brain specialization?

LAMINAR COMPUTING
Why are all neocortical circuits organized in layers?
How do laminar circuits give rise to biological intelligence?

SOME COMPLEMENTARY PROCESSES

Visual Boundary **Interbob Stream V1-V4**	**Visual Surface** **Blob Stream V1-V4**
Visual Boundary **Interbob Stream V1-V4**	**Visual Motion** **Magno Stream V1-MT**
WHAT Steam **Perception & Recognition** **Inferotemporal and Prefrontal areas**	**WHERE Stream** **Space & Action** **Parietal and Prefrontal areas**
Object Tracking **MT Interbands and MSTv**	**Optic Flow Navigation** **MT Bands and MSTd**
Motor Target Position **Motor and Parietal Cortex**	**Volitional Speed** **Basal Ganglia**

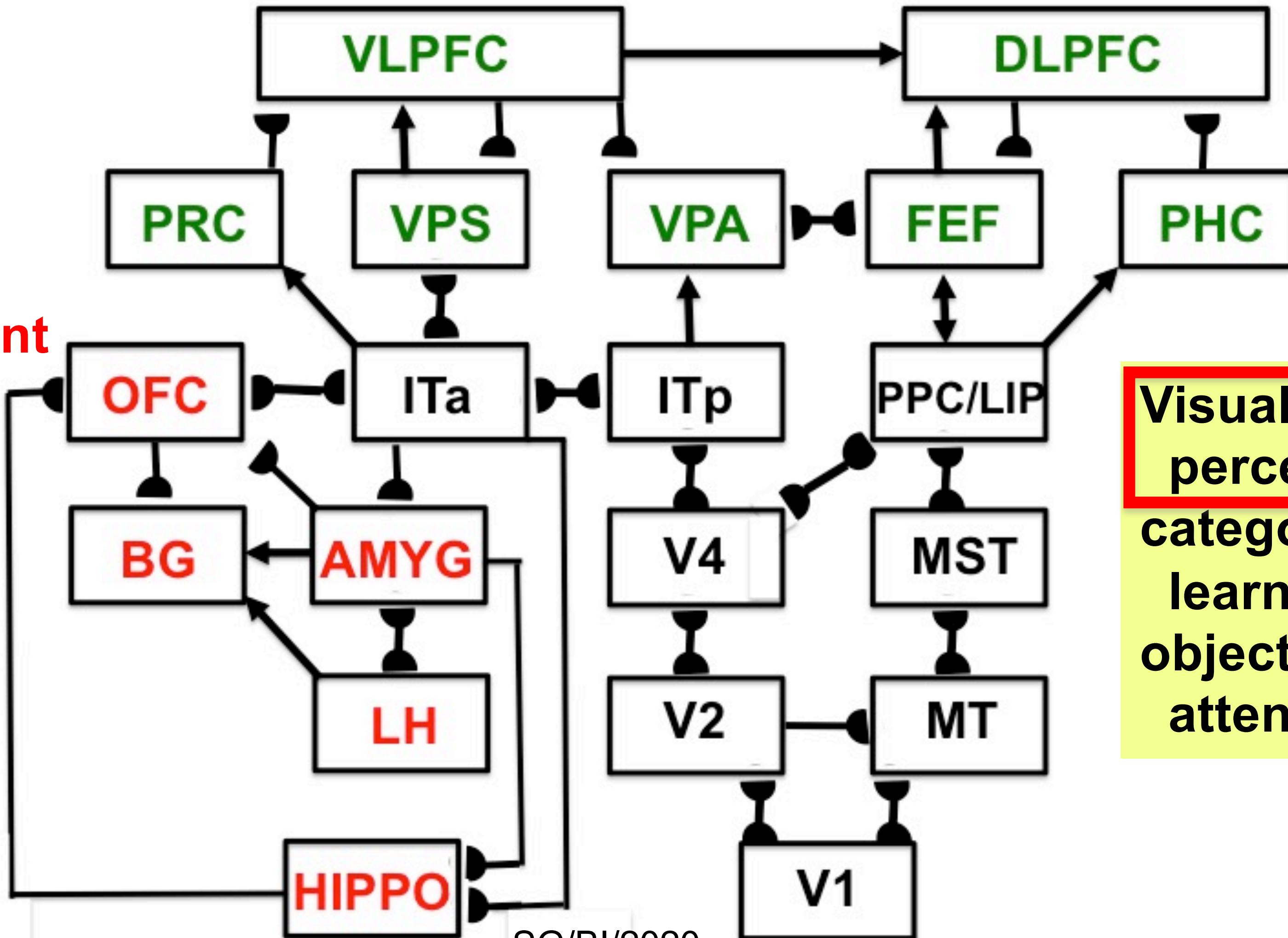
Predictive ART, or pART, architecture macrocircuit

How prefrontal cortex learns to control all higher-order intelligence

Grossberg (2018)

Working memory, learned plans, prediction, optimized action

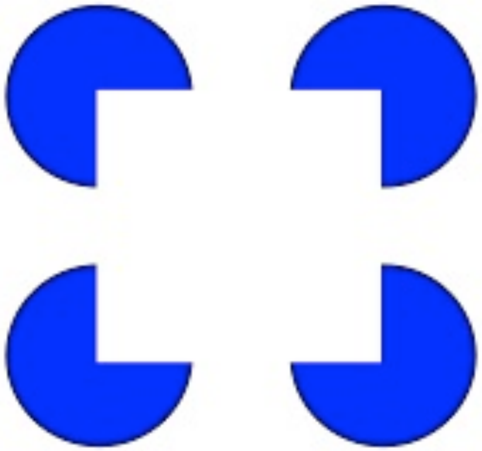
Reinforcement learning, emotion, motivation, adaptively-timed learning,

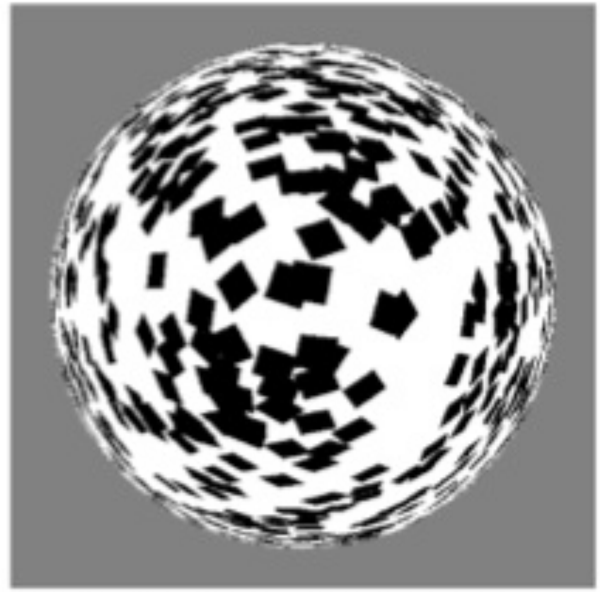


Visual perception, category learning, object attention

WHAT IS A VISUAL BOUNDARY OR GROUPING?

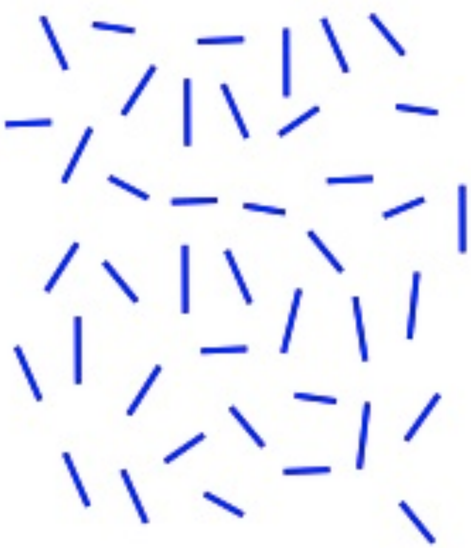
Illusory contour





3D shape from texture

Texture pop-out



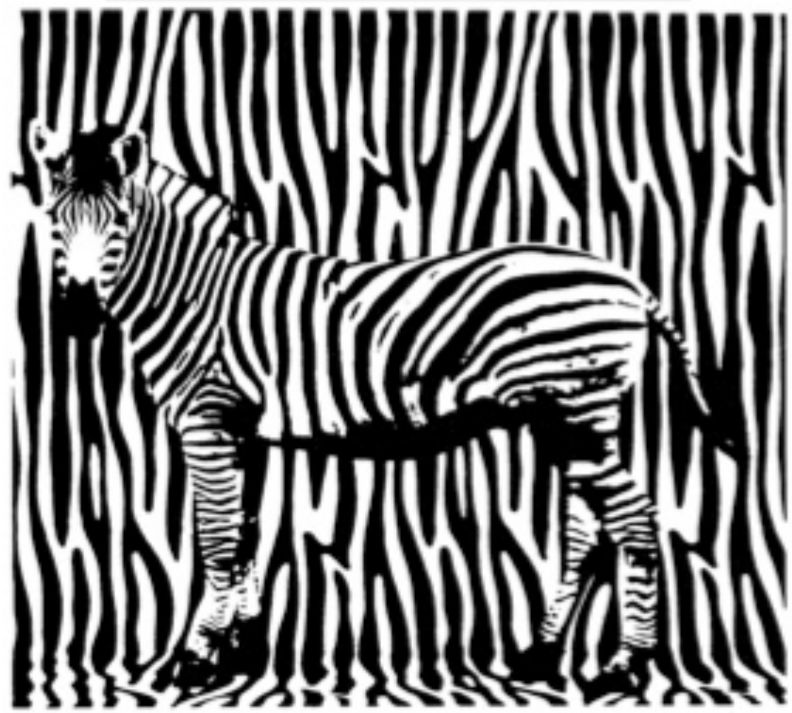
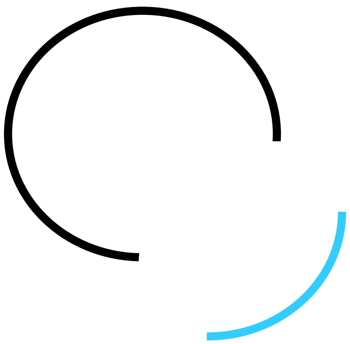
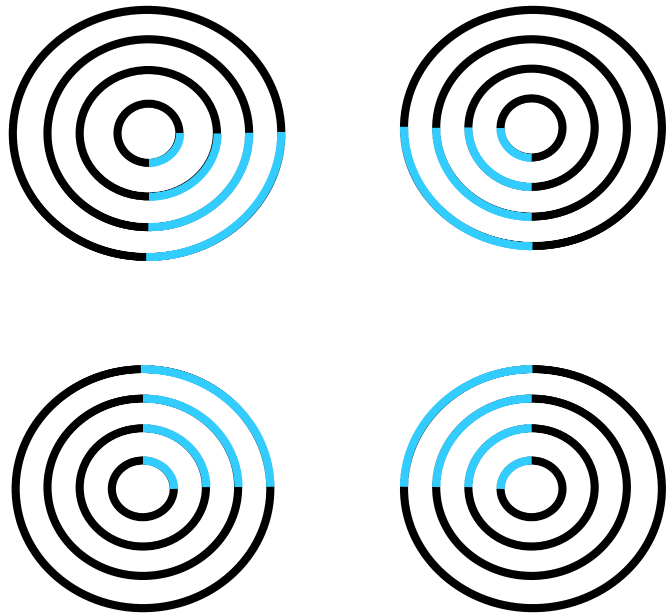


Figure-ground separation

VISUAL BOUNDARY AND SURFACE COMPUTATIONS ARE COMPLEMENTARY

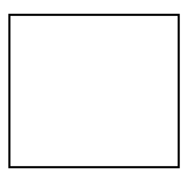
Grossberg (1984)





Neon color spreading

BOUNDARY COMPLETION

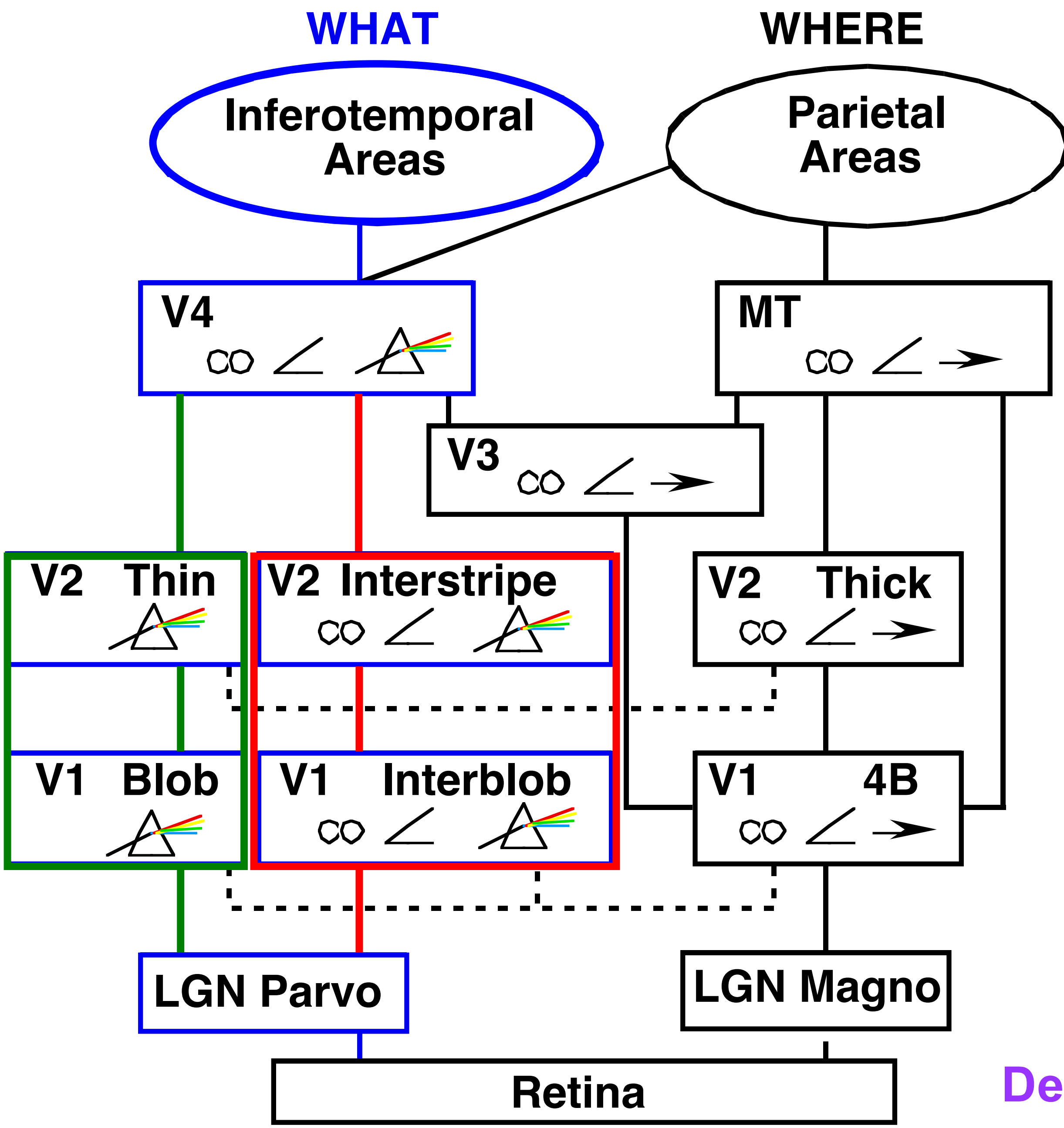


oriented
inward
insensitive to
direction-of-contrast

SURFACE FILLING-IN

unoriented
outward
sensitive to
direction-of-contrast

BOUNDARY AND SURFACE CORTICAL STREAMS



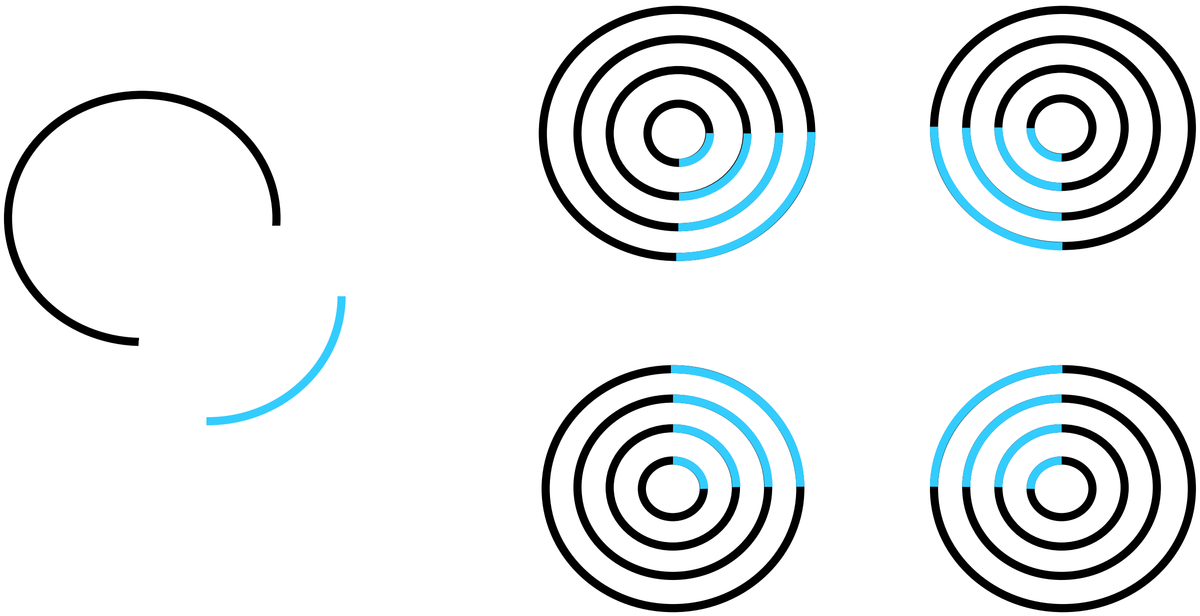
Boundaries
interblob stream

Surfaces
blob stream

DeYoe and van Essen (1988)

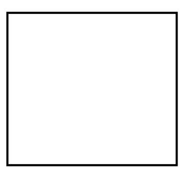
VISUAL BOUNDARY AND SURFACE COMPUTATIONS ARE COMPLEMENTARY

Grossberg (1984)



Neon color spreading

BOUNDARY COMPLETION



What about

oriented
inward
insensitive to
direction-of-contrast

SURFACE FILLING-IN

unoriented
outward
sensitive to
direction-of-contrast

SEEING vs. KNOWING

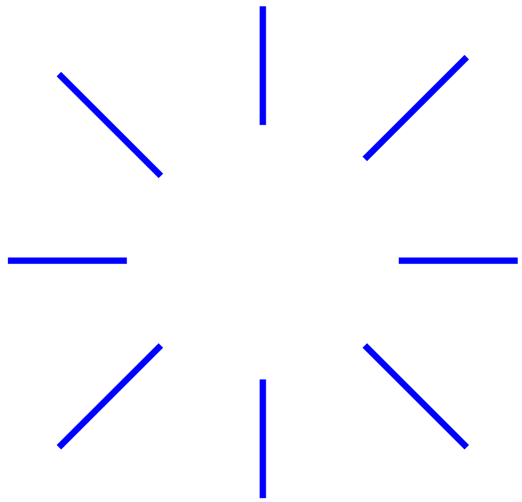
SEEING vs. **KNOWING**

an object — **what it is**

Epstein, Gregory, Helmholtz, Kanizsa, Kellman, Michotte,…

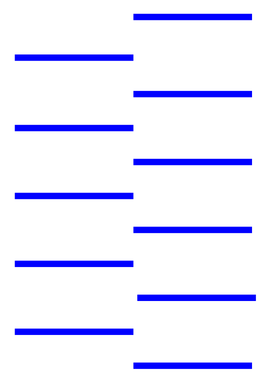
SEEING vs. **RECOGNIZING**

Ehrenstein Figure



See
Recognize

Offset Grating



Some boundaries are invisible, or amodal

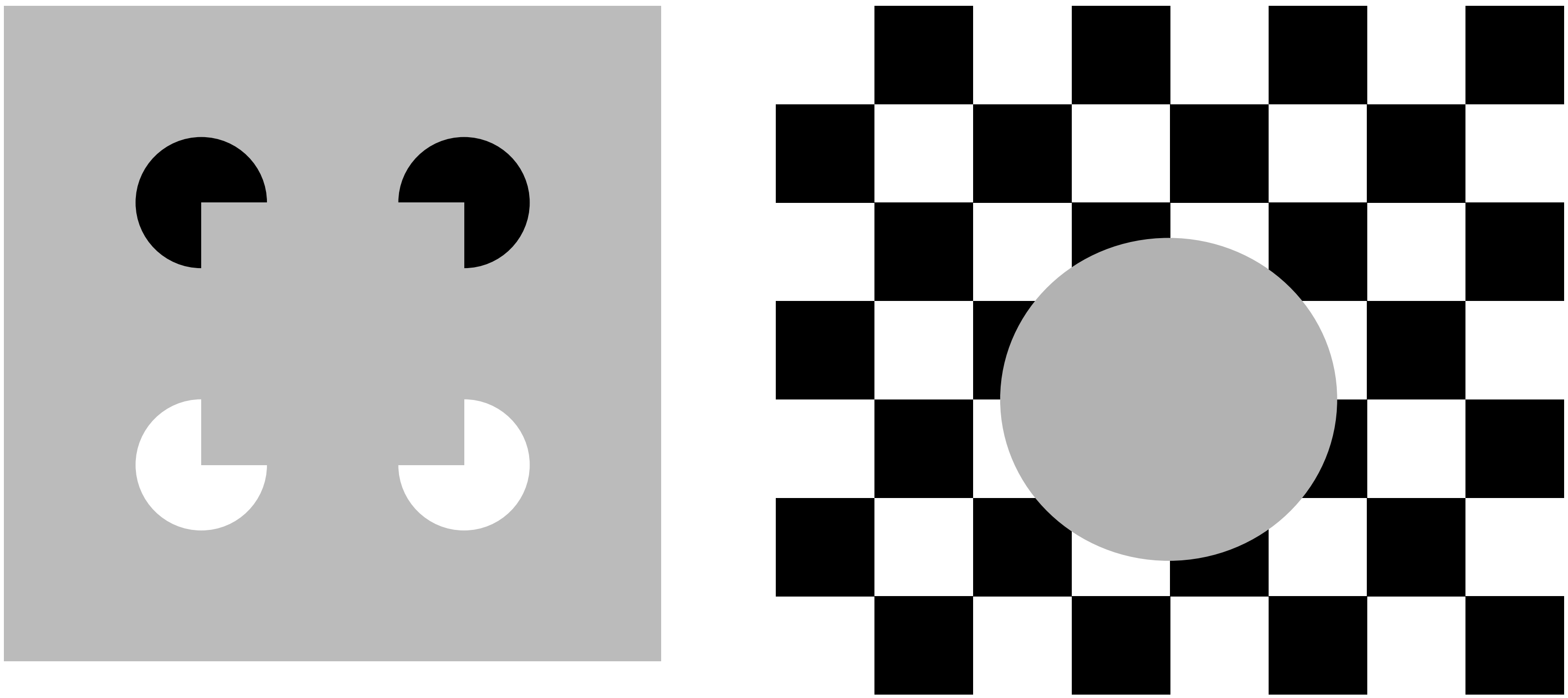
Do not see
Recognize

ALL BOUNDARIES ARE INVISIBLE!

within the Boundary Stream

Grossberg (1984)

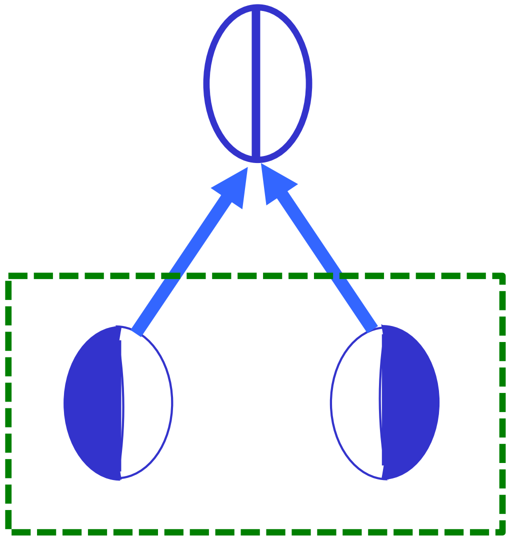
WHY? To recognize object boundaries in front of textured backgrounds



ALL BOUNDARIES ARE INVISIBLE: COMPLEX CELLS

complex cells pool inputs from opposite-polarity simple cells in V1

V1



complex cells

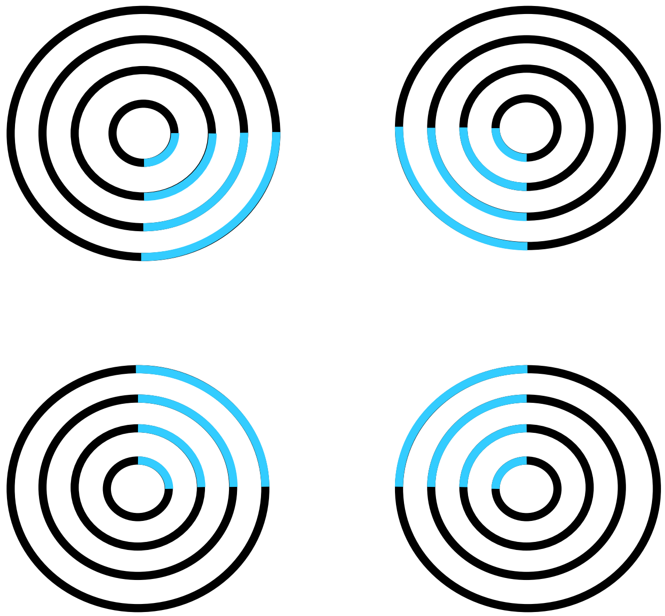
simple cells

Complex cells are amodal boundary detectors Grossberg (1984)

vs

"color cells in the broadest sense" Thorell, DeValois & Albrecht (1984)

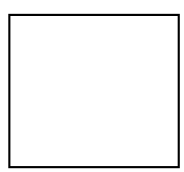
VISUAL BOUNDARY AND SURFACE COMPUTATIONS ARE COMPLEMENTARY



Neon color spreading

All Boundaries Are Invisible!

BOUNDARY COMPLETION



oriented
inward
insensitive to
direction-of-contrast

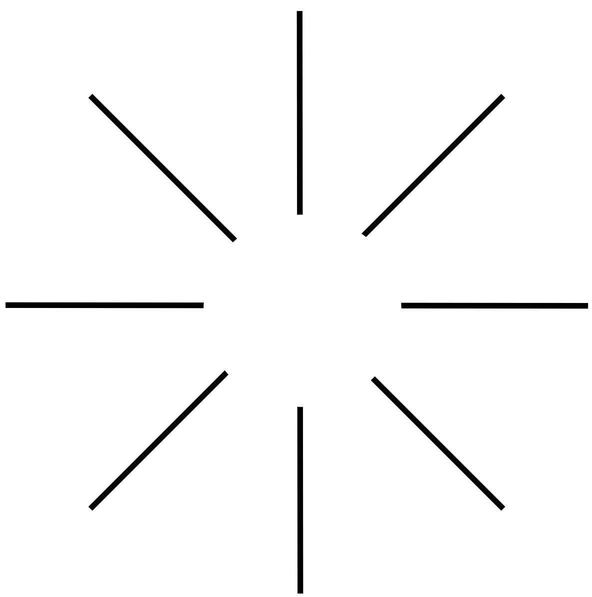
SURFACE FILLING-IN

unoriented
outward
sensitive to
direction-of-contrast

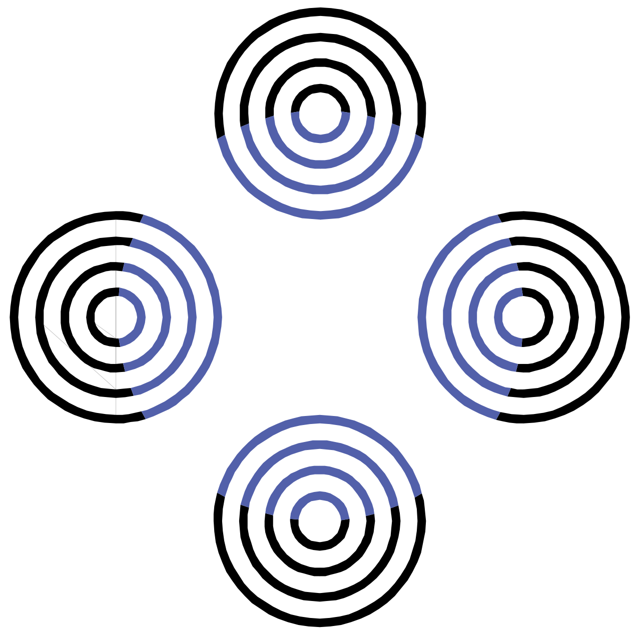
IF BOUNDARIES ARE INVISIBLE, HOW DO WE SEE?

Filling-In of Surface Color

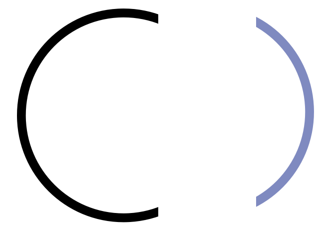
Boundaries define the compartments
within which lightness and color spread



Ehrenstein (1941)

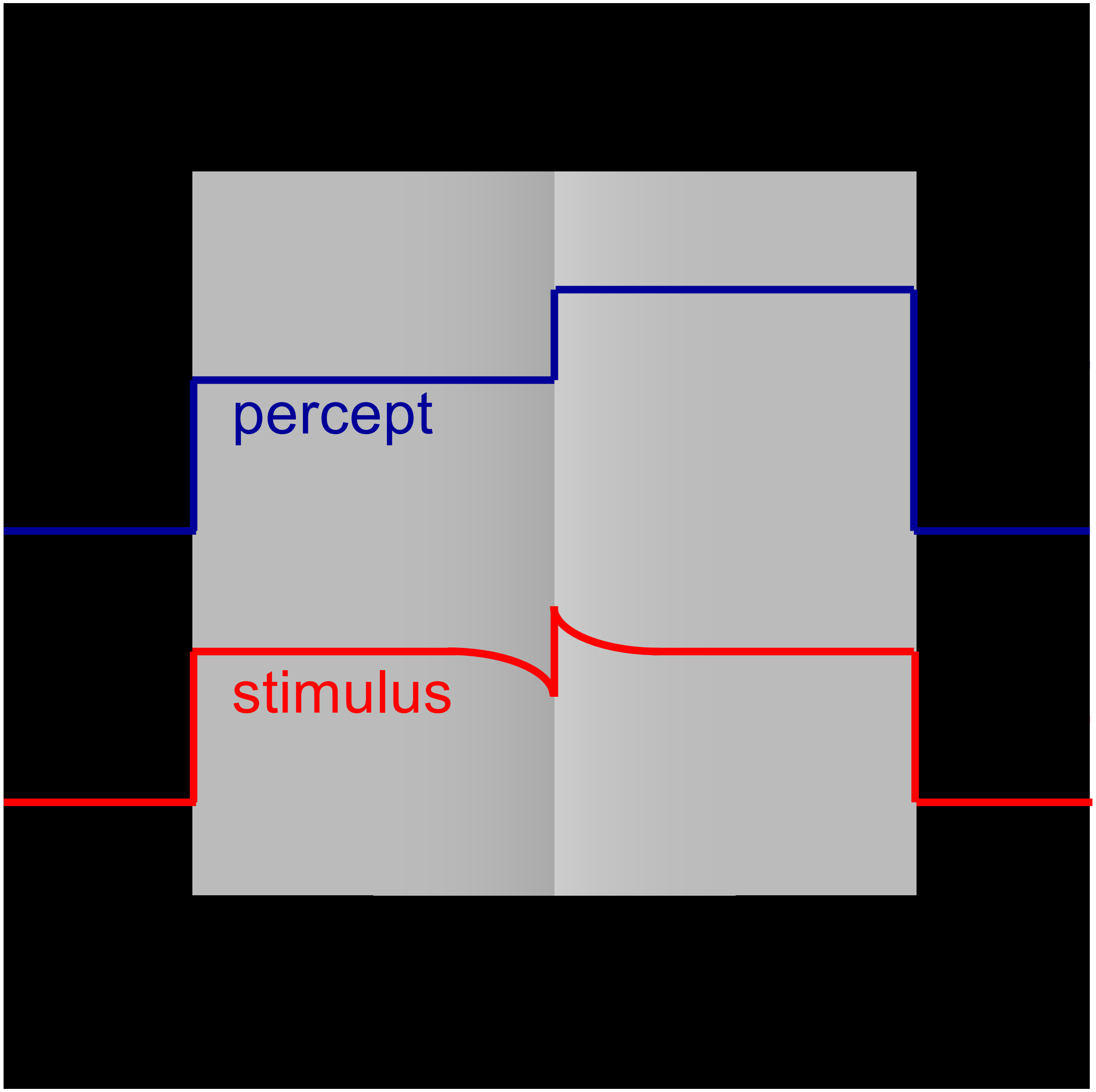


Varin (1971)



Neon color spreading

Craik-O’Brien-Cornsweet Effect

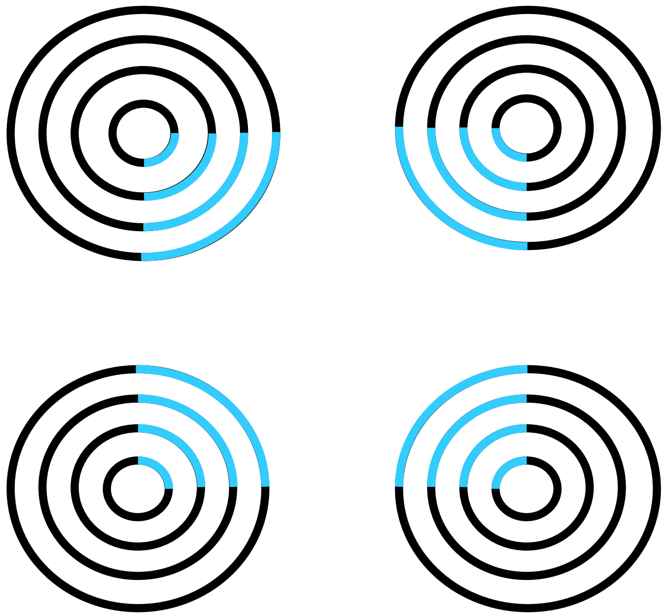


Boundary completion defines filling-in compartments

Filling-in determines what we see in each compartment

Grossberg (1984)
Todorović (1987)

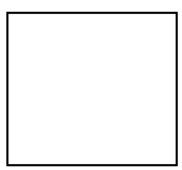
VISUAL BOUNDARY AND SURFACE COMPUTATIONS ARE COMPLEMENTARY



Neon color spreading

All Boundaries Are Invisible!

BOUNDARY COMPLETION



oriented
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direction-of-contrast

SURFACE FILLING-IN

unoriented
outward
sensitive to
direction-of-contrast

Filling-in of Visible Color and Lightness

PREDICTIONS

Grossberg (1984)

ALL BOUNDARIES ARE INVISIBLE
in the interblob stream

VISIBLE QUALIA ARE SURFACE PERCEPTS
in the blob stream

PREDICTIONS

ALL CONSCIOUS STATES ARE RESONANT STATES

Grossberg (1976)

VISIBLE QUALIA ARE SURFACE PERCEPTS

Grossberg (1984)

PREDICTIONS

ALL CONSCIOUS STATES ARE RESONANT STATES

Grossberg (1976)

VISIBLE QUALIA ARE SURFACE PERCEPTS

Grossberg (1984)

WHAT KIND OF RESONANCE SUPPORTS VISIBLE SURFACE QUALIA?

How do we see?!

PREDICTIONS

ALL CONSCIOUS STATES ARE RESONANT STATES

Grossberg (1976)

VISIBLE QUALIA ARE SURFACE PERCEPTS

Grossberg (1984)

WHAT KIND OF RESONANCE SUPPORTS VISIBLE SURFACE QUALIA?

How do we see?!

A SURFACE-SHROUD RESONANCE

Grossberg (2009+)

“ALL CONSCIOUS STATES ARE RESONANT STATES”

Surface-shroud resonances support conscious seeing of visual qualia EXPLAINABLE!

Feature-category resonances support conscious recognition of visual objects and scenes

Stream-shroud resonances support conscious hearing of auditory qualia

Spectral-pitch-and-timbre resonances support conscious recognition of sources in auditory streams

Item-list resonances support conscious recognition of speech and language

Cognitive-emotional resonances support conscious feelings and recognition of them

“ALL CONSCIOUS STATES ARE RESONANT STATES”

Surface-shroud resonances support conscious seeing of visual qualia — SEEING

Feature-category resonances support conscious recognition of visual objects and scenes — KNOWING

Stream-shroud resonances support conscious hearing of auditory qualia

Spectral-pitch-and-timbre resonances support conscious recognition of sources in auditory streams

Item-list resonances support conscious recognition of speech and language

Cognitive-emotional resonances support conscious feelings and recognition of them

WHAT IS A SURFACE-SHROUD RESONANCE?

WHAT IS AN ATTENTIONAL SHROUD?

Surface-fitting spatial attention

ATTENTIONAL SHROUD!

marks the object-hood of the
as-yet-undefined object category

Tyler and Kontsevich (1995)
used shrouds to study
perceptual transparency

Cf. Cavanagh, Pylyshyn, Yantis,…

Magritte (1928)

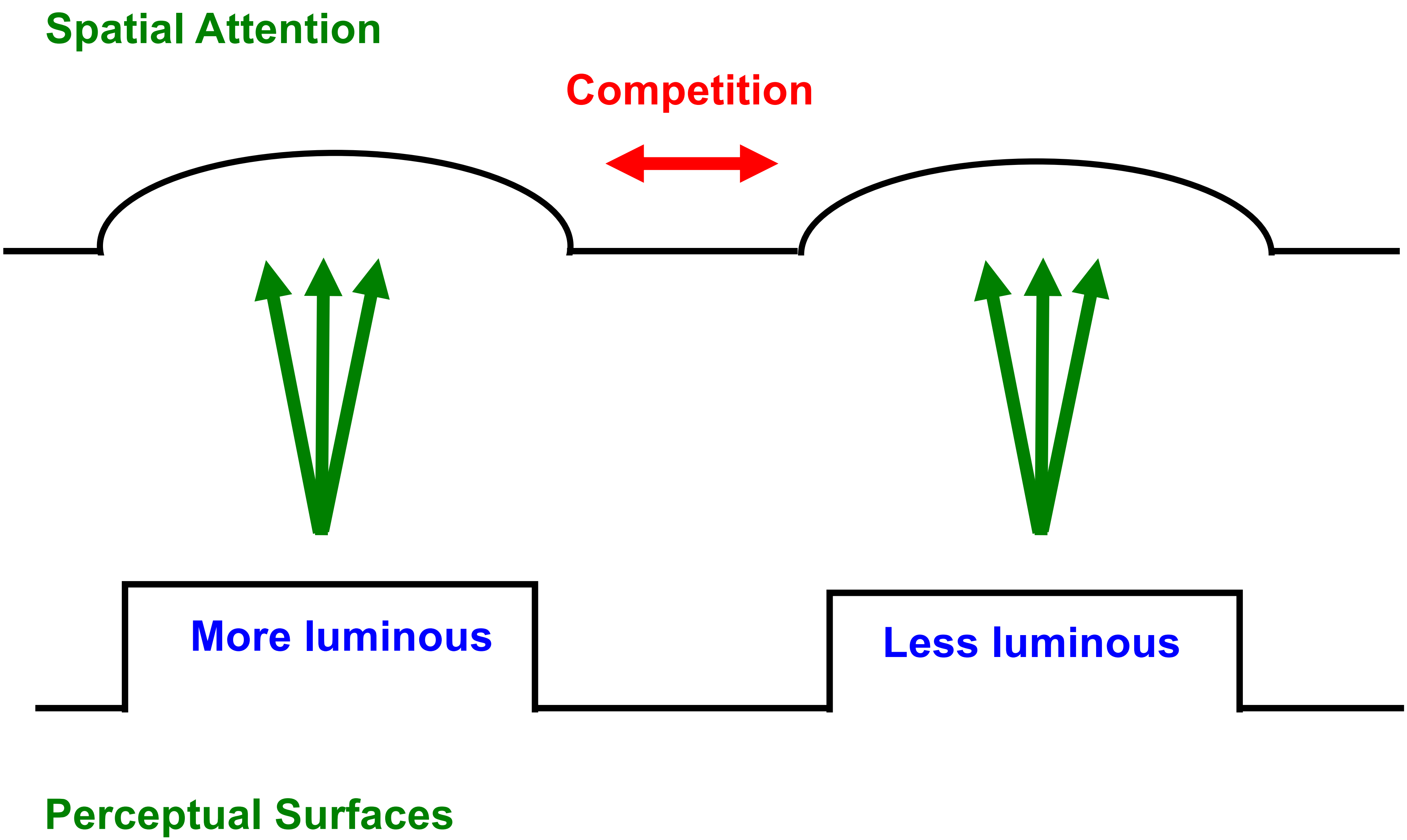
PREDICTION:

Shrouds enable learning of invariant object categories

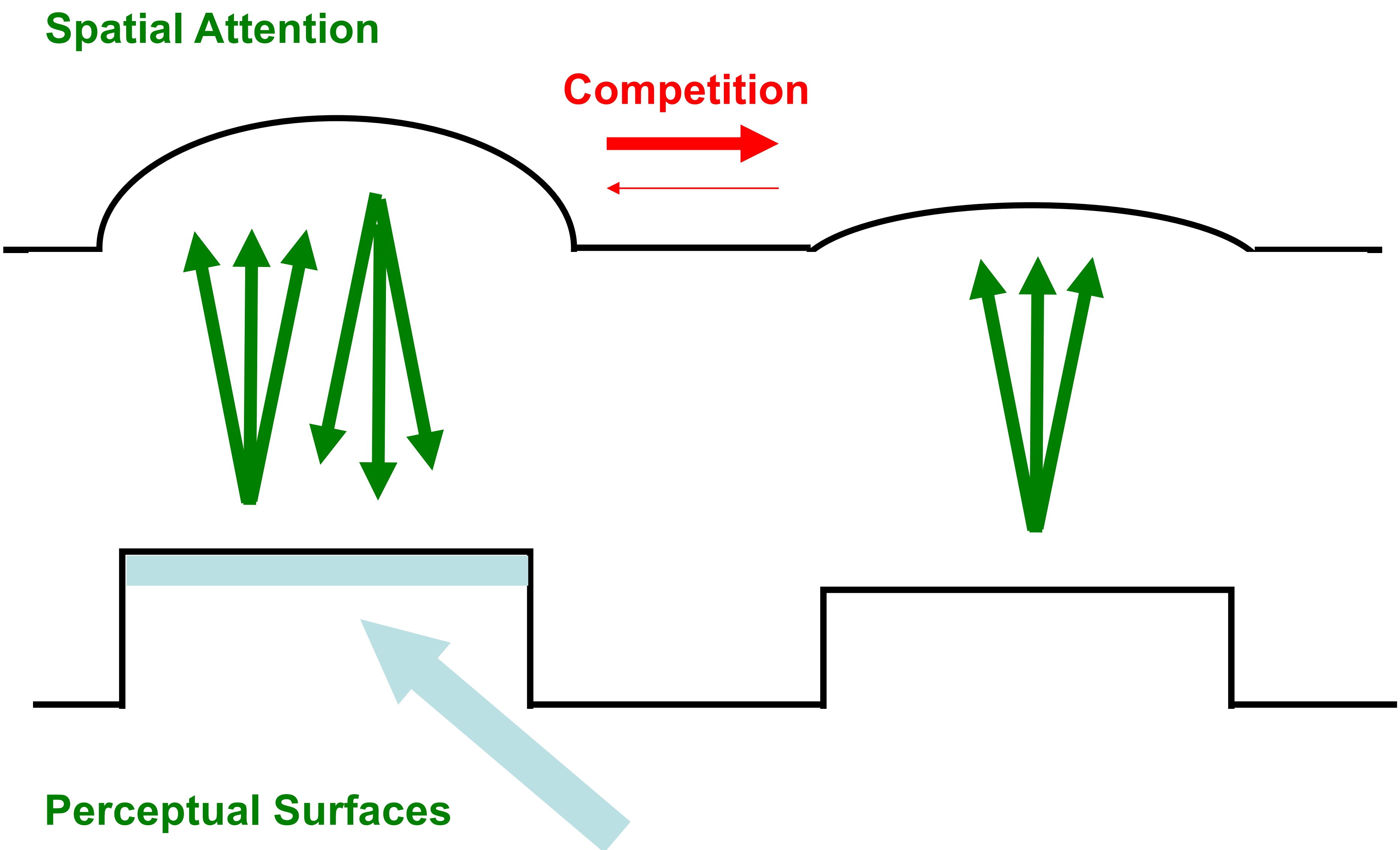
Not explained in this talk, but see:

Grossberg (2007, 2009, 2017)
Fazl, Grossberg, and Mingolla (2009)
Cao, Grossberg, and Mingolla (2011)
Grossberg, Markowitz, and Cao (2011)
Foley, Grossberg, and Mingolla (2012)
Chang, Grossberg, and Cao (2014)

BOTTOM-UP SPATIAL ATTENTIONAL COMPETITION



SURFACE-SHROUD RESONANCE



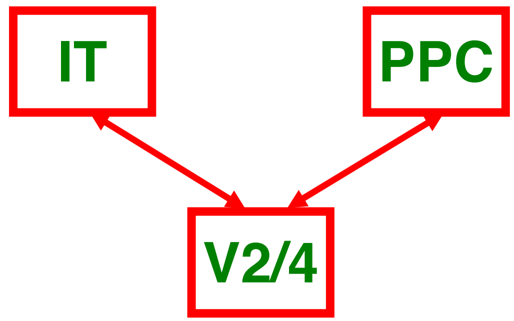
Psychophysics: **Carrasco, Penpeci-Talgar, and Eckstein (2000)**
Neurophysiology: **Reynolds and Desimone (2003)**

SURFACE-SHROUD RESONANCE

An active
SURFACE-SHROUD RESONANCE
means that sustained
SPATIAL ATTENTION IS FOCUSED
ON THE OBJECT SURFACE

WHAT KINDS OF RESONANCES SUPPORT KNOWING VS. SEEING?

What Stream **Where Stream**



KNOWING
Feature-Category Resonance

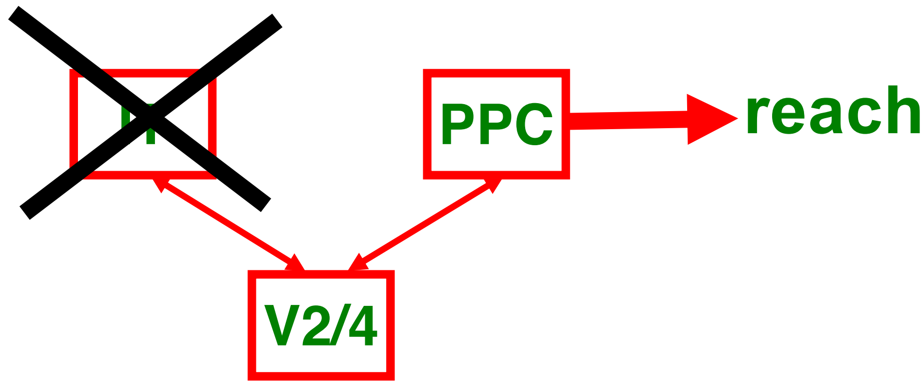
SEEING
Surface-Shroud Resonance

Synchronous linkage between resonances enables us to KNOW what the object is as we SEE it

Many data support this prediction; e.g.:

WHAT KINDS OF RESONANCES SUPPORT KNOWING VS. SEEING?

What Stream **Where Stream**



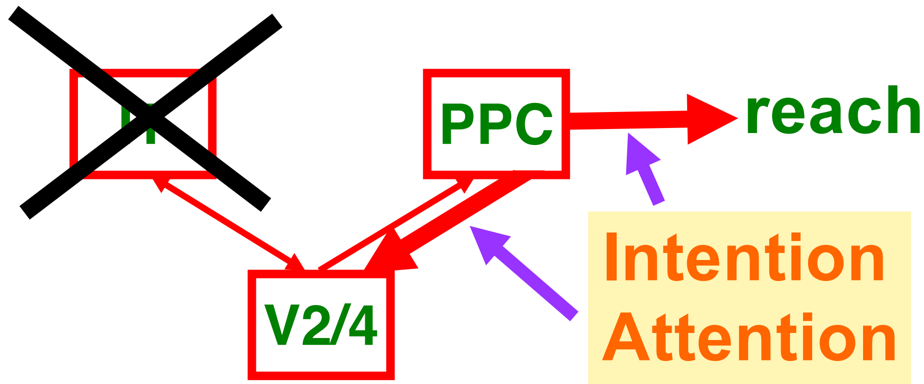
KNOWING
Feature-Category Resonance

SEEING
Surface-Shroud Resonance

VISUAL AGNOSIA: reaching without knowing
Patient DF Goodale et al, 1991

WHAT KINDS OF RESONANCES SUPPORT KNOWING VS. SEEING?

What Stream **Where Stream**



KNOWING
Feature-Category Resonance

SEEING
Surface-Shroud Resonance

VISUAL AGNOSIA: reaching without knowing

Patient DF Goodale et al, 1991

Attention and Intention both parietal cortical functions

Andersen, Essick, and Siegel, 1985; Gnadt and Andersen, 1988; Snyder, Batista, and Andersen, 1997, 1998

"ALL CONSCIOUS STATES ARE RESONANT STATES"

Surface-shroud resonances support conscious seeing of visual qualia

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UNIFYING THREE BASIC BEHAVIORAL COMPETENCES

1. Pay attention quickly to salient events, both positive and negative

The fast motivated attention pathway includes the AMYGDALA

However, a rapid attention shift to focus on a salient event could cause a premature response to that event

This problem is eliminated by the second and third competences

2. Adaptively time and maintain motivated ATTENTION on a salient event until the response is executed

This ability involves the HIPPOCAMPUS, notably its dentate-CA3 region

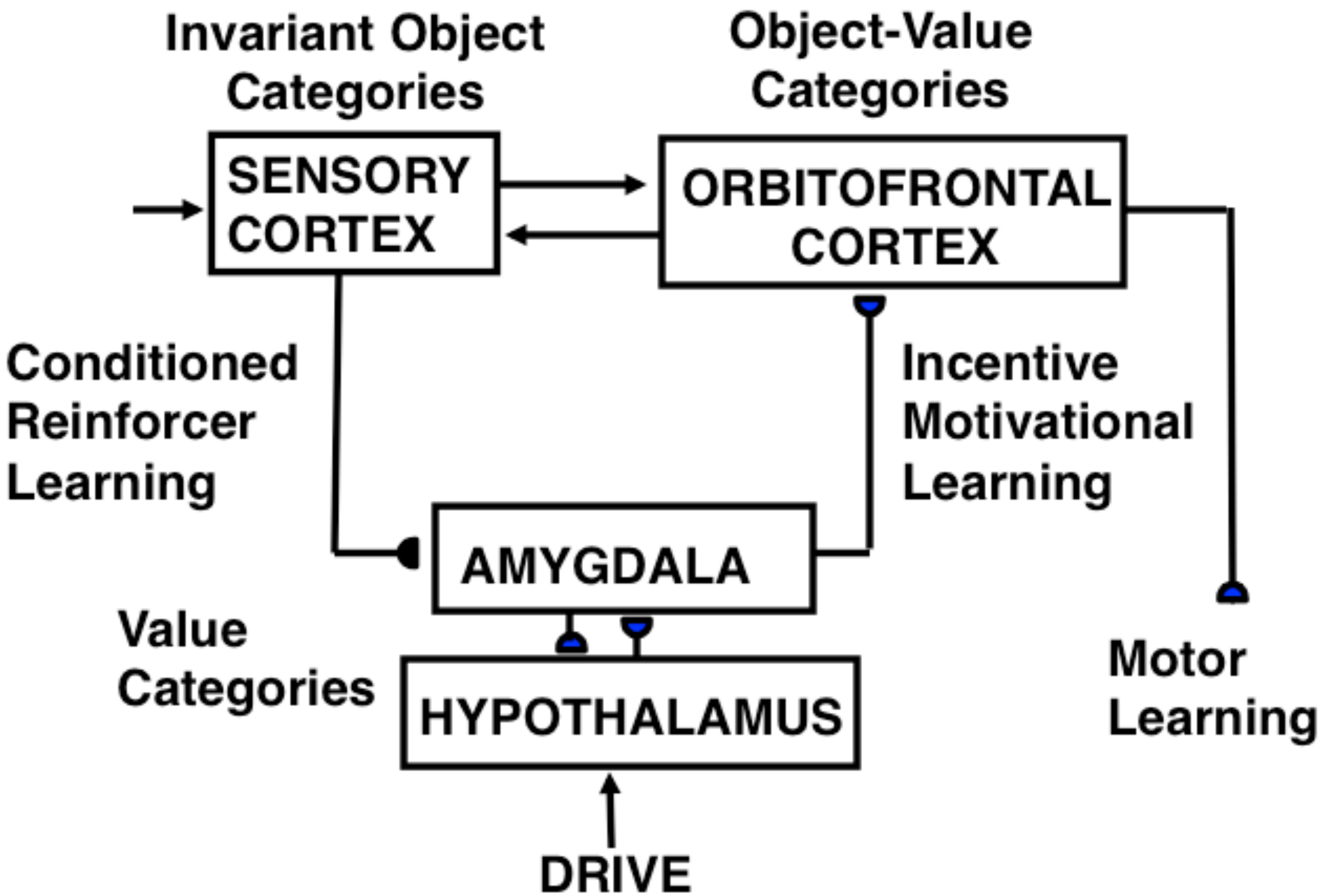
3. Adaptively time and execute an appropriate RESPONSE to the salient event

This ability involves the CEREBELLUM

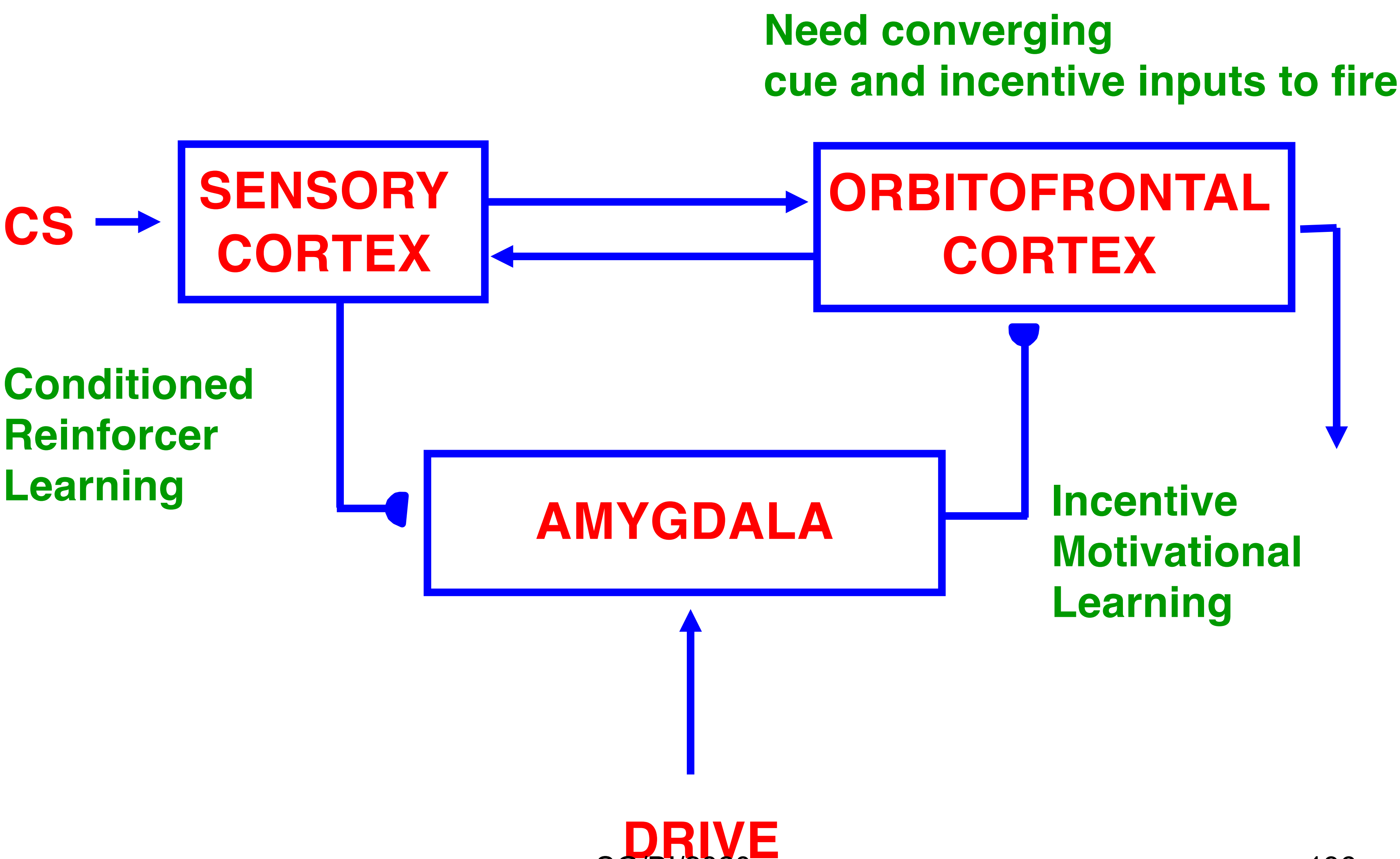
Cognitive-Emotional-Motor (CogEM) model

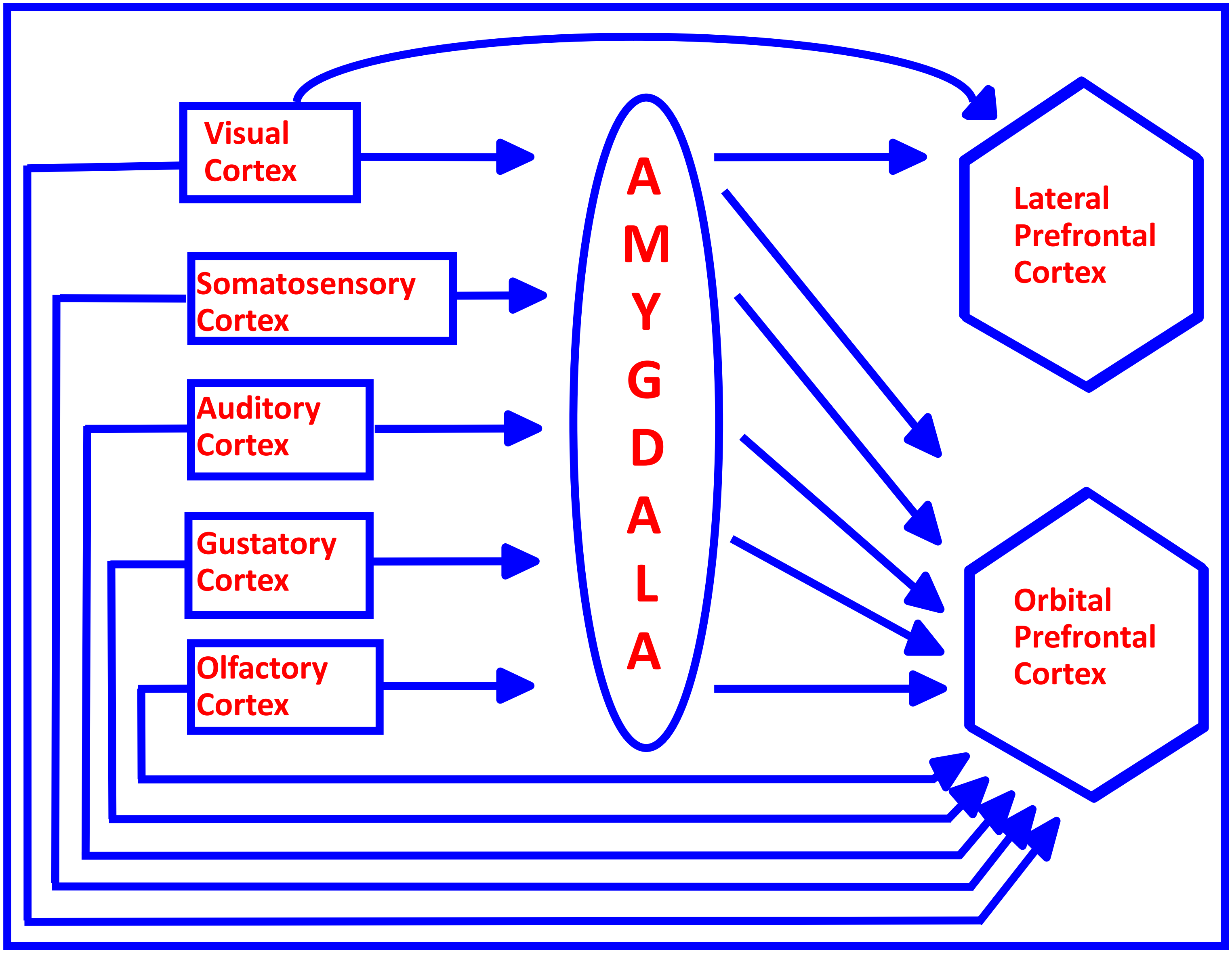
…and its further developments…

Grossberg (1971, 1972, 1975, 1982, 1984), Grossberg and Schmajuk (1987, 1989), Grossberg and Levine (1989), Grossberg and Merrill (1992, 1996), Dranias, Grossberg, and Bullock (2008), Grossberg, Bullock, and Dranias (2008),…



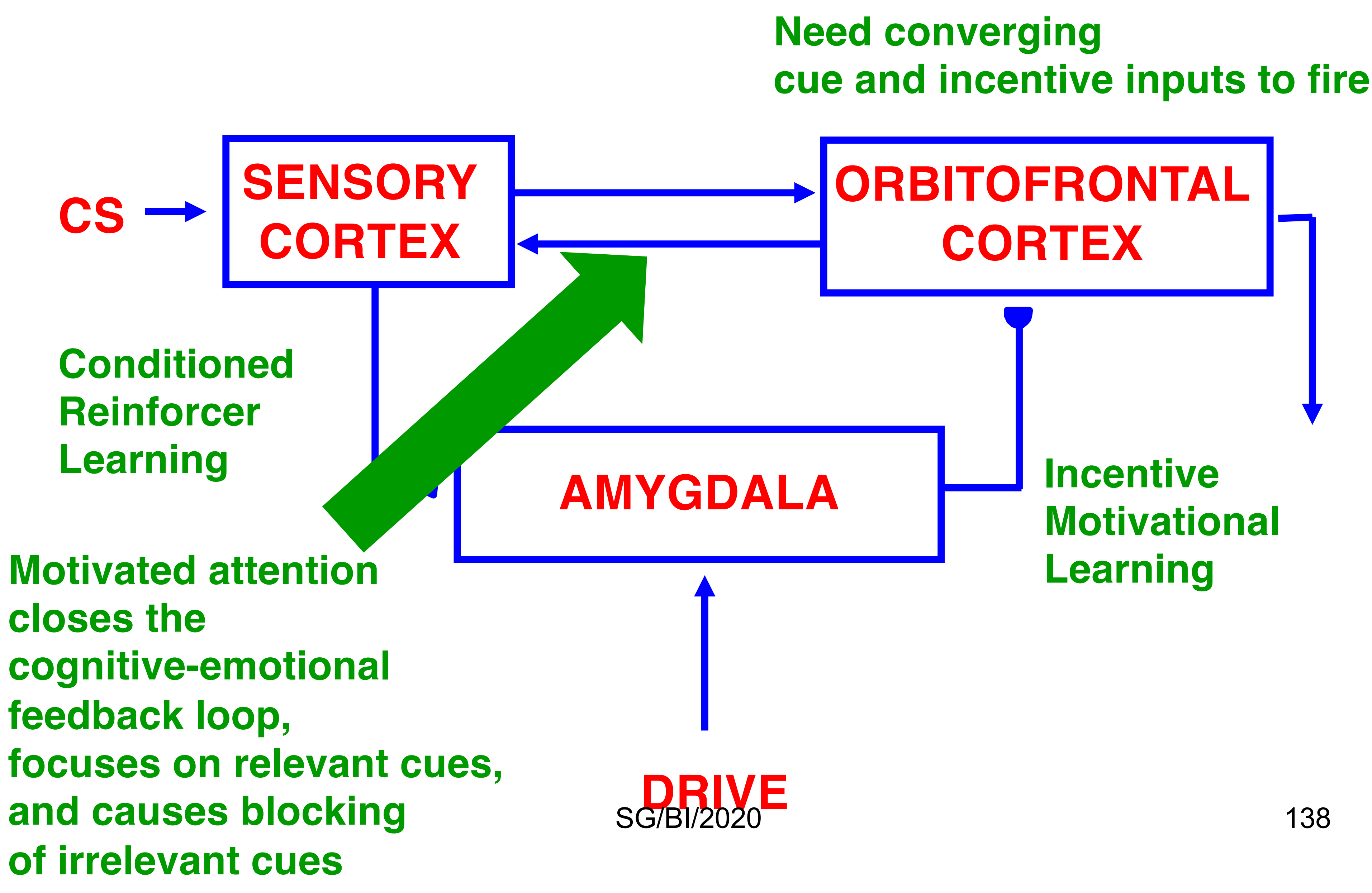
Cognitive-Emotional-Motor (CogEM) model





Adapted from Barbas (1995)

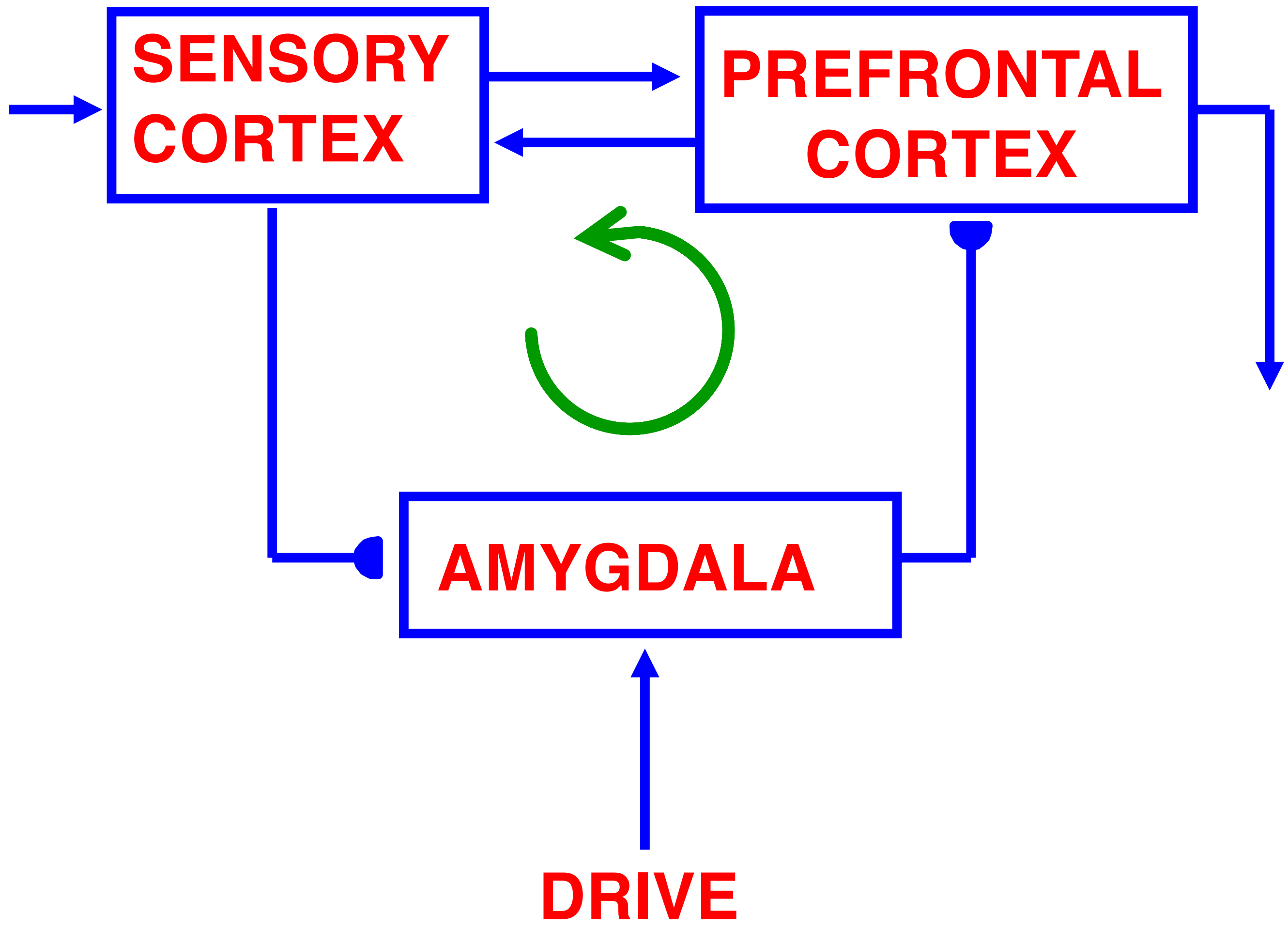
Cognitive-Emotional-Motor (CogEM) model



COGNITIVE-EMOTIONAL RESONANCE

Basis of "core consciousness" and "the feeling of what happens"

Damasio (1999) derives heuristic version of CogEM model from his clinical data



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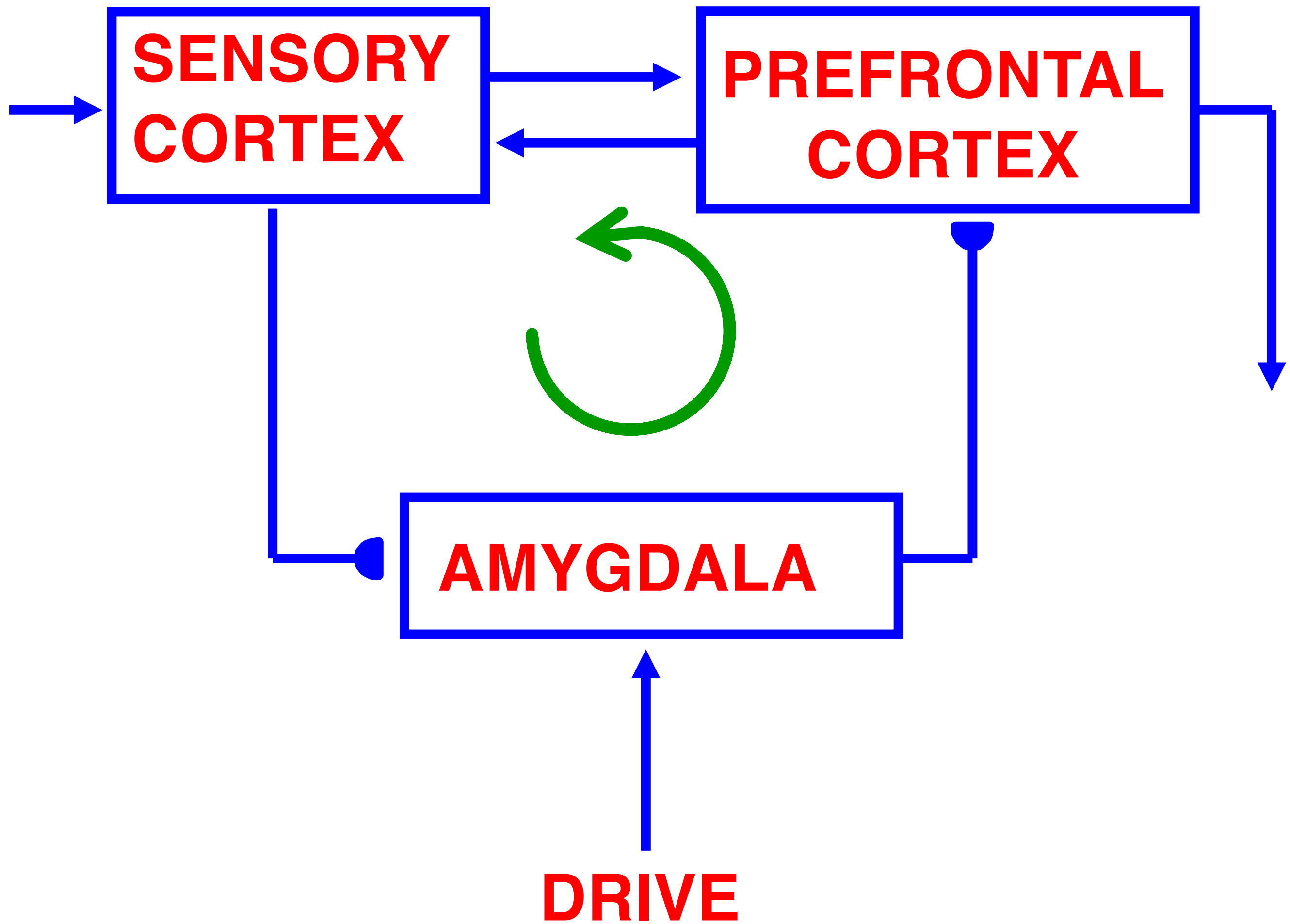
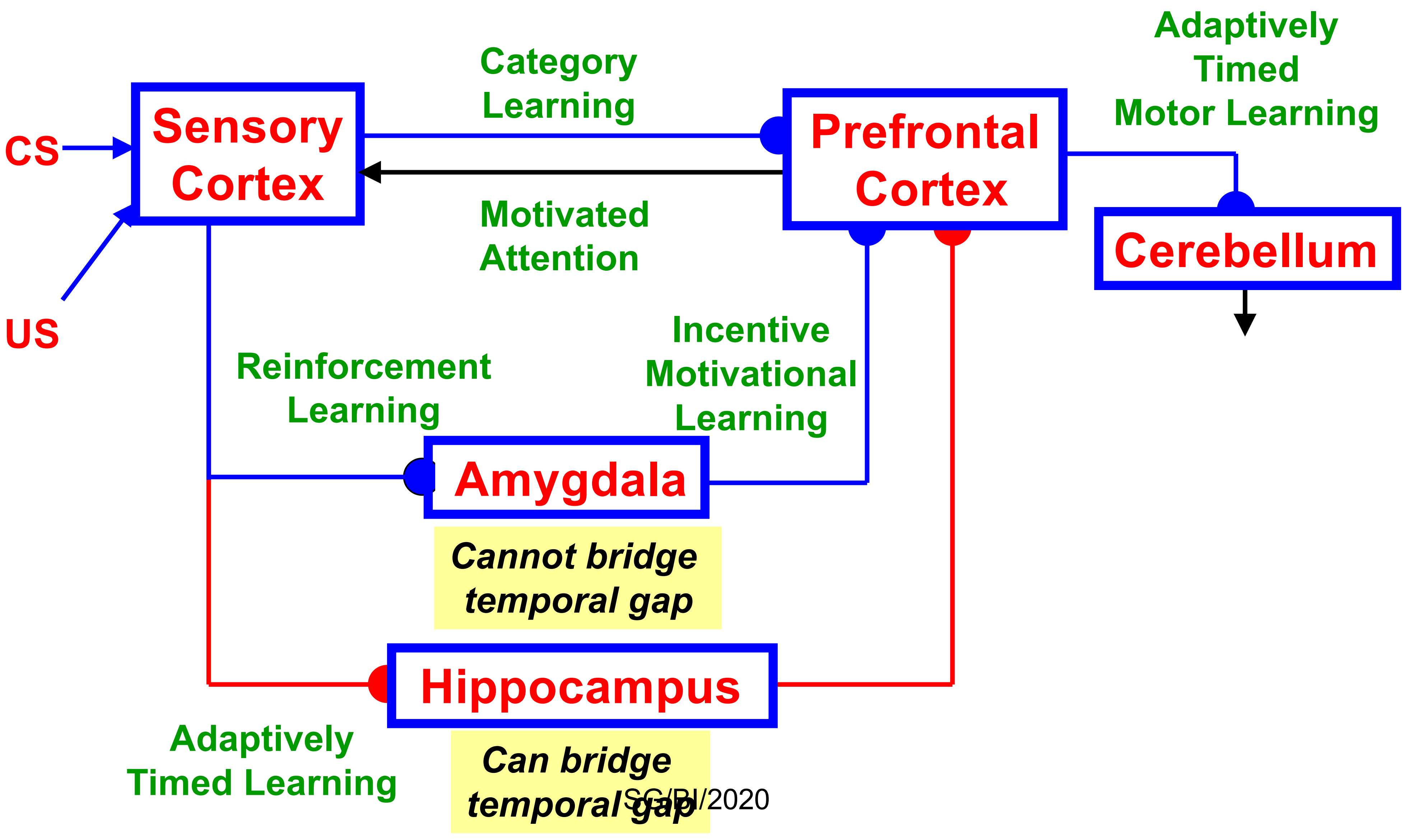


HOW IS THIS RESONANCE MAINTAINED LONG ENOUGH TO BECOME CONSCIOUS?!

HIPPOCAMPUS CAN SUSTAIN A COGNITIVE-EMOTIONAL RESONANCE

that can support “the feeling of what happens” and knowing what event caused that feeling



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HIPPOCAMPUS CAN SUSTAIN A COGNITIVE-EMOTIONAL RESONANCE

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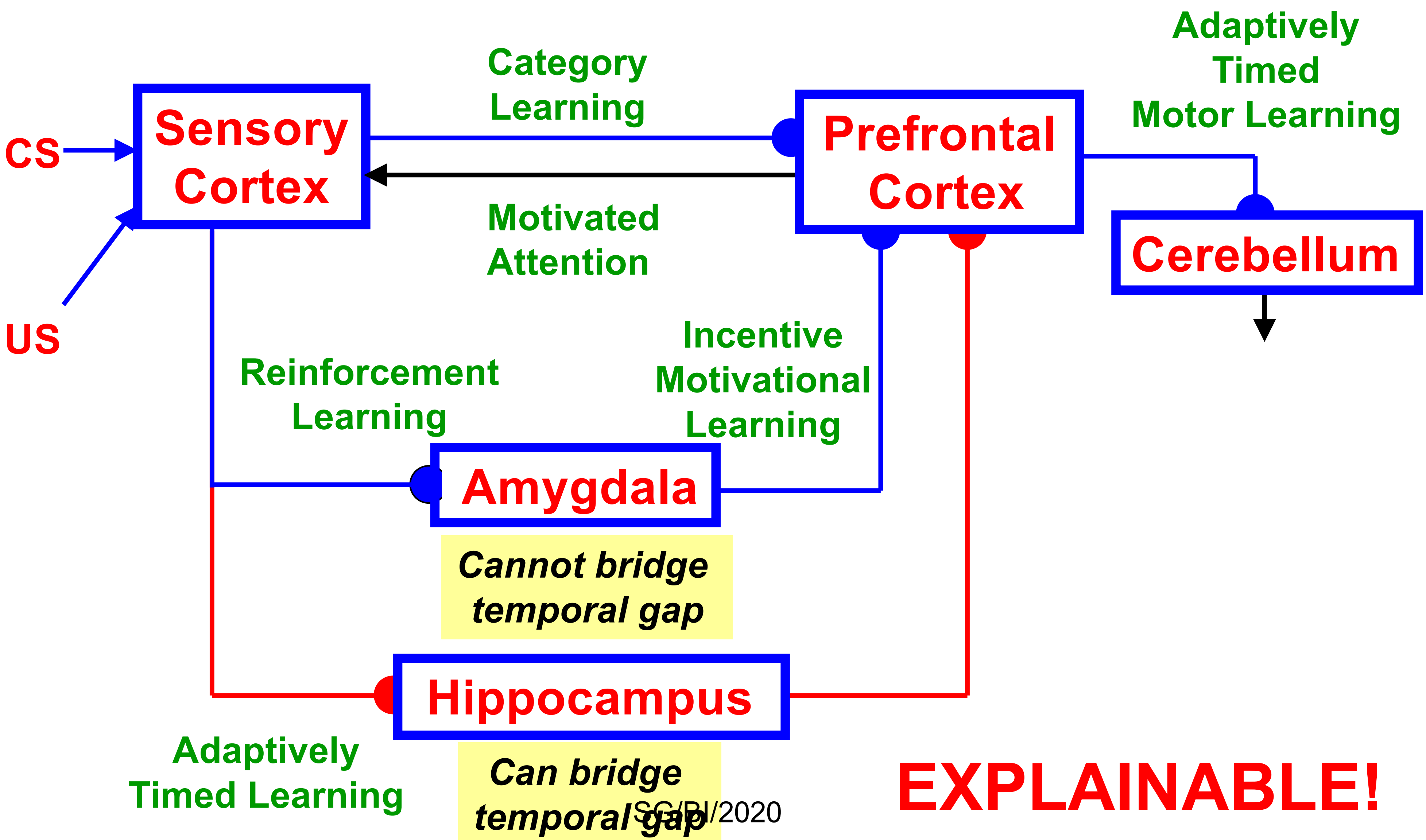

EXPLAINABLE!

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A representation can be explainable without potentially being conscious

e.g., MOTOR REPRESENTATIONS

Their matching and learning laws are not resonant!

SOME COMPLEMENTARY PROCESSES

Visual Boundary **Interbob Stream V1-V4**	**Visual Surface** **Blob Stream V1-V4**
Visual Boundary **Interbob Stream V1-V4**	**Visual Motion** **Magno Stream V1-MT**
WHAT Steam **Perception & Recognition** **Inferotemporal and** **Prefrontal areas**	**WHERE Stream** **Space & Action** **Parietal and** **Prefrontal areas**
Object Tracking **MT Interbands and MSTv**	**Optic Flow Navigation** **MT Bands and MSTd**
Motor Target Position **Motor and Parietal Cortex**	**Volitional Speed** **Basal Ganglia**

WHAT and WHERE/HOW LEARNING and MATCHING are COMPLEMENTARY

Spatially-invariant object learning and recognition

Fast learning without catastrophic forgetting

IT

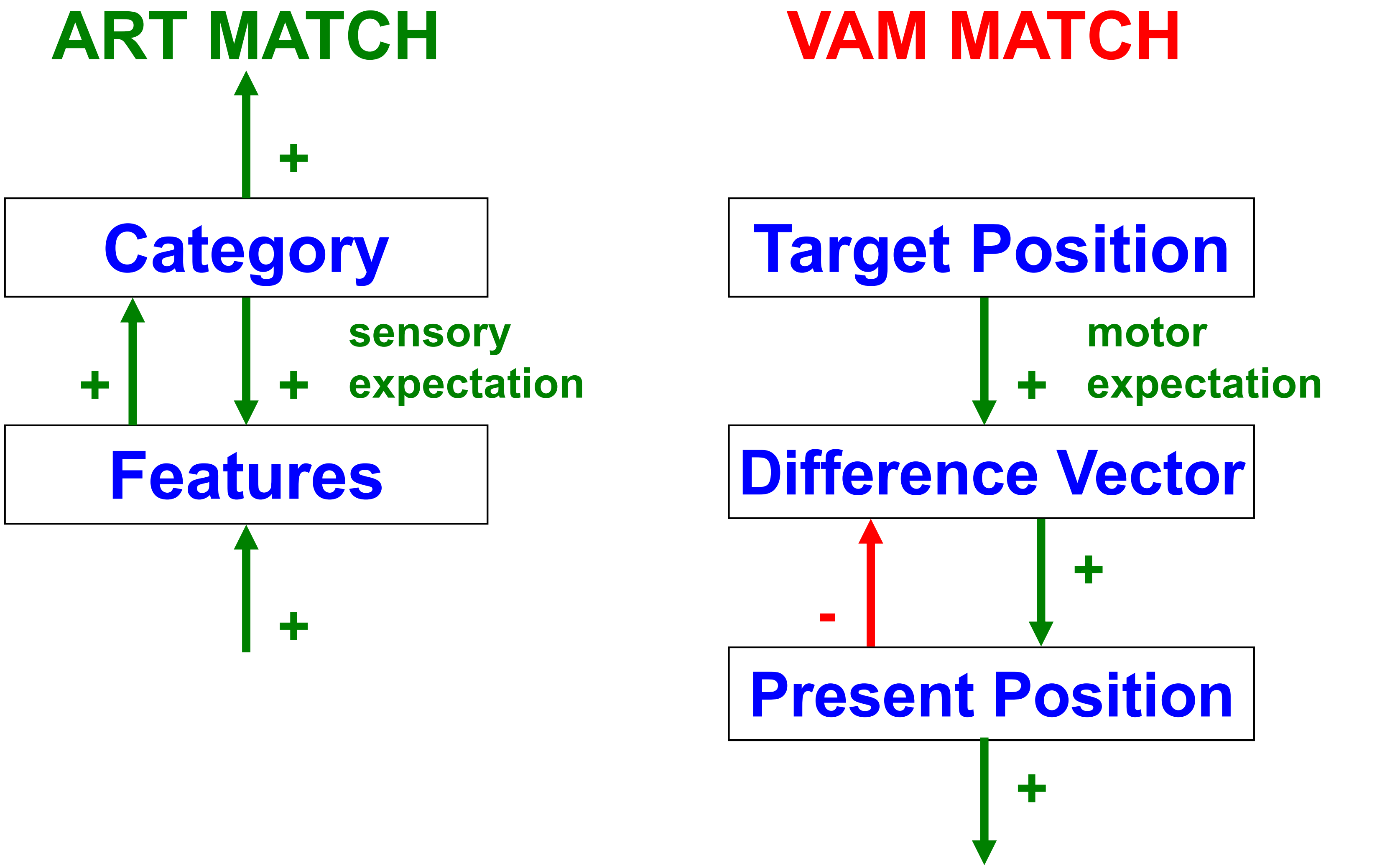
Spatially-variant reaching and movement

Continually update sensory-motor maps and gains

PPC

	WHAT	WHERE/HOW
MATCHING	EXCITATORY	INHIBITORY
LEARNING	MATCH	MISMATCH
	ART	VAM

SENSORY EXPECTATION vs MOTOR EXPECTATION

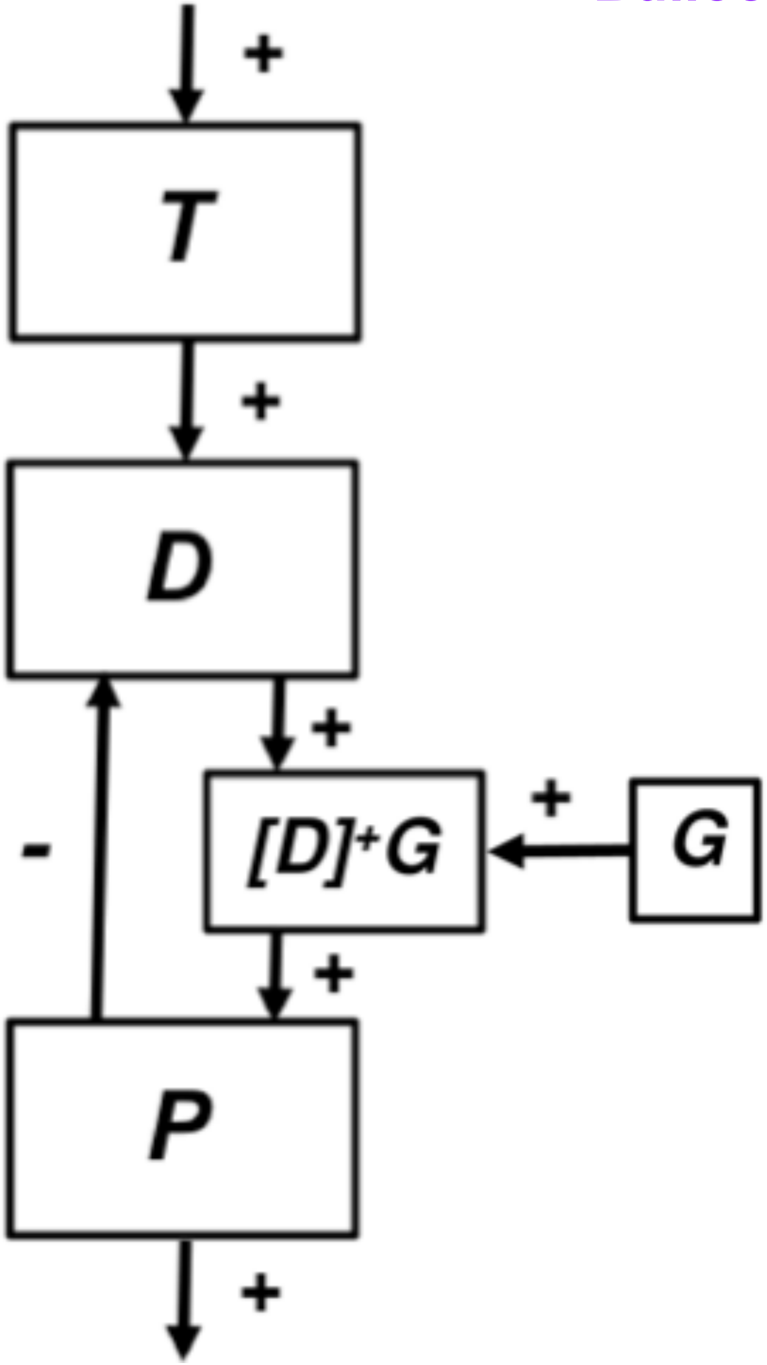


Match Amplifies
Match Learning

Match Suppresses
Mismatch Learning

VECTOR INTEGRATION TO ENDPOINT (VITE): EXPLAINABLE!

Bullock & Grossberg (1988)



Target Position Vector T

Present Position Vector P

Difference Vector V

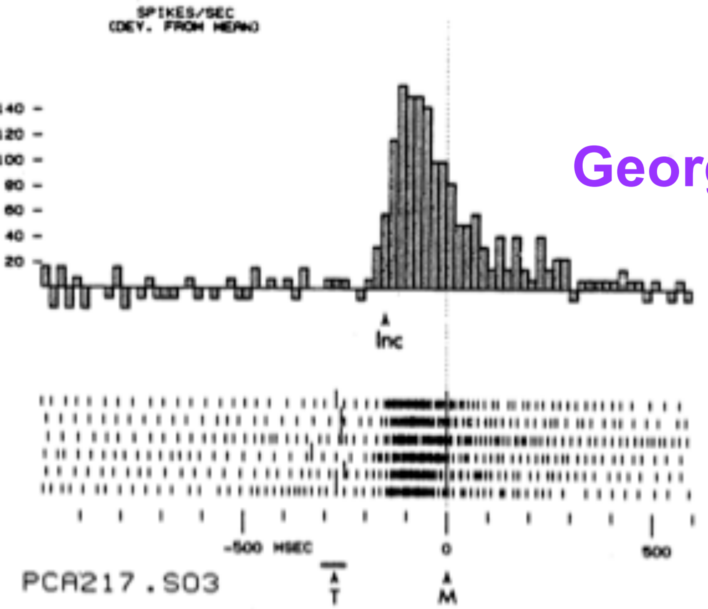
GO signal G

Outflow Movement Speed $[D]^+G$

are all EXPLAINABLE!

VITE HAS BEEN MEASURED PHYSIOLOGICALLY

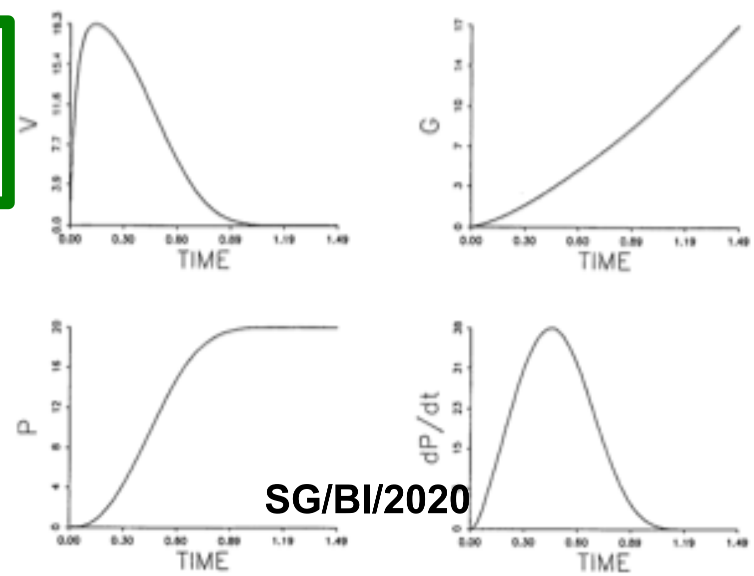
e.g., DIFFERENCE VECTOR



Georgopoulos et al., (1982)

Difference Vector

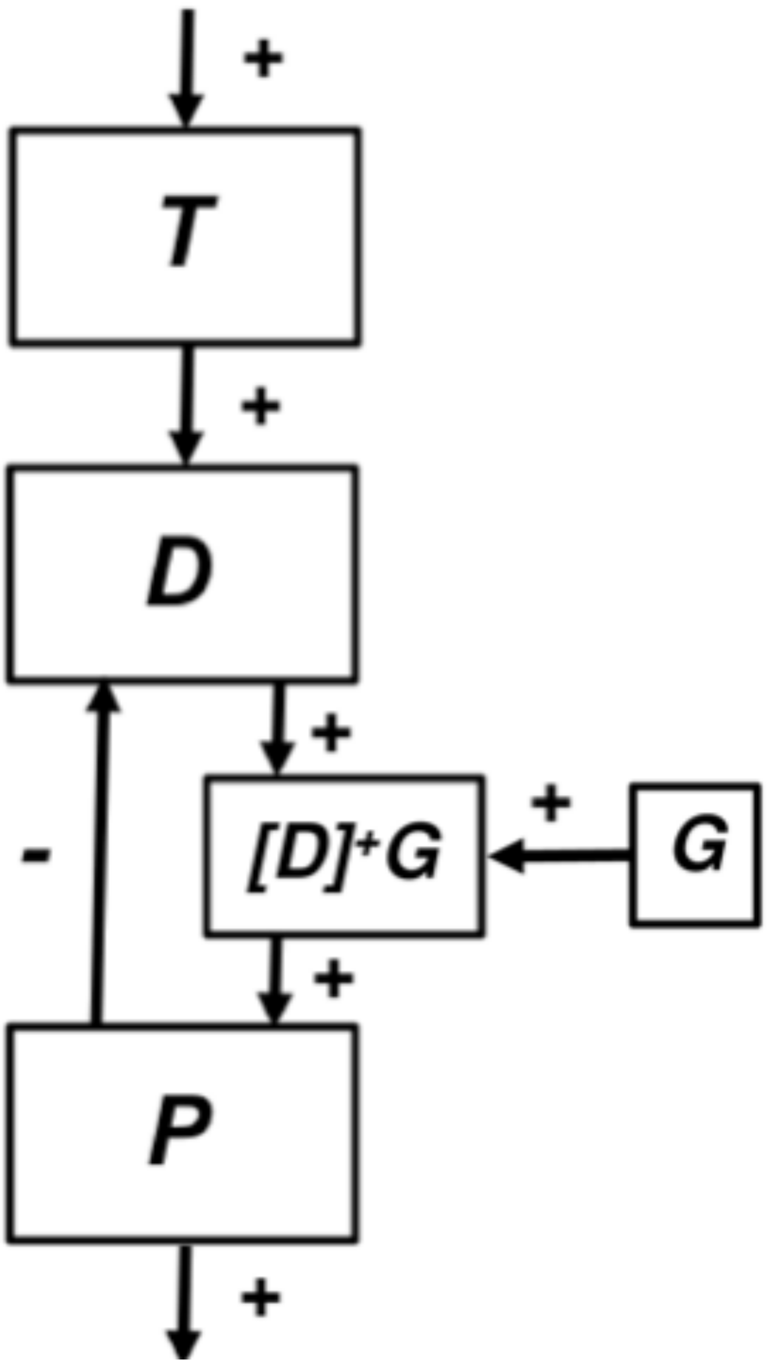
GO Signal



Present Position Vector

Outflow Velocity Vector

THE THREE S'S OF MOVEMENT CONTROL



SYNERGY

Defining *T* determines the muscle groups that will contract during the movement

SYNCHRONY

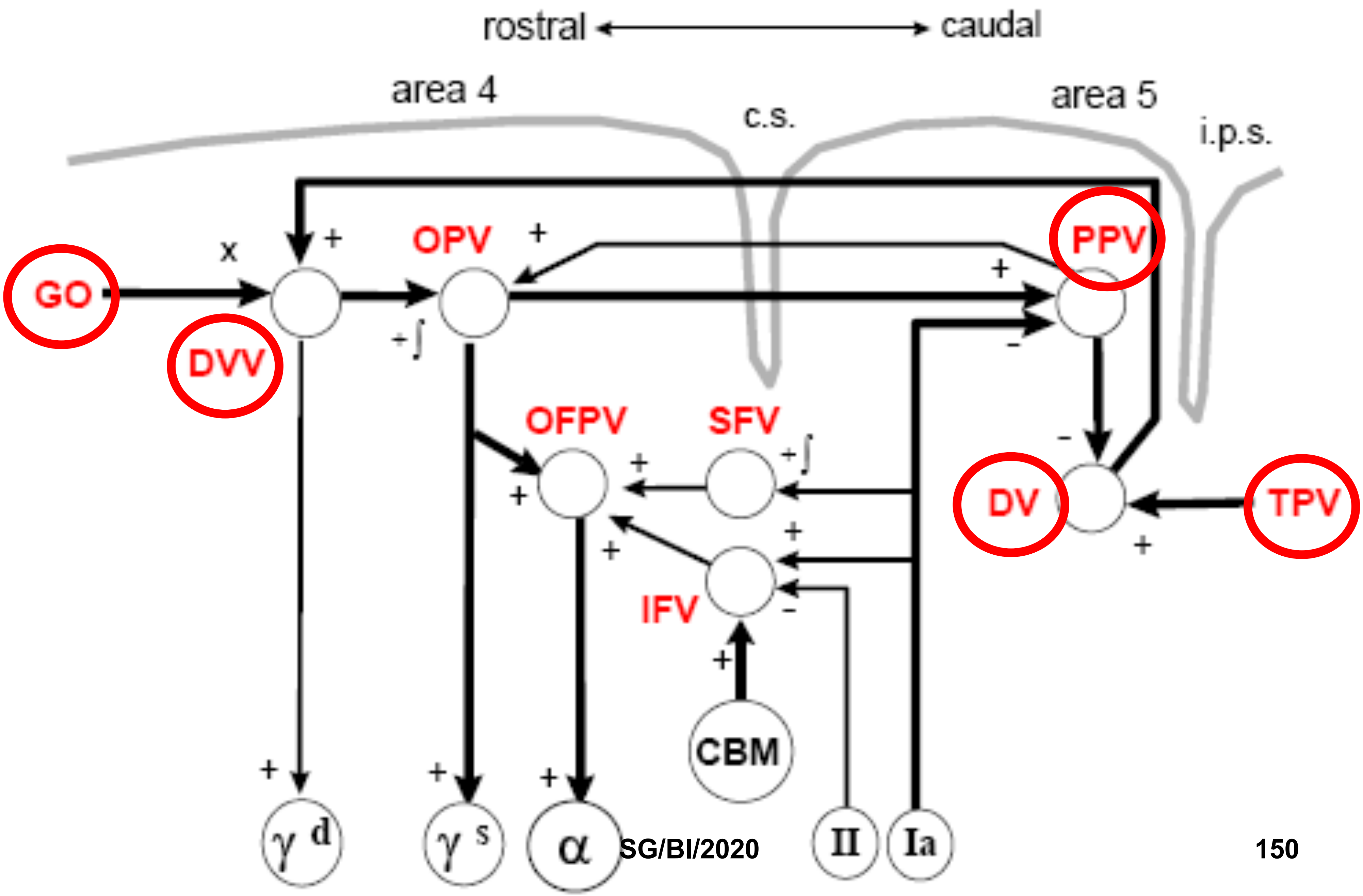
When G turns on, all muscle groups for which $D \neq 0$ contract by variable amounts in equal time
Because *G* multiplies *D*, it does not change the direction in which *P* moves to acquire *T*:
Straight line movement

SPEED

P integrates *D* at rate *G* until $P = T$
Increasing (decreasing) *G* makes the movement faster (slower)

VITE HAS BEEN UNLUMPED TO REVEAL FINER STRUCTURE

Bullock, Cisek, & Grossberg (1998)



ALL THESE BIOLOGICAL MODELS OF PERCEPTION, COGNITION, EMOTION, AND ACTION ARE EXPLAINABLE

Perceptual and cognitive processes use ART-like excitatory matching and match-based learning to create self-stabilizing attentive and conscious representations of objects and events that embody increasing expertise about the world

Complementary spatial and motor processes use inhibitory matching and mismatch-based learning to continually update spatial and motor representations to compensate for bodily changes throughout life

Together they provide a self-stabilizing perceptual and cognitive front end for conscious awareness and knowledge acquisition, which can intelligently manipulate more labile spatial and motor processes that enable our changing bodies to act effectively on a changing world