I’m very grateful to have the opportunity to speak to you today, but I do so while feeling deep sadness and grief about the tragic loss of life and health due to the coronavirus pandemic, and the economic devastation that it has unleashed upon millions around the world.

These feelings have only deepened as the Original Sin of systemic racism has traumatized the United States once again, and galvanized concerned citizens around the world to demand that black and brown people be finally given equal opportunities and justice.

Scientific truth and progress have the power to guide us steadily to a better future. Let us dedicate ourselves to realizing the hope that they will continue to do so.

From designs for autonomous adaptive agents to clinical disorders:
Linking cortically-mediated learning to
Alzheimer's disease, autism, amnesia, and sleep

Stephen Grossberg

Center for Adaptive Systems
Graduate Program in Cognitive and Neural Systems
Department of Mathematics & Statistics, Psychological & Brain Sciences,
and Biomedical Engineering
Boston University

steve@bu.edu
sites.bu.edu/steveg

HOW CAN A TALK ON THIS TOPIC EVEN BE GIVEN?

The results are based on the most advanced neural models of

HOW OUR BRAINS SEE, RECOGNIZE, AND PREDICT
objects and events in a changing world

The models emerged through 50 years of research

They also offer an explanation of

what goes on in each brain as it
consciously sees, hears, feels, or knows

HOW MUCH PROGRESS HAS BEEN MADE?

It has led to a major scientific PARADIGM SHIFT
that has required

new design principles that unify multiple disciplines

new mathematical concepts and methods

major computer resources

multiple experimental techniques

WHAT IS THIS PARADIGM SHIFT?

It began in the late 1800's

when great scientists such as Helmholtz, Maxwell, and Mach worked in both psychology and physics

This shift accelerated in the 1970's - 1980's

See Grossberg (1988, Neural Networks, 1, 17)

This paradigm shift is about:

Understanding how an individual
adapts
on its own
in real time
to a complex and changing world

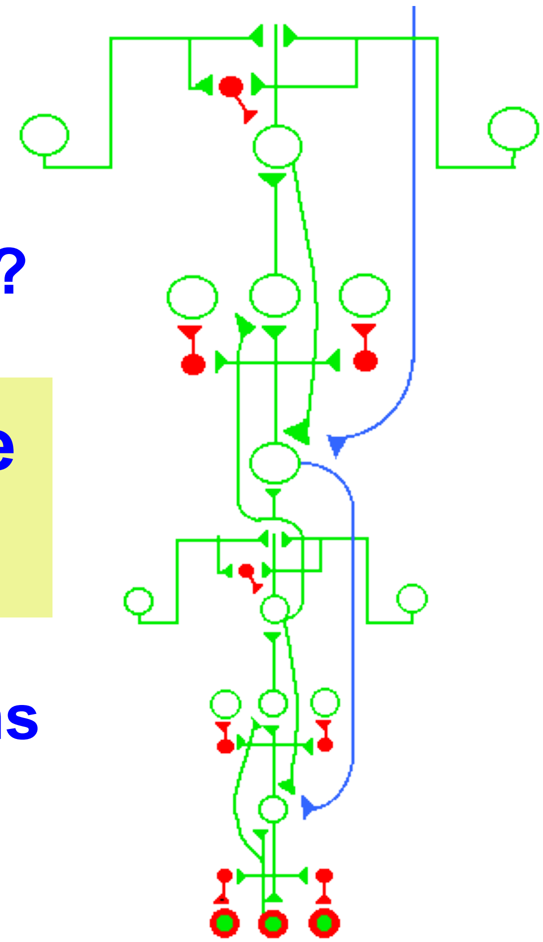
AUTONOMOUS adaptation to a changing world filled with unexpected events

For AI, designs for autonomous adaptive intelligence

My own work focuses on
HOW DOES A BRAIN GIVE RISE TO A MIND?
Link Brain MECHANISMS to Mental FUNCTIONS

What level of brain organization controls behavior?

What is the functional unit of behavior?



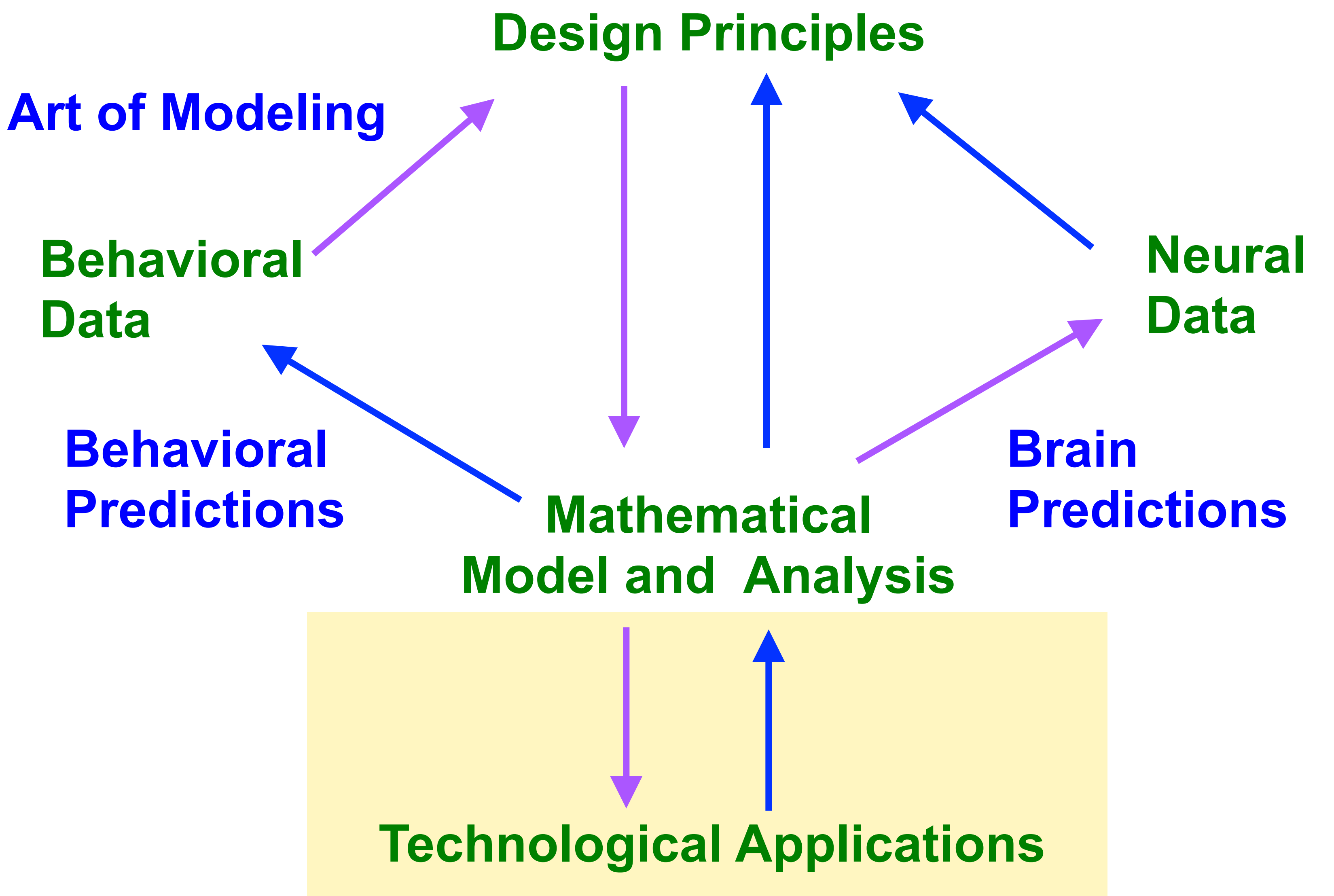
BRAIN evolution needs to achieve BEHAVIORAL success

What level of BRAIN processing governs BEHAVIORAL success?

The NETWORK and SYSTEM levels!

Why we study neural networks

MODELING METHOD AND CYCLE



At every stage, spin off new model designs and mechanisms to technologists who need autonomous adaptive intelligence

TRUE THEORIES ARE EMERGING

A small number of equations

e.g., shunting activation dynamics (STM)
habituative transmitter gates (MTM)
activity-gated learning (LTM) …

A larger number of modules*

e.g., on-center off-surround nets
resonant matching nets
opponent processing nets
spectral timing nets
boundary completion nets
filling-in nets…

Specialized combinations of modules*, using a few basic equations, are assembled in architectures that solve modal problems

A still larger number of modal architectures

e.g. vision
audition
smell
touch
cognition
emotion…

*Modules are microcircuits, not the "independent modules" of AI

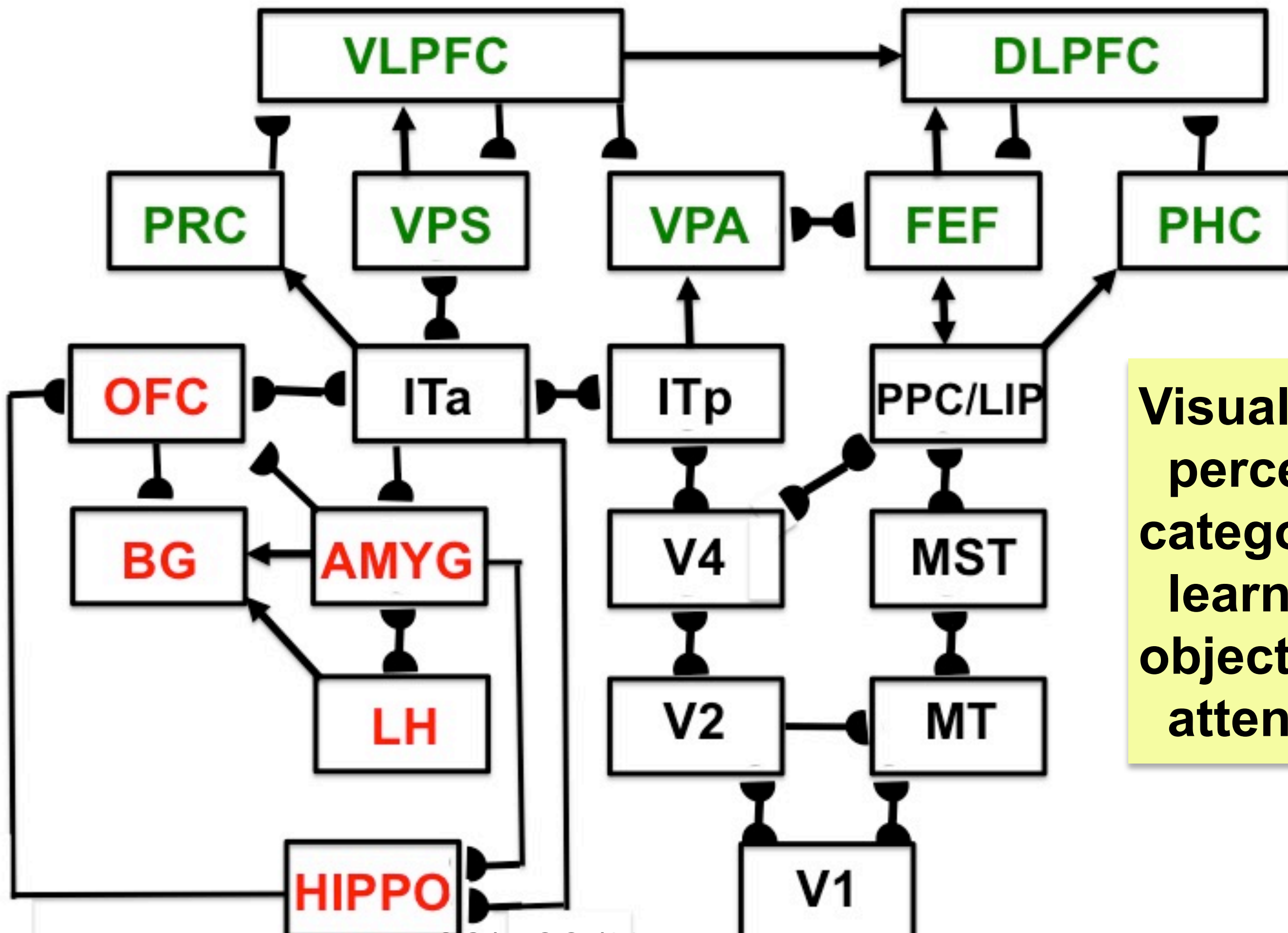
Predictive ART, or pART, architecture macrocircuit

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

WHAT PRINCIPLES DETERMINE HOW MODAL ARCHITECTURES ARE DESIGNED?

BREAKTHROUGHS IN BRAIN COMPUTING

Models that link detailed BRAIN CIRCUITS to the ADAPTIVE BEHAVIORS that they control

Mind/Body Problem

Describe 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?

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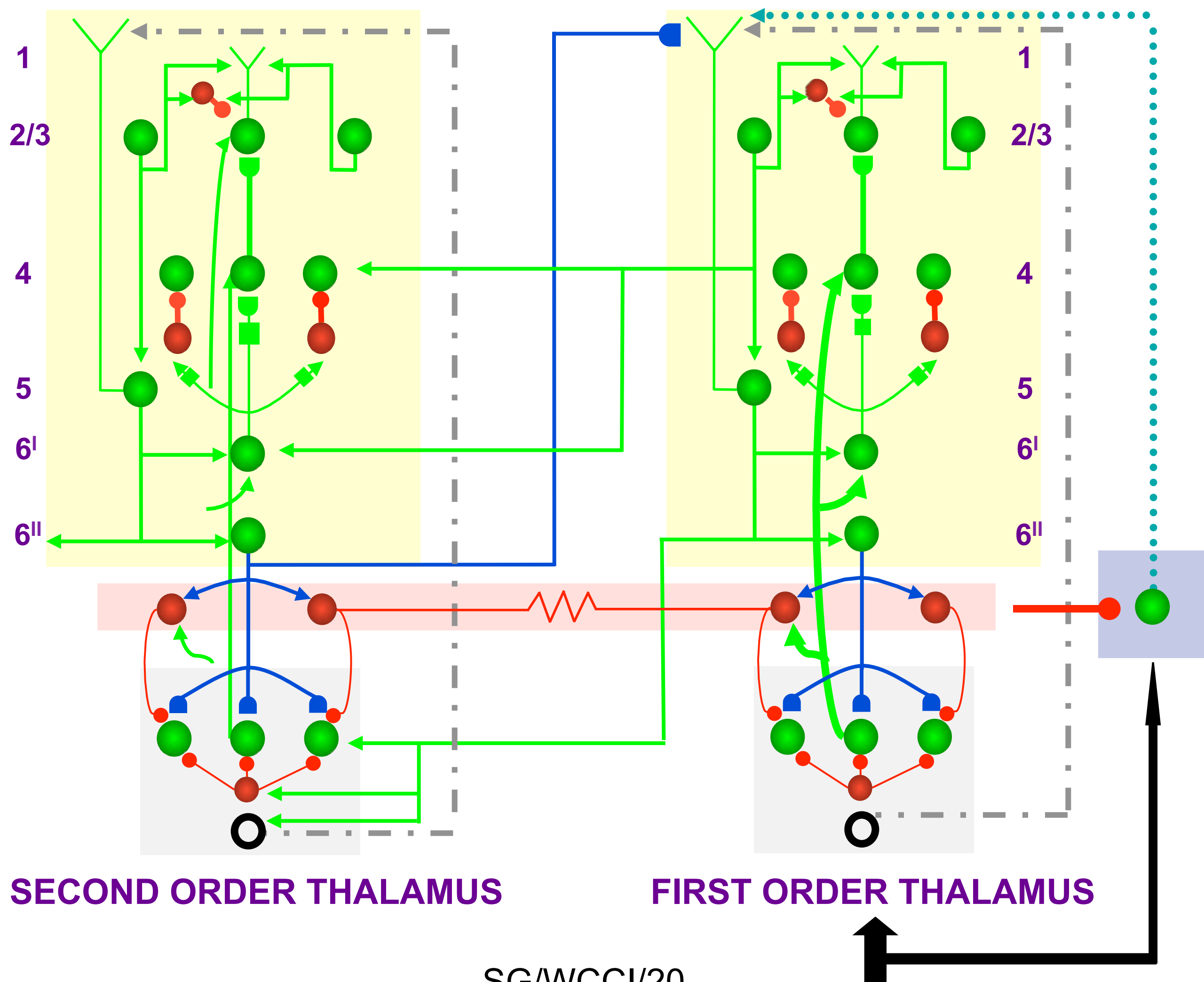
A KEY RESEARCH GOAL

Develop a comprehensive theory of how laminar neocortical circuits are specialized for different types of intelligence



A KEY RESEARCH GOAL

Develop a comprehensive theory of how laminar neocortical circuits are specialized for different types of intelligence

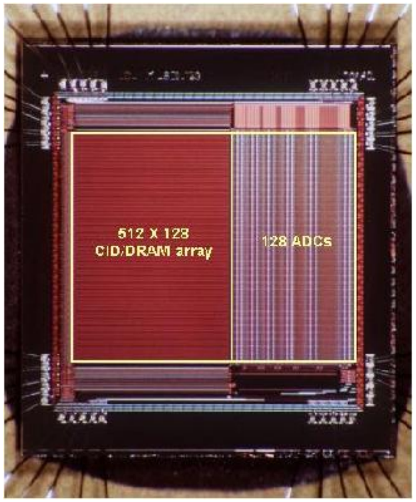
3D Vision	**3D LAMINART**
Speech	**cARTSCAN**
Cognition	**LIST PARSE**

These models use specializations of the same canonical laminar circuitry: An Existence Proof!

Grossberg (2013; see sites.bu.edu/steveg)

A KEY RESEARCH GOAL

A self-organizing VLSI chip set whose modules are computationally consistent and can therefore be assembled into autonomous adaptive agents to carry out multiple intelligent tasks



A potentially huge technological impact in multiple areas of intelligent computation

BREAKTHROUGHS IN BRAIN COMPUTING

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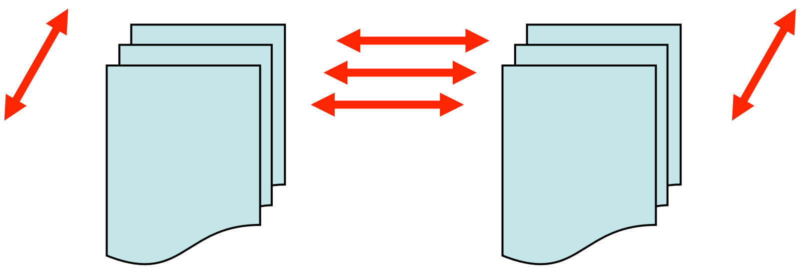
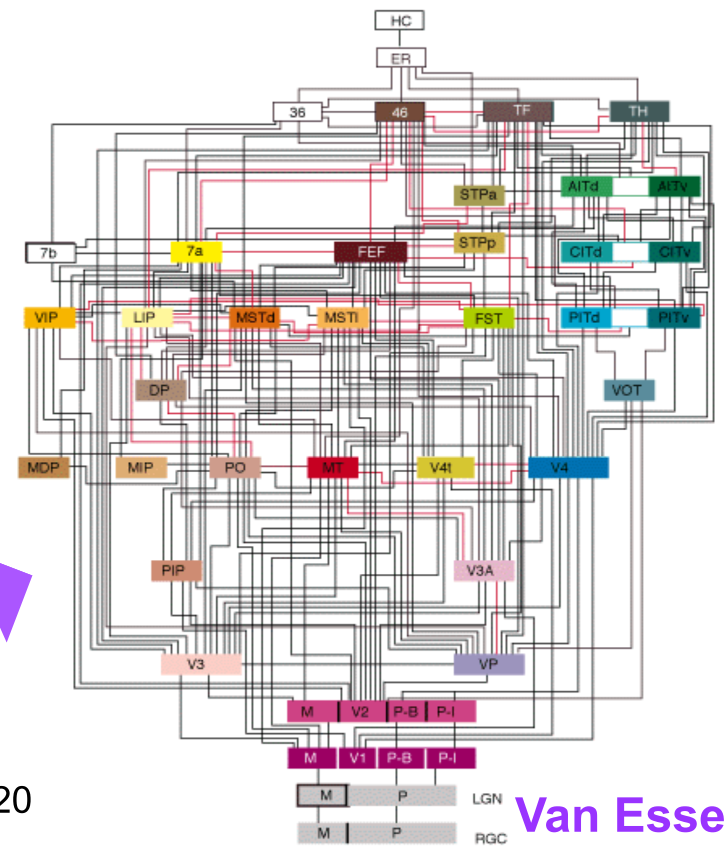
COMPLEMENTARY COMPUTING

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

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**
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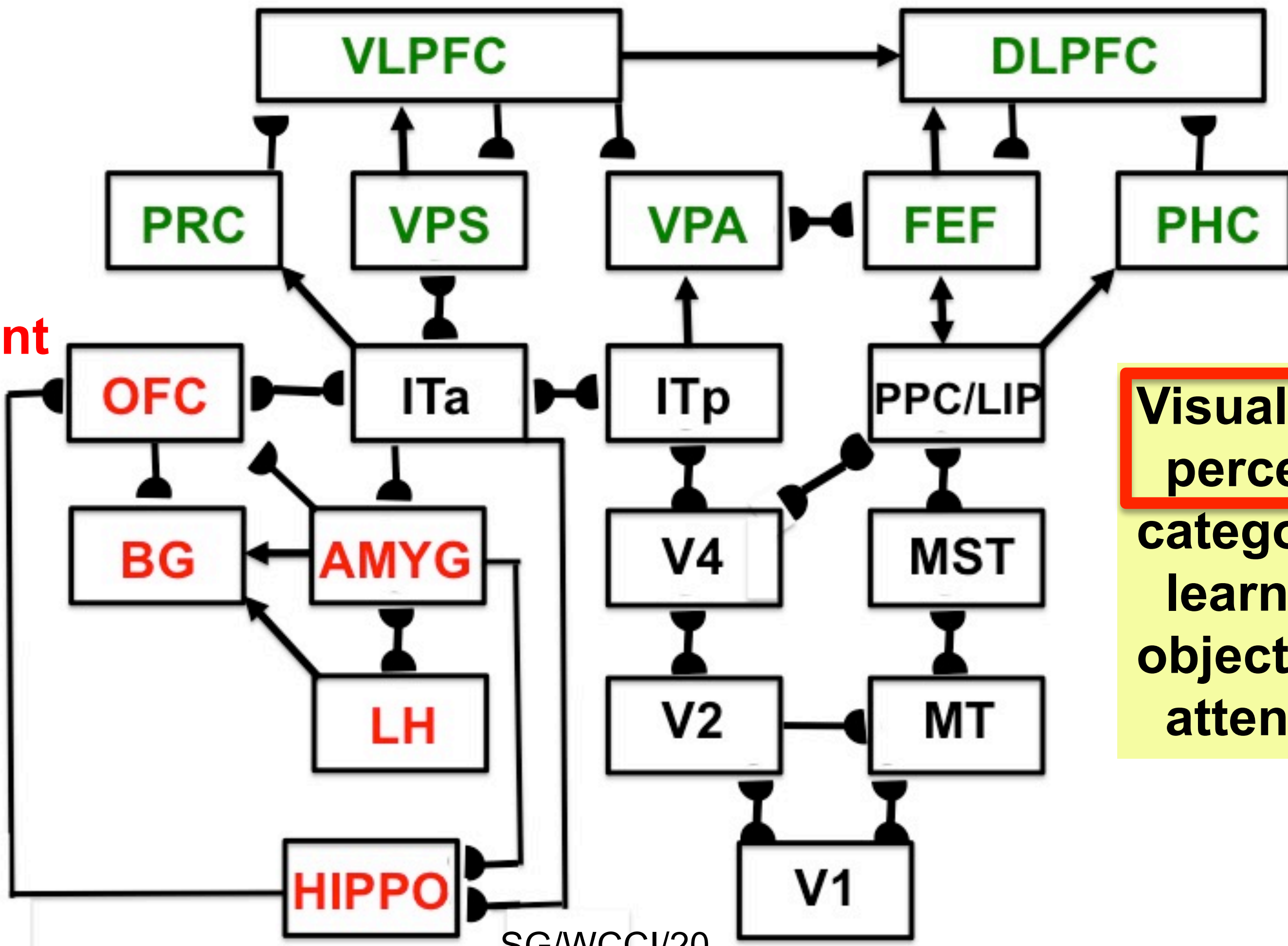
Predictive ART, or pART, architecture macrocircuit

How prefrontal cortex learns to control all higher-order intelligence

Grossberg (2018)

Working memory, learned plans, prediction, optimized action

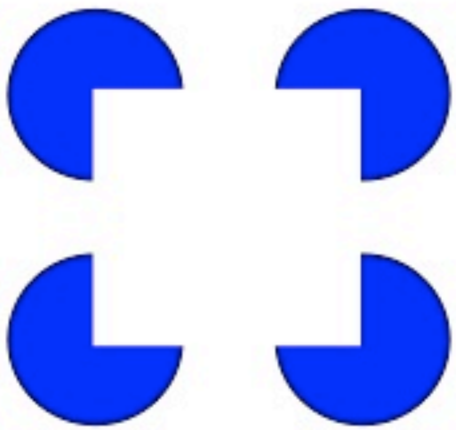


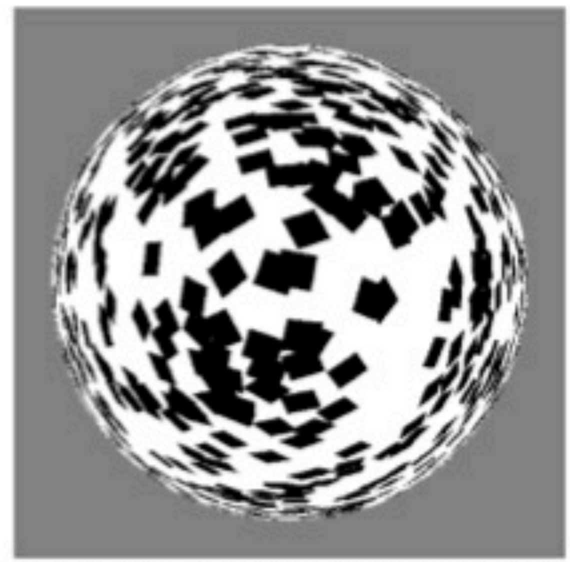
Reinforcement learning, emotion, motivation, adaptively-timed learning,

Visual perception, category learning, object attention

WHAT IS A VISUAL BOUNDARY OR GROUPING?

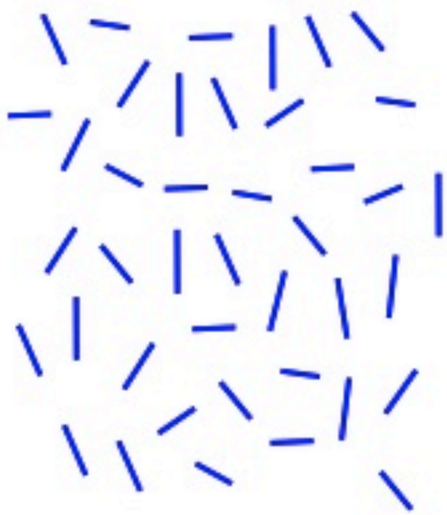
Illusory contour





3D shape from texture

Texture pop-out



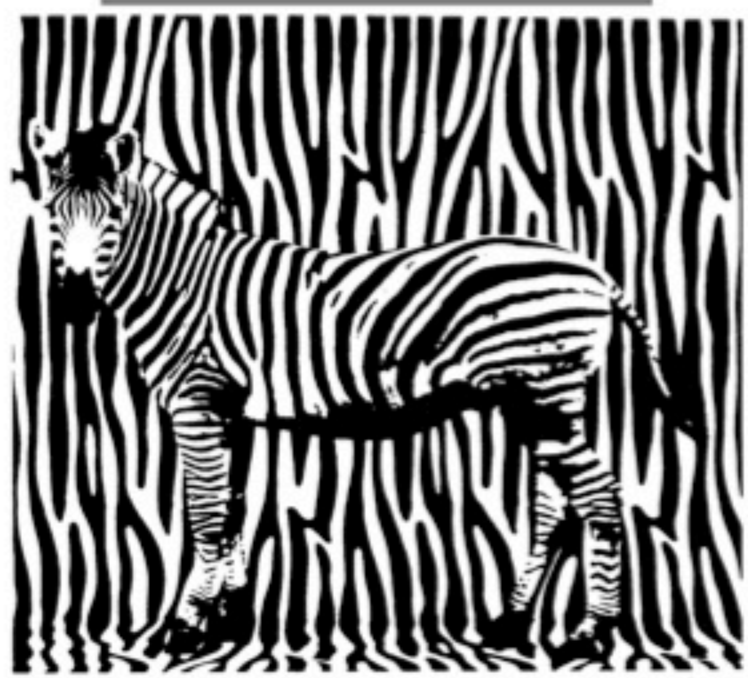
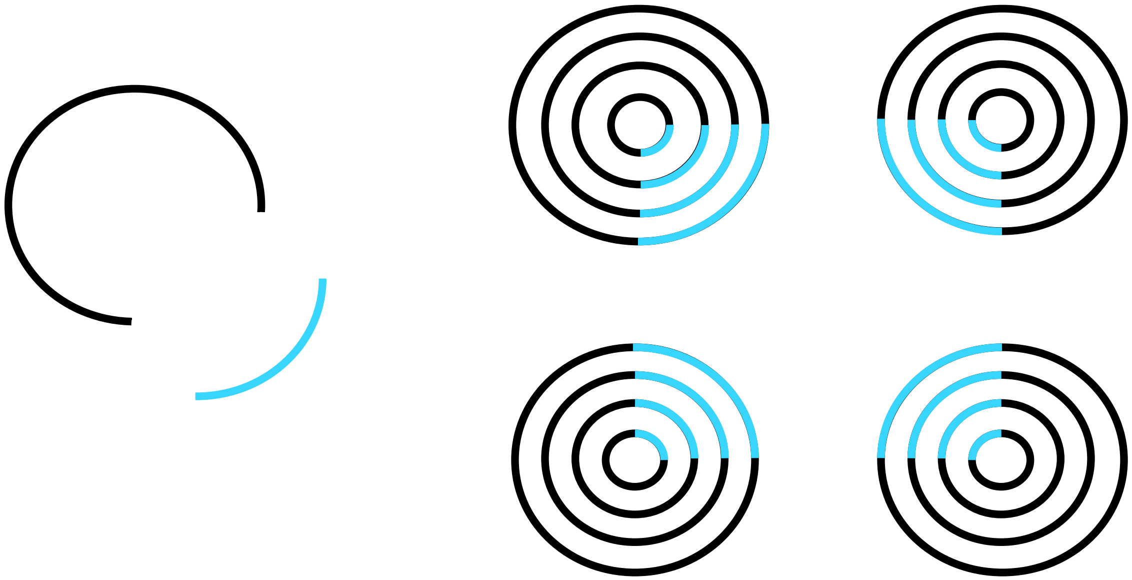


Figure-ground separation

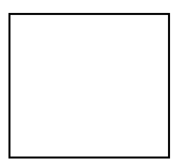
VISUAL BOUNDARY AND SURFACE COMPUTATIONS ARE COMPLEMENTARY

Grossberg (1984)



Neon color spreading

BOUNDARY COMPLETION

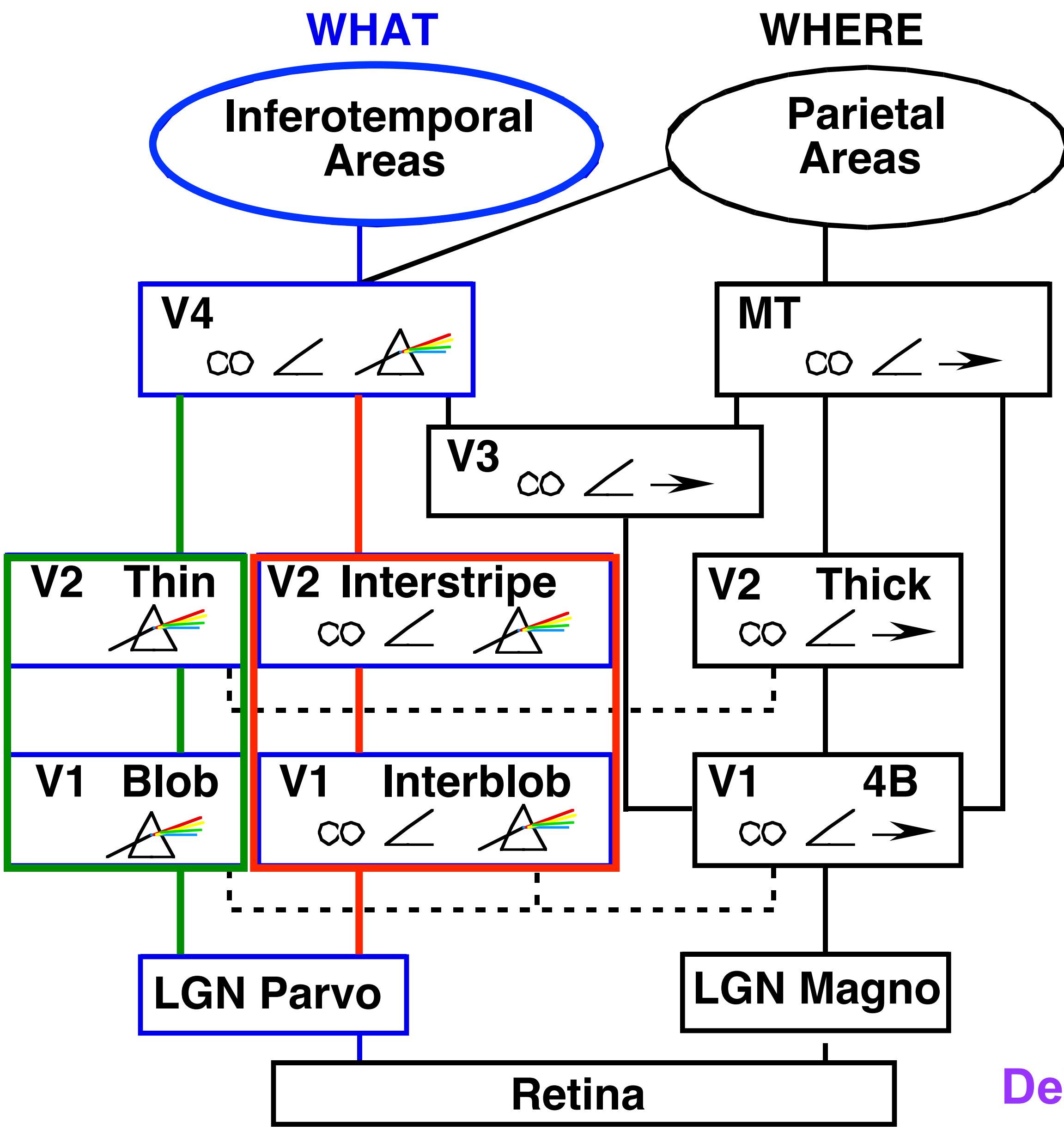


oriented
inward
insensitive to
direction-of-contrast

SURFACE FILLING-IN

unoriented
outward
sensitive to
direction-of-contrast

BOUNDARY AND SURFACE CORTICAL STREAMS



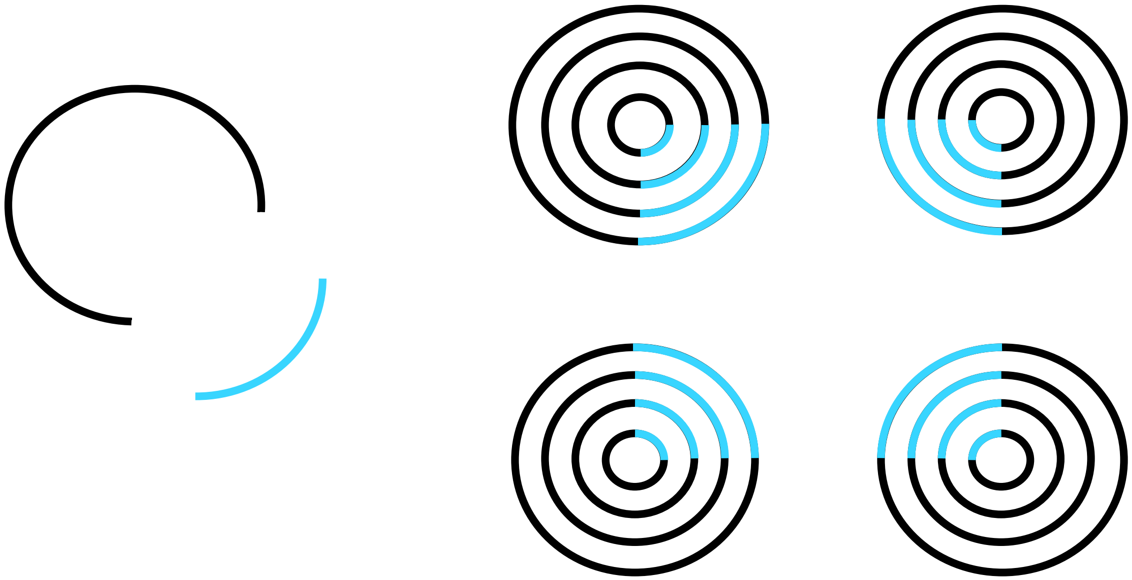
Boundaries
interblob stream

Surfaces
blob stream

DeYoe and van Essen (1988)

VISUAL BOUNDARY AND SURFACE COMPUTATIONS ARE COMPLEMENTARY

Grossberg (1984)



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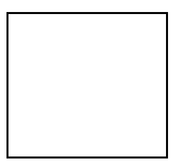
BOUNDARY COMPLETION



SURFACE FILLING-IN

What about

oriented
inward
insensitive to
direction-of-contrast

unoriented
outward
sensitive to
direction-of-contrast

SEEING vs. KNOWING

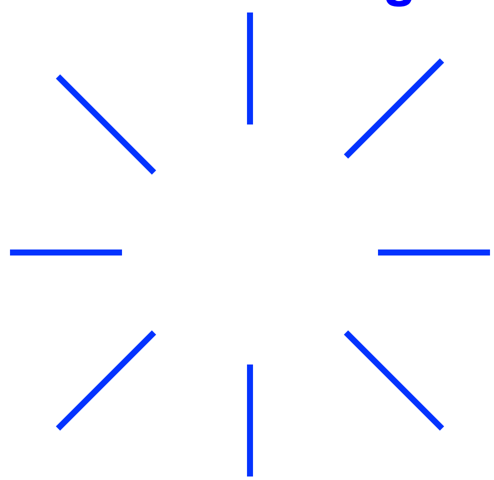
SEEING vs. **KNOWING**

an object / **what it is**

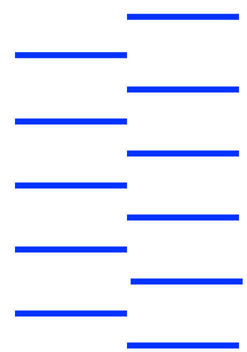
Epstein, Gregory, Helmholtz, Kanizsa, Kellman, Michotte,…

SEEING vs. **RECOGNIZING**

Ehrenstein Figure



Offset Grating



Some boundaries are invisible, or amodal

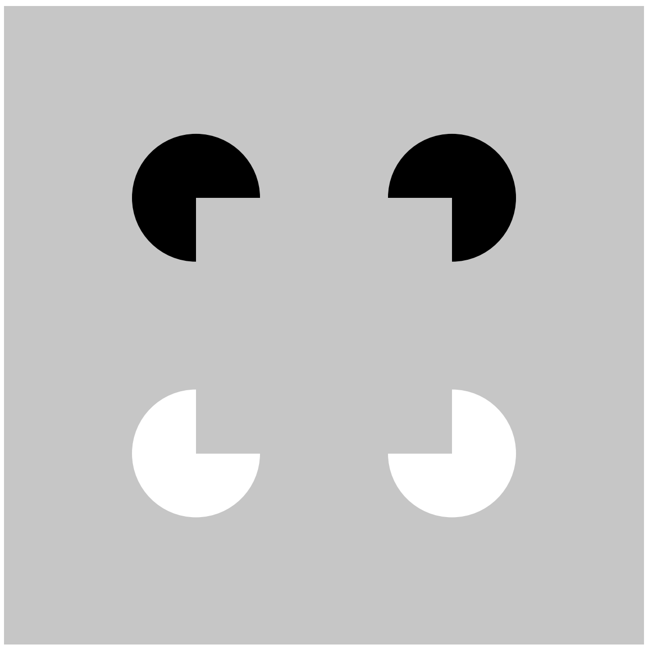
See
Recognize

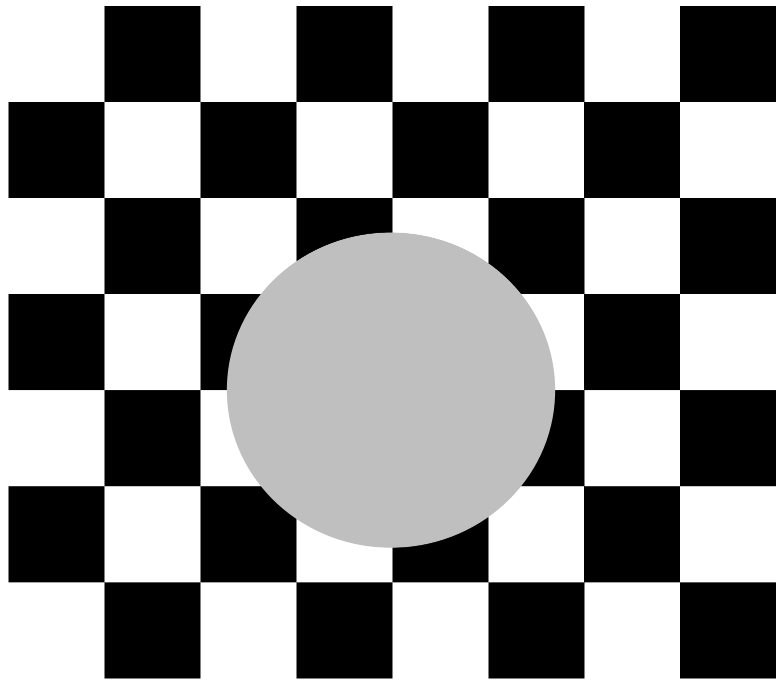
Do not see
Recognize

ALL BOUNDARIES ARE INVISIBLE!
within the Boundary Stream

Grossberg (1984)

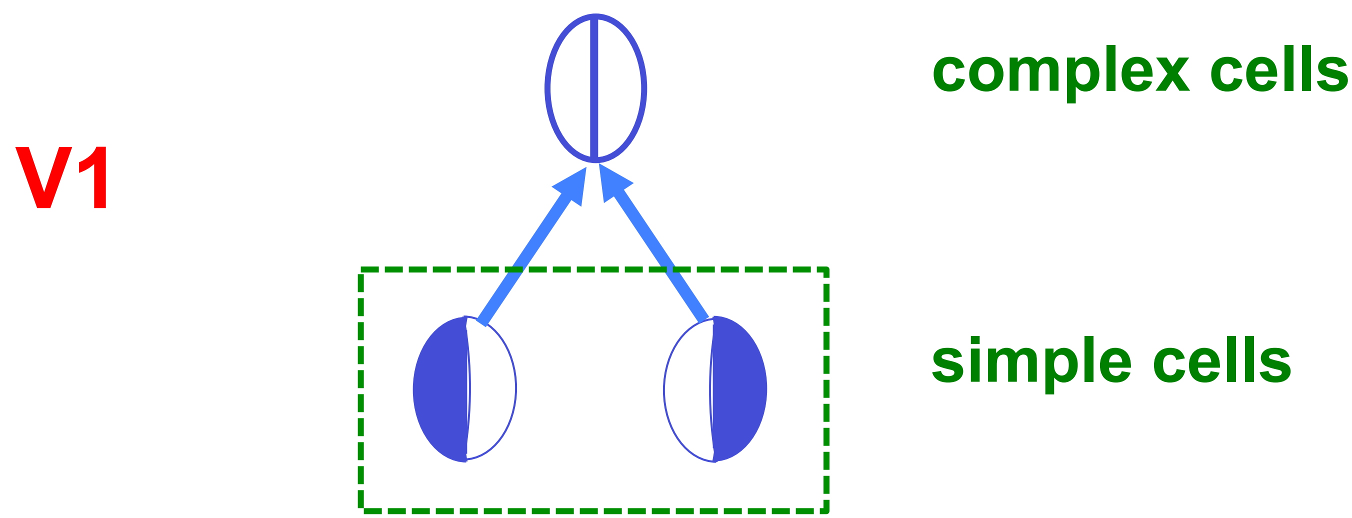
WHY? To recognize object boundaries in front of textured backgrounds





ALL BOUNDARIES ARE INVISIBLE: COMPLEX CELLS

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

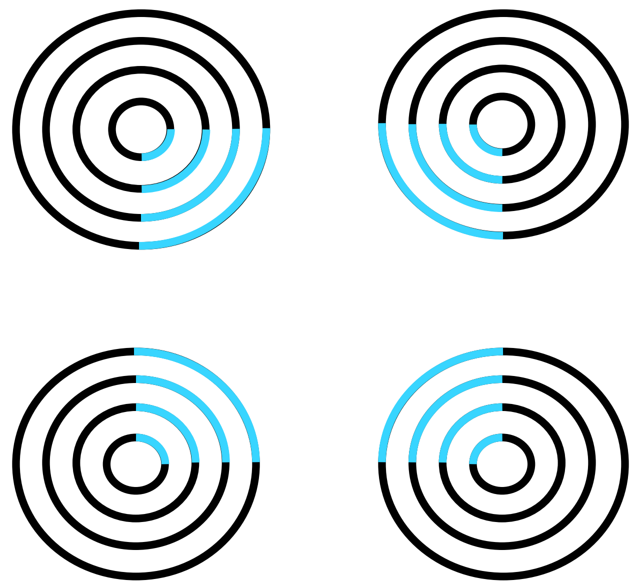


Complex cells are amodal boundary detectors Grossberg (1984)

vs

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

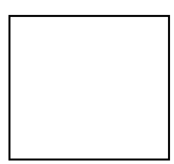
VISUAL BOUNDARY AND SURFACE COMPUTATIONS ARE COMPLEMENTARY



Neon color spreading

All Boundaries Are Invisible!

BOUNDARY COMPLETION



oriented
inward
insensitive to
direction-of-contrast

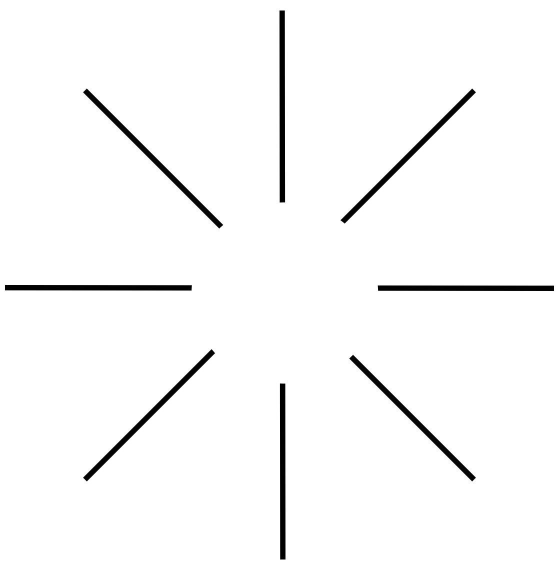
SURFACE FILLING-IN

unoriented
outward
sensitive to
direction-of-contrast

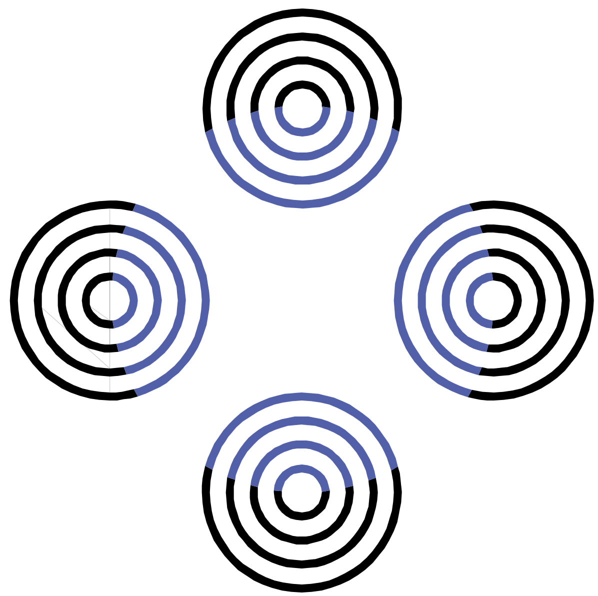
IF BOUNDARIES ARE INVISIBLE, HOW DO WE SEE?

Filling-In of Surface Color

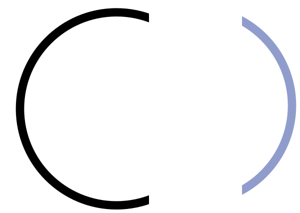
Boundaries define the compartments within which lightness and color spread



Ehrenstein (1941)

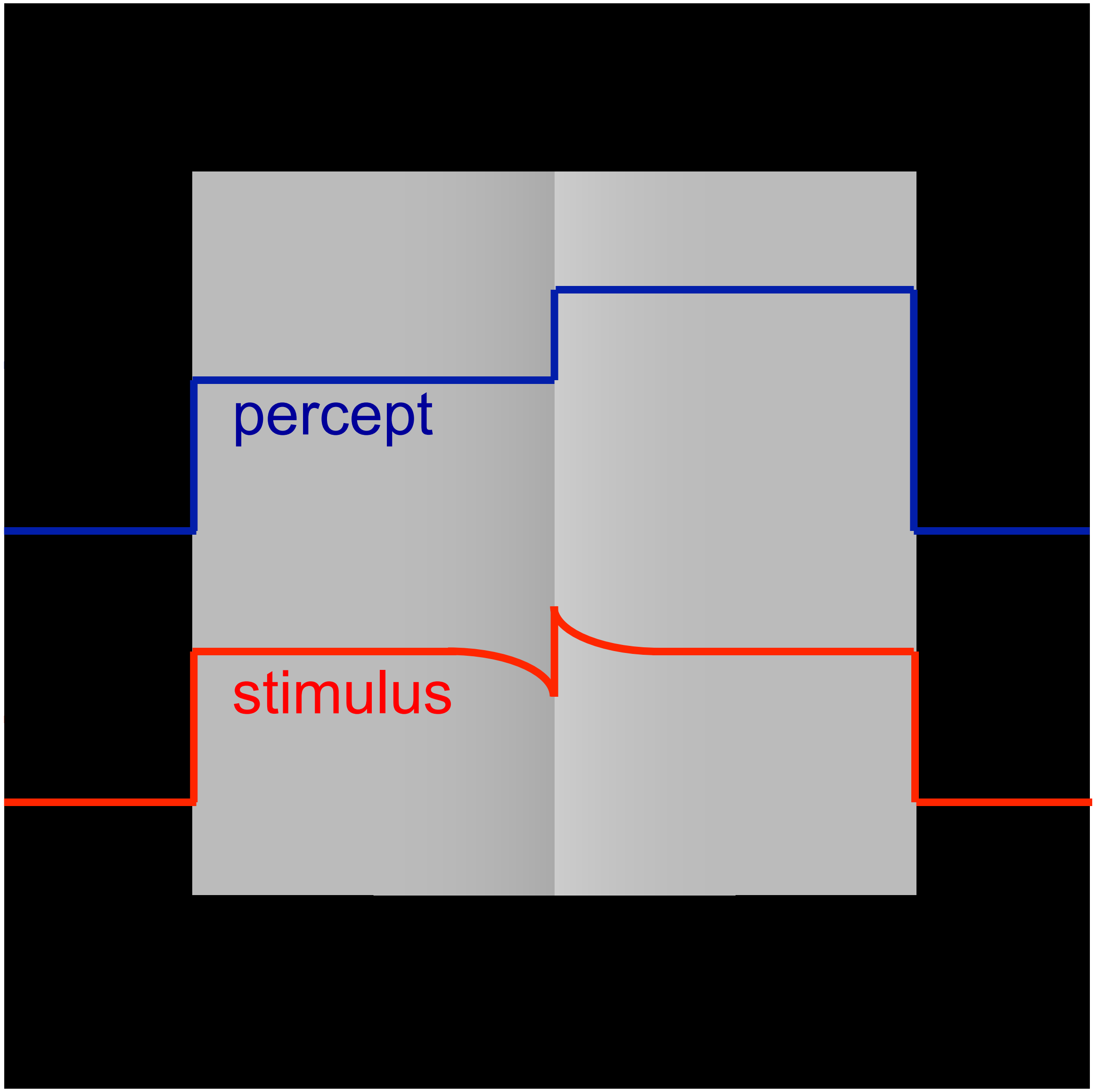


Varin (1971)



Neon color spreading

Craik-O' Brien-Cornsweet Effect

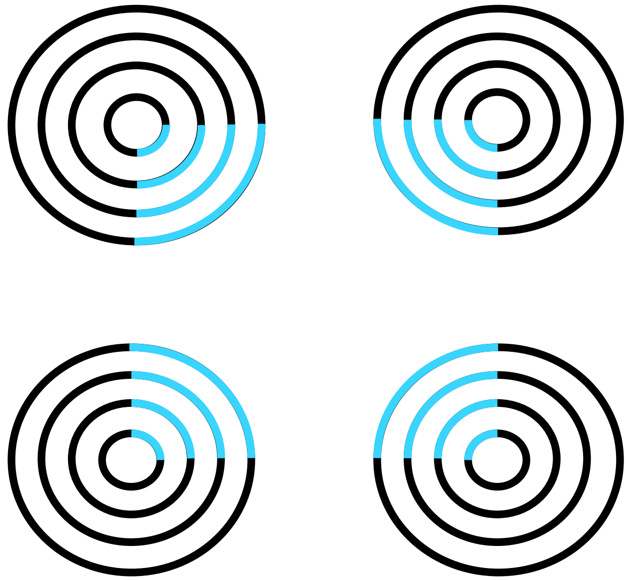


Boundary completion defines filling-in compartments

Filling-in determines what we see in each compartment

Grossberg (1984)
Todorović (1987)

VISUAL BOUNDARY AND SURFACE COMPUTATIONS ARE COMPLEMENTARY



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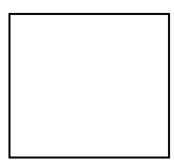
BOUNDARY COMPLETION



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unoriented
outward
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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

THIS IS A TALK IN TWO PARTS

The first part:

Acetylcholine neuromodulation in normal and abnormal learning and memory:

Vigilance control in waking, sleep, autism, amnesia, and Alzheimer's disease

Article with the same title published OPEN ACCESS in 2017 in *Frontiers in Neural Circuits*; also on my web page

sites.bu.edu/steveg

This work illustrates the importance of

BALANCING PARAMETERS

i.e., homeostatic regulation

to generate adaptive behaviors

A unifying theme of this part of the talk is

VIGILANCE CONTROL

and how it can break down during various mental disorders

A unifying theme of this part of the talk is

VIGILANCE CONTROL

and how it can break down during various mental disorders

Most discussions of Alzheimer's disease focus
on the terrible STRUCTURAL degeneration that occurs

I will explain how these structural events may affect the
DYNAMICS of learning, recognition, and cognition
during the disease

Model provides a LINKING HYPOTHESIS
between STRUCTURE and FUNCTION (SYMPTOMS)

LOTS OF EXPERIMENTAL EVIDENCE FOR STRUCTURAL EVENTS THAT SEEM TO CAUSE ALZHEIMER'S

Beta-amyloid plaque and neurofibrillary tangles are implicated
Dickson, 1997; Godert, 1993; Hardy and Allsop, 1991; Ikeda et al., 1987; Lacor et al, 2007; Poksay et al., 2017

Anti-amyloid antibodies, BAN2401 and aducanumab, slow disease
Lannfelt et al., 2014; Logovinsky et al., 2016; Mendes & Palmer, 2018

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How do these structural events cause the DYNAMICS of LEARNING, MEMORY, and COGNITION to collapse?

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How do these structural events cause the DYNAMICS of LEARNING, MEMORY, and COGNITION to collapse?

VERY COMPLICATED!
But here is one line of experiments and an explanation of them

This explanation also clarifies links between Alzheimer's and DISORDERED SLEEP

PLAQUES AND TANGLES DISRUPT ACh FUNCTION

Plaques and neurofibrillary tangles primarily in layers 3 and 5
Tomlinson et al., 1968; Arnold et al., 1991

Nucleus basalis of Meynert sends ACh-releasing neurons to layer 5
Saar et al., 2001; Zhang et al., 2004

Cholinergic agonists produce cognitive improvement in Alzheimer's
Zhang et al., 2004

α7 nicotinic ACh receptor (α7nAChR) is highly expressed
in basal forebrain neurons that project to cortex
Perry et al., 1992
The 42-amino acid β-amyloid peptide (Aβ1-42)
binds with high affinity to α7nAChR
and accumulates in Alzheimer patient neurons
This peptide inhibits release of ACh
Kar et al., 1996

ACh-releasing neurons with cell bodies in basal forebrain degenerate
Coyle, Price, and DeLong (1981)

Postmortem studies demonstrate profound reduction in presynaptic markers for ACh neurons in Alzheimer's patients
Whitehouse et al. (1982)

Alzheimer's animal models show that anticholinergic drugs and nucleus basalis lesions disrupt learning or memory in multiple paradigms including passive avoidance learning and Morris water maze
Friedman, Lerer, and Kuster, 1981; LoConte et al., 1982; Francis et al., 1999; Iqbal and Grundke-Iqbal, 2008; Pimplikar, 2009

Acetylcholinesterease (AChE) is the main enzyme to break down ACh
Inhibition of AChE is used to ameliorate Alzheimer's symptoms
Mukherjee et al., 2007; Orban et al., 2004

Extensive network of cortical pyramidal neurons in human brain with AChE activity
Adults above age 80 with excellent memories (SuperAgers) show much lower staining of AChE neurons compared with same-age peers
Low AChE could counterbalance declining memory during normal aging
Janeczek et al., 2017

Zizypus jujube (ZJ) activates choline acetyltransferase (ChAT), an enzyme that induces ACh synthesis
Used ZJ in a rat model of Alzheimer's with nucleus basalis lesions
ZJ has repairing effects on memory and behavioral disorders
Rabiei et al., 2014

HOW DO THESE NUCLEUS BASALIS AND ACh PROBLEMS AFFECT LEARNING, MEMORY, AND COGNITION?

They cause a breakdown of both
TONIC and PHASIC VIGILANCE CONTROL

VIGILANCE CONTROL regulates learning, recognition, and cognition

TONIC vigilance sets the baseline of cortical sensitivity

PHASIC vigilance changes are triggered by unexpected events that drive new learning

In this regard, Alzheimer's patients have
lower levels of overall vigilance
and poorer concentration to stimuli over time than controls
Bernardi, Parsuraman, and Haxby, 2005

ADAPTIVE RESONANCE THEORY

ART

Grossberg (1976)

A unifying theme:

Stability-Plasticity Dilemma

How can learning continue into adulthood without causing catastrophic forgetting?

How can we LEARN quickly without being forced to FORGET just as quickly?

e.g., why learning your faces does not force me to forget faces of my family and friends!

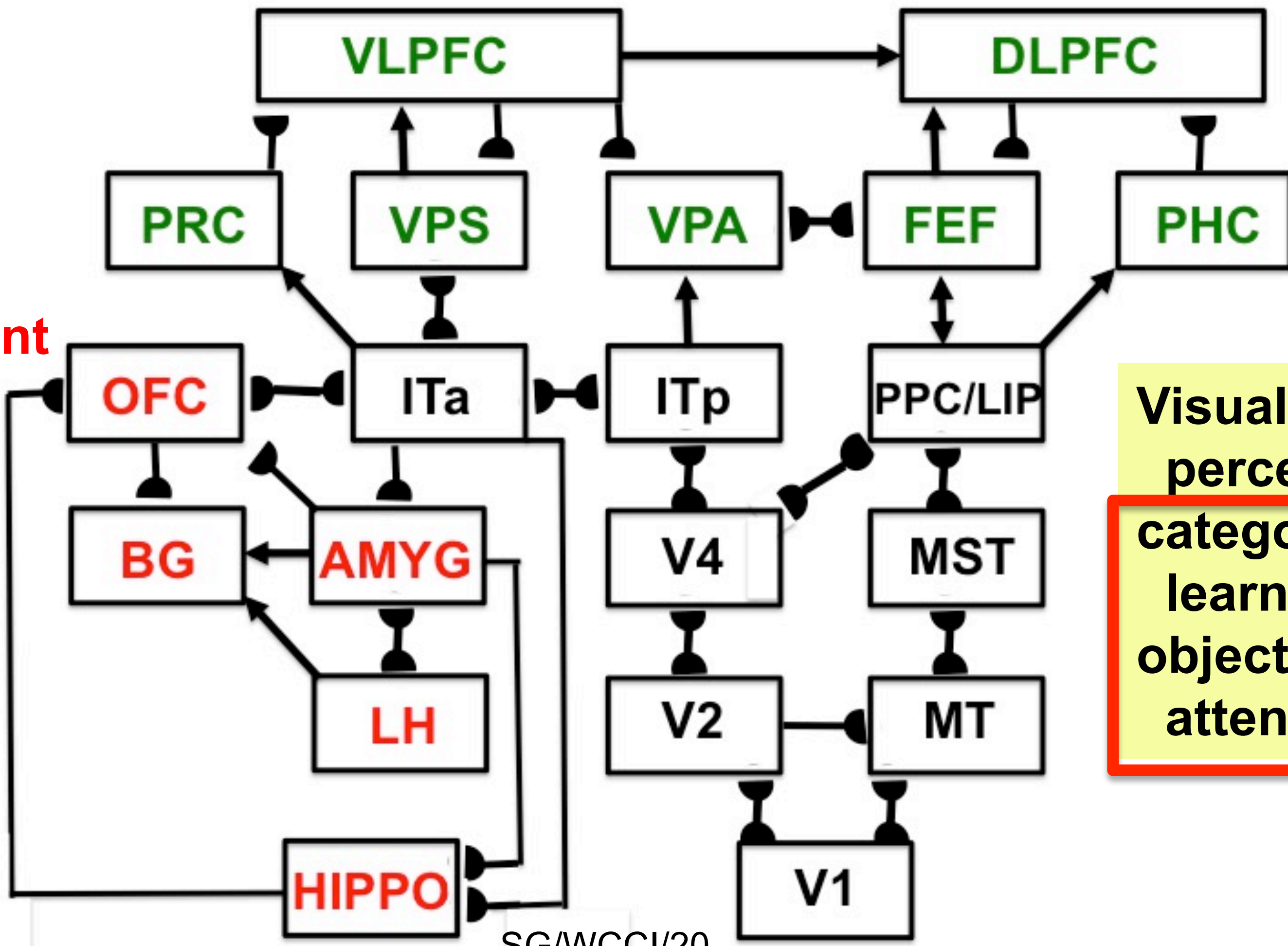
Predictive ART, or pART, architecture macrocircuit

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

RECENT HEURISTIC REVIEW ARTICLES OF ART AS A COGNITIVE AND NEURAL THEORY

sites.bu.edu/steveg

Grossberg, S. (2019). The resonant brain: How attentive conscious seeing regulates action sequences that interact with attentive cognitive learning, recognition, and prediction. *Attention, Perception & Psychophysics.* Published online: June 19, 2019.

Grossberg, S. (2018). Desirability, availability, credit assignment, category learning, and attention: Cognitive-emotional and working memory dynamics of orbitofrontal, ventrolateral, and dorsolateral prefrontal cortices. *Brain and Neuroscience Advances*. Published online: May 8, 2018. pART!

Grossberg, S. (2017). Towards solving the hard problem of consciousness: The varieties of brain resonances and the conscious experiences that they support. *Neural Networks*, 87, 38-95.

Grossberg, S. (2013). Adaptive Resonance Theory: How a brain learns to consciously attend, learn, and recognize a changing world, *Neural Networks*, 37, 1-47.

ART HELPS TO SOLVE AN OLD PROBLEM

Why do we pay attention?

Why do we learn expectations about the world?

Role of top-down processing

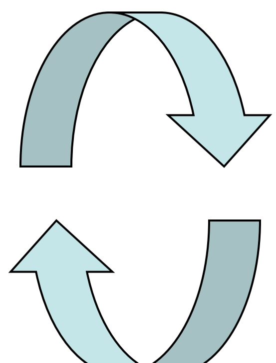
Helmholtz	Unconscious Inference
William James	Pragmatism
Tolman	Learn Expectations
Gregory	Cognitive Contours

ART MAIN IDEA

Top-down attentive feedback
encodes
learned expectations
that
DYNAMICALLY STABILIZE LEARNING AND MEMORY
in response to a
rapidly changing world
that is filled with
unexpected events

Attentive Information Processing

FAST



Learning and Memory

SLOW

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

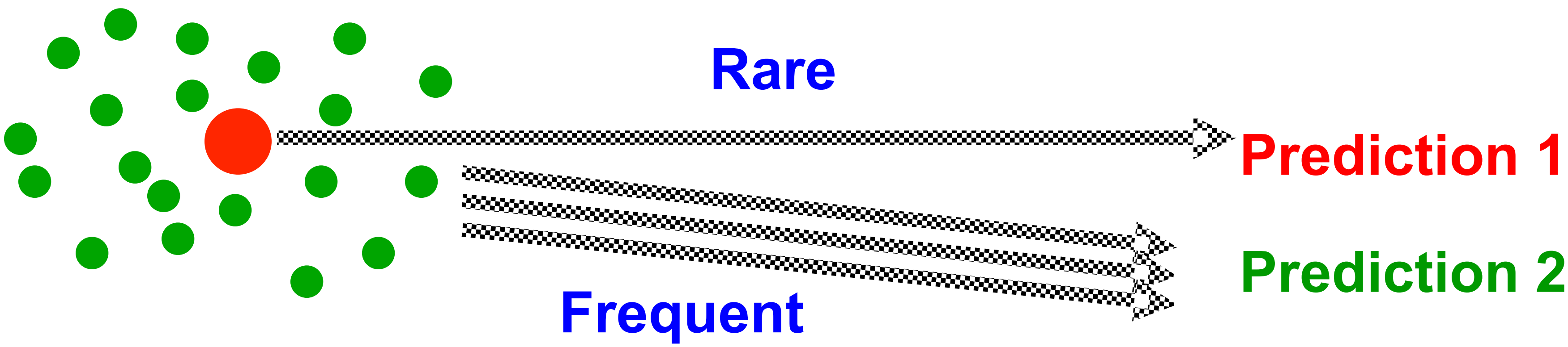
WHY IS ART USED IN SO MANY APPLICATIONS?

It has desirable learning properties that other models do not

Contrast Deep Learning

Learn rare events

need fast learning



Learn large non-stationary data bases

need self-stabilizing learning and memory

Learn morphologically variable events (concrete/abstract)

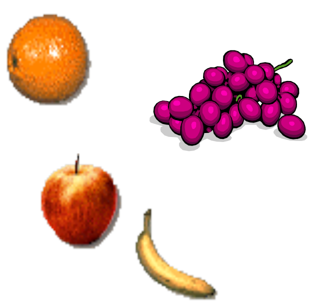
need multiple scales of generalization: vigilance!

Learn many-to-one and one-to-many relationships

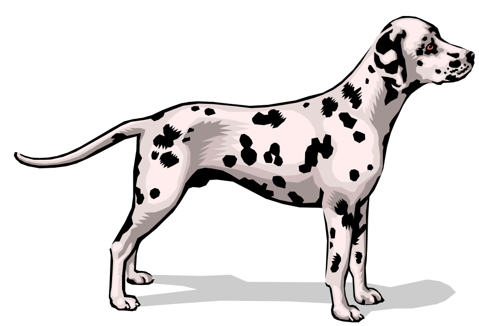
need categorization, naming, and expert knowledge

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

Many-to-One (DL)	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"

ARTMAP PROPERTIES

To realize these properties, ARTMAP systems:

Learn self-stabilizing recognition categories
  solve the catastrophic forgetting problem

Pay attention
  ignore masses of irrelevant data

Test hypotheses (self-organizing production system)
  discover predictive constraints hidden in data streams

Choose best answers (solve local minimum problem)
  direct access to globally optimal solution at any time

Calibrate confidence
  measure on-line how well a hypothesis matches the data

Discover rules, and hierarchies of cognitive rules
  identify transparent IF-THEN rules on each learning trial

Scale
  all properties hold for arbitrarily large databases

ART vs. BACK PROPAGATION and DEEP LEARNING

Grossberg, 1988, *Neural Networks*, 1, 17-61, Section 17

17 basic differences between BP and brain learning sites.bu.edu/steveg

A. Real-Time (On-Line) Learning versus Lab-Time (Off-Line) Learning
B. Nonstationary Unexpected World Versus Stationary Controlled World
C. Self-Organization Versus Teacher as a Source of Expected Output
D. Self-Stabilization Versus Capacity Catastrophe
E. Maintain Plasticity on an Unexpected World versus Externally Shut Off Plasticity
F. Self-Scaling Computational Units
G. Learn Internal Expectations Versus Impose External Costs
H. Active Attentional Focusing and Priming Versus Passive Weight Change
I. Closing Versus Opening the Fast-Slow Feedback Loop
J. Expectant Priming Versus Grinding All Memory Cycles
K. Learning in the Approximate Match Phase Versus in the Mismatch Phase: Hypothesis Testing Avoids the Noise Catastrophe
L. Fast or Slow Learning: The Oscillation Catastrophe
M. Self-Adjusting Parallel Memory Search Trees and Global Energy Landscape Upheaval Versus Search Trees and Local Minima
N. Rapid Direct Access Versus Increase of Recognition Time with Code Complexity
O. Asynchronous Versus Synchronous Learning
P. Discriminative Tuning via Attentional Vigilance
Q. Towards a General-Purpose Machine for Cognitive Hypothesis Testing, Data Search, and Classification

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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)

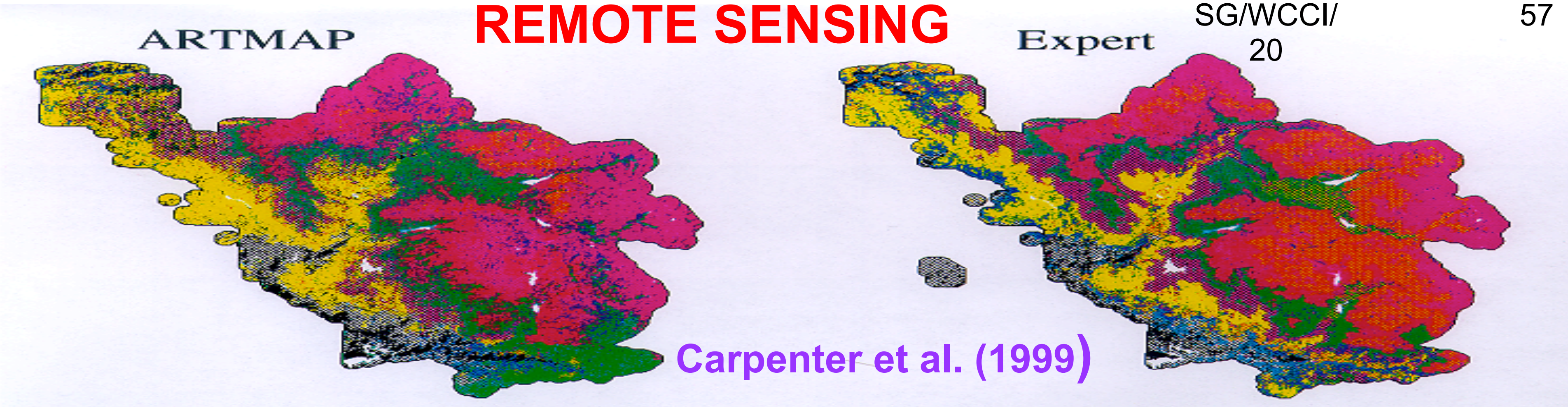
Used in applications where other algorithms fail

e.g. Boeing CAD Group Technology

Part design reuse and inventory compression

Need fast (e.g., 1 trial and stable learning and search of a huge (16 million 1 million dimensional vectors) and continually growing non-stationary parts inventory

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

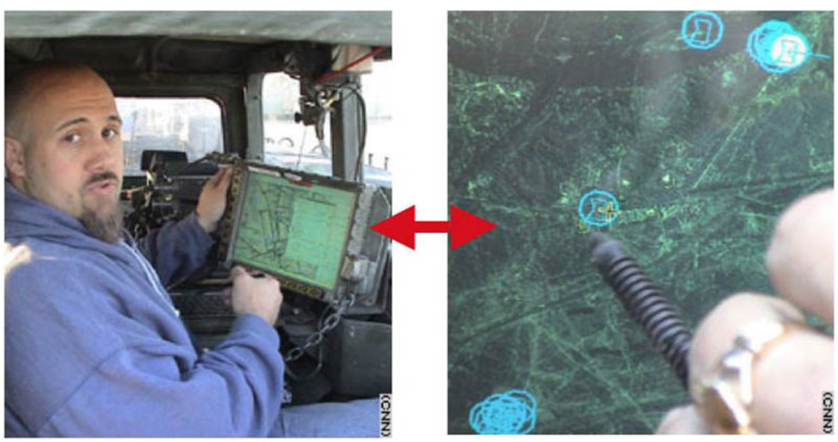
- **Rapid, automatic, no natural regions or rules**
- **Confidence map**
- **30*m* (pixel–level) scale: can see roads**
- **Equal accuracy at test sites**

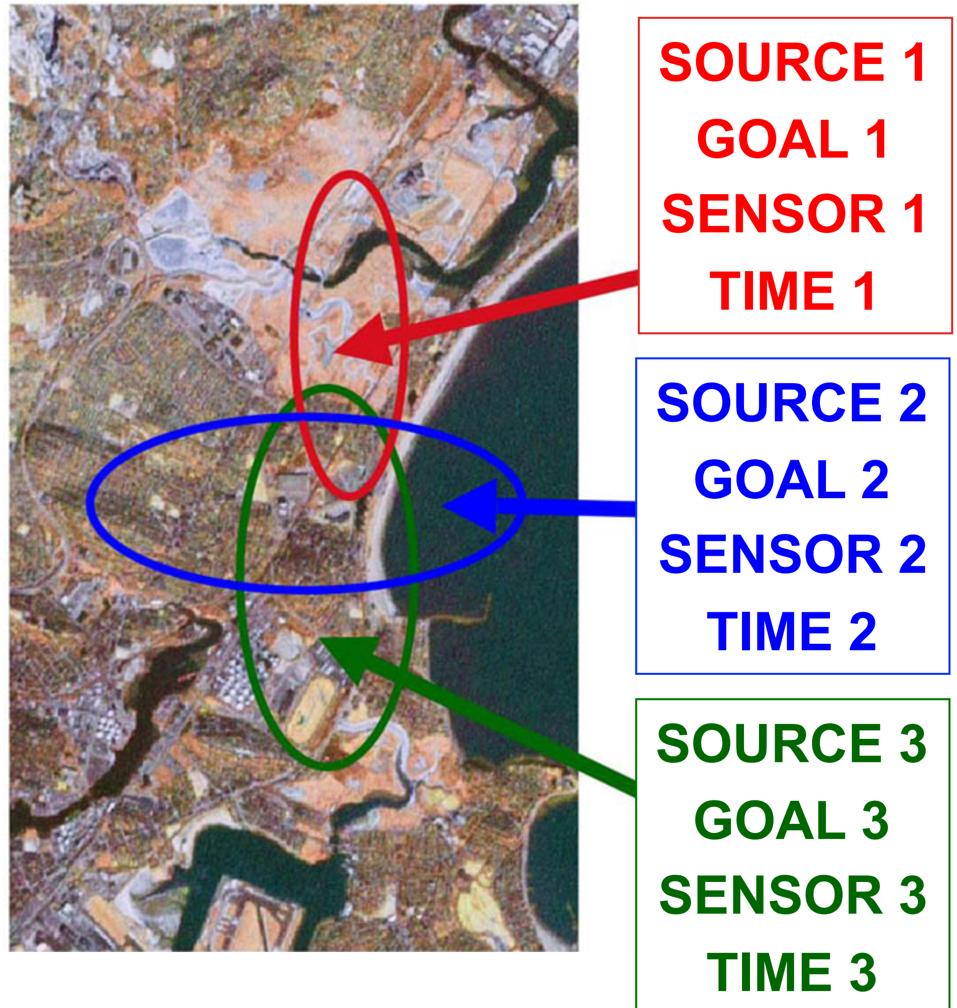
INFORMATION FUSION IN REMOTE SENSING

Carpenter et al. (2004)

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

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

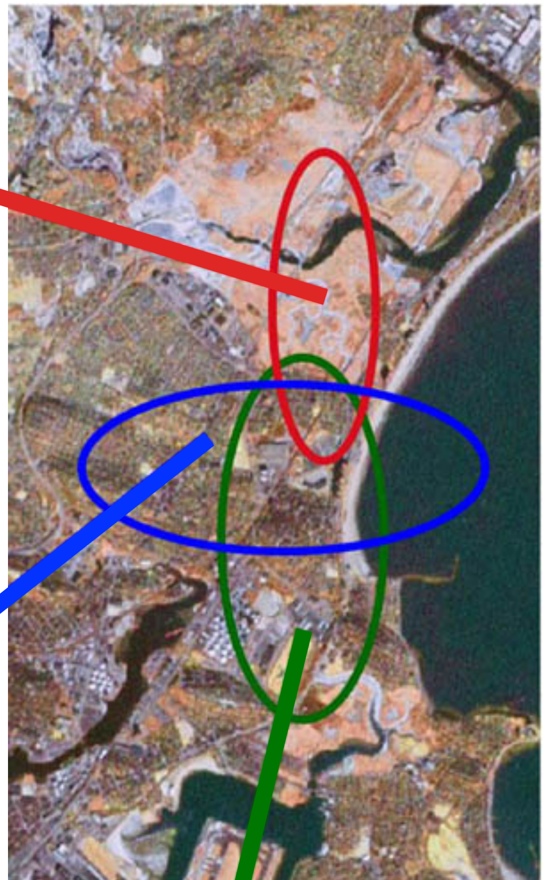




Boston testbed

CONSISTENT KNOWLEDGE FROM INCONSISTENT DATA

Automatically learns and stably stores one-to-many mappings



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

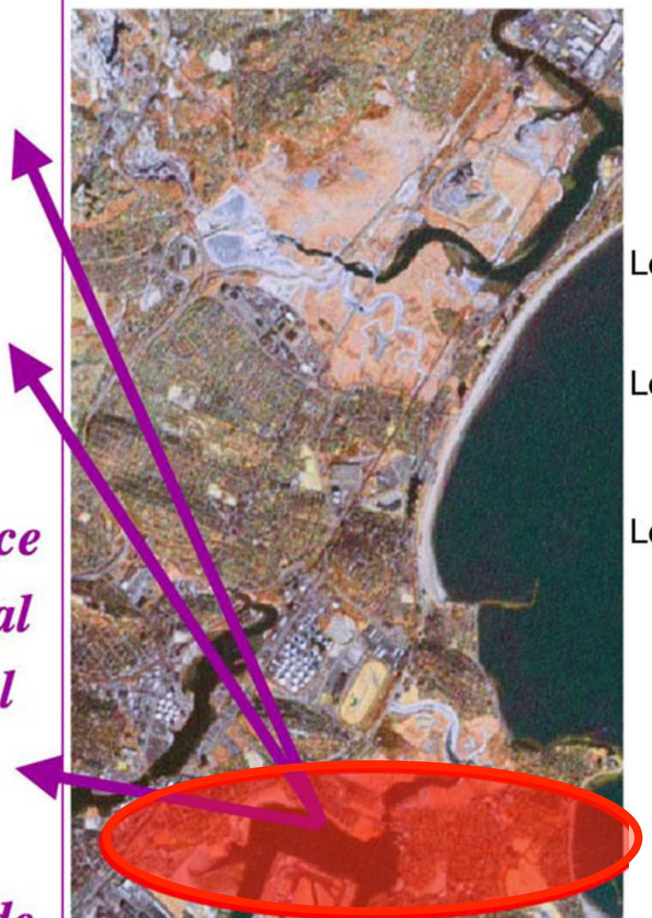
NO PRIOR RULES OR DOMAIN KNOWLEDGE

Self-organizing expert system

SELF-ORGANIZES a HIERARCHY of COGNITIVE RULES

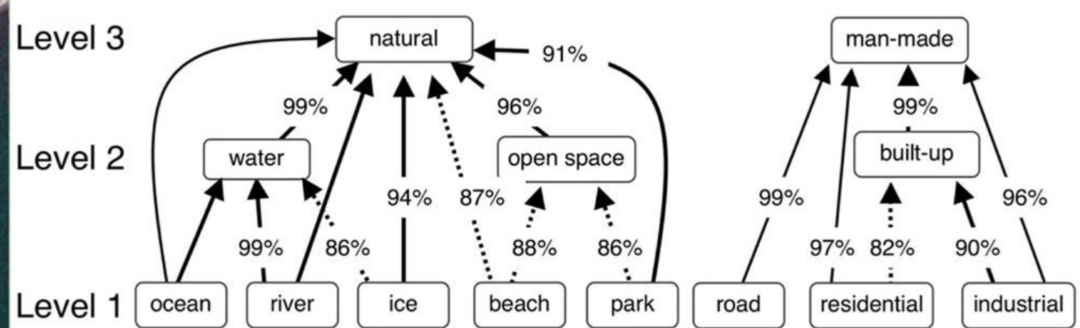
Distributed predictions across test set pixels →

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 MATCHING AND RESONANCE RULES

help to solve the Stability-Plasticity Dilemma

BOTTOM-UP ACTIVATION

by itself can activate learned categories

(automatic activation)

TOP-DOWN EXPECTATIONS

learn prototypes that

select consistent bottom-up signals
(hypothesis testing)

suppress inconsistent bottom-up
signals (attentional focusing)

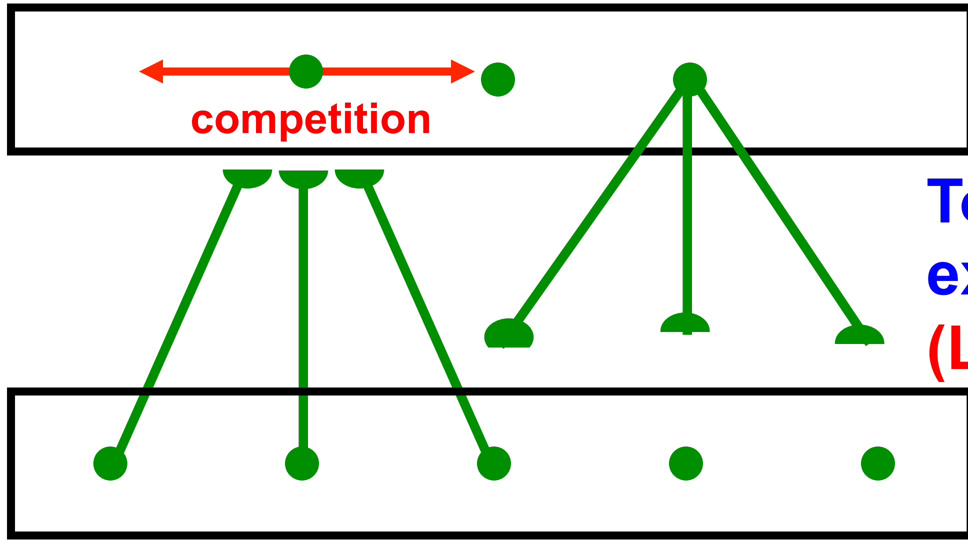
cannot by themselves fully activate
target cells (sensitize, modulate, prime)

EXPECTATIONS FOCUS ATTENTION

Categories (STM)

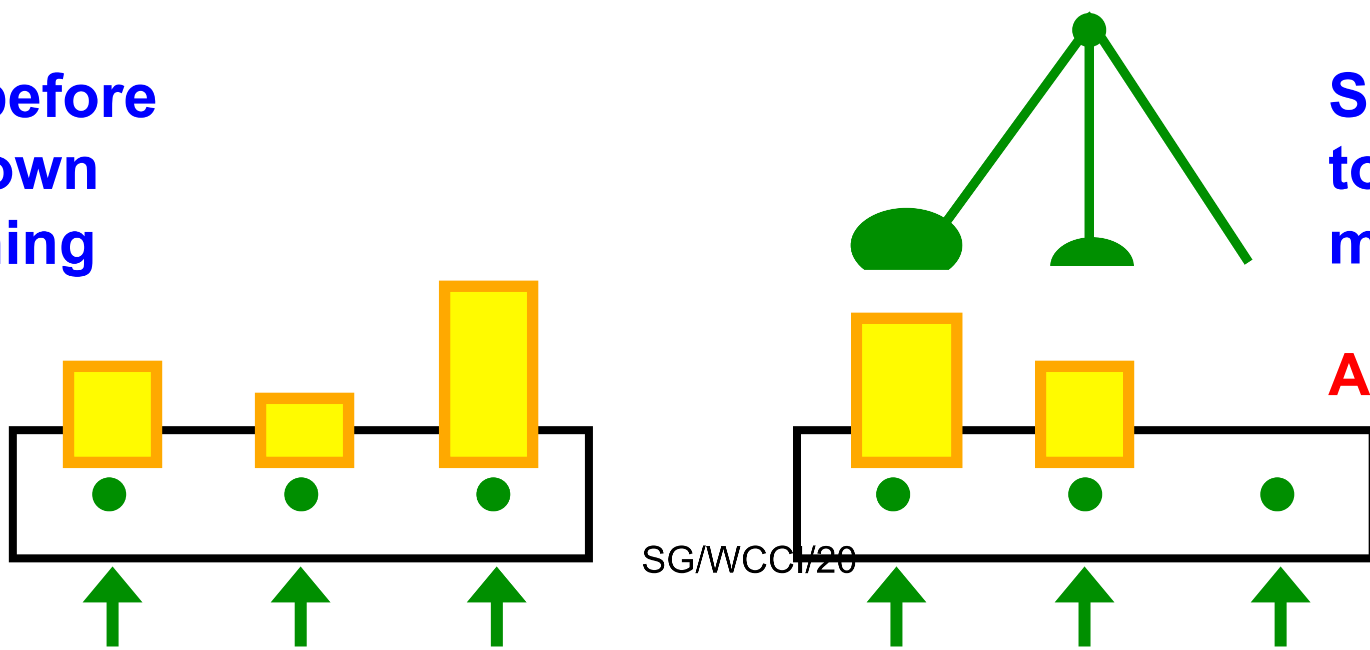
Bottom-up adaptive filter (LTM)

Distributed feature pattern (STM)



Top-down expectations (LTM)

STM before top-down matching

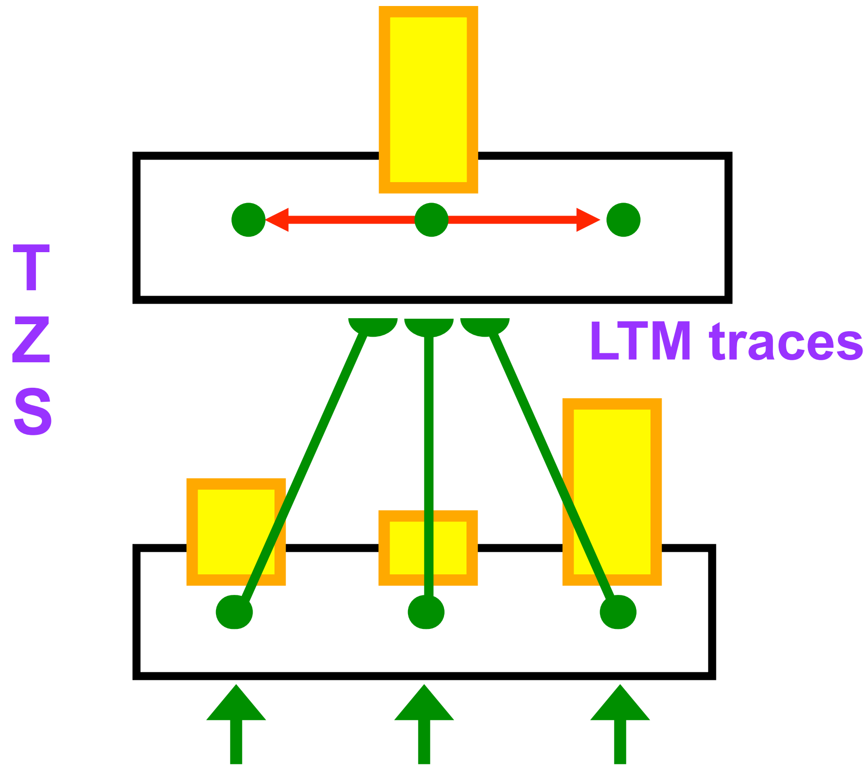


STM after top-down matching

Attention!

Why are
LEARNED TOP-DOWN EXPECTATIONS
and
ATTENTION
needed to solve the
STABILITY-PLASTICITY DILEMMA?

COMPETITIVE LEARNING AND SELF-ORGANIZING MAPS



Input Patterns

Categories

Compressed STM representation

competition

Adaptive Filter T=ZS

Features

Distributed STM representation

Grossberg, 1972, 1976; von der Malsburg, 1973; Kohonen, 1982

STABLE SPARSE LEARNING THEOREM

Grossberg, 1976

If a sequence of feature patterns does not form too many clusters relative to the number of category coding cells, then learning is

stable

self-normalizing

tracks input statistics

Bayesian

STABLE SPARSE LEARNING THEOREM

Grossberg, 1976

If a sequence of feature patterns does not form too many clusters relative to the number of category coding cells, then learning is

stable

self-normalizing

tracks input statistics

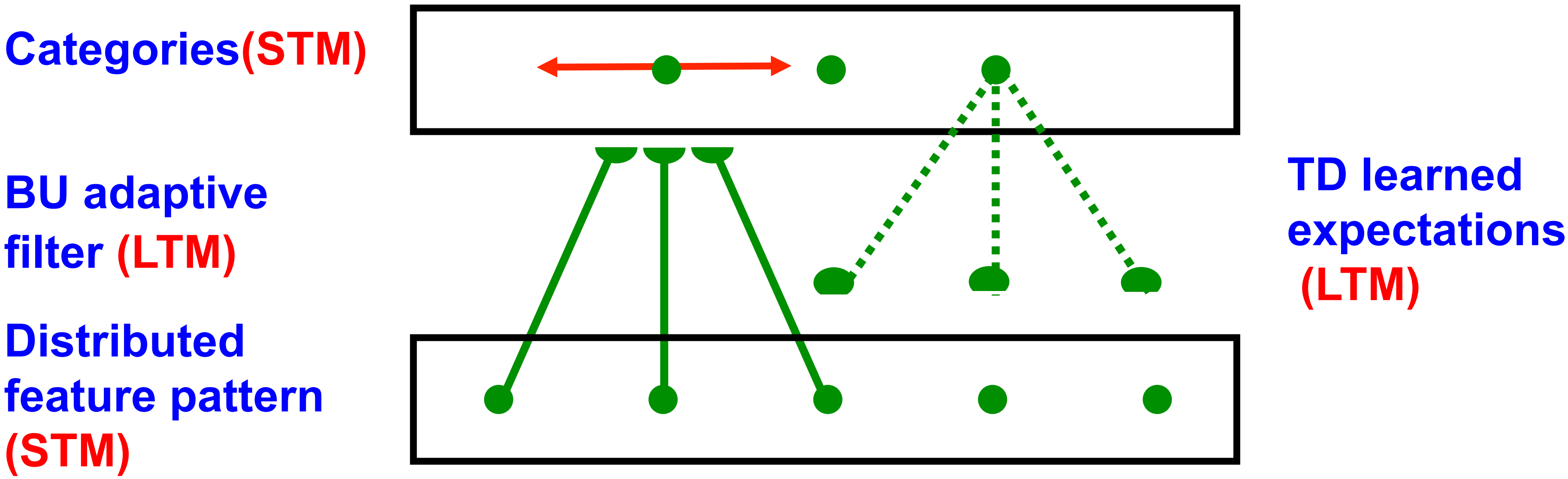
Bayesian

In general, learning is unstable in response to a dense series of inputs whose statistics change through time

Recent learning can force unselective forgetting or catastrophic forgetting of older learning

FROM COMPETITIVE LEARNING AND SELF-ORGANIZING MAPS TO ADAPTIVE RESONANCE THEORY

ART was introduced to dynamically stabilize recognition learning using top-down EXPECTATIONS and ATTENTION



Cf. experiments of C. Gilbert, E. Kandel, M. Merzenich, etc.

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Categories(STM)

BU adaptive filter (LTM)

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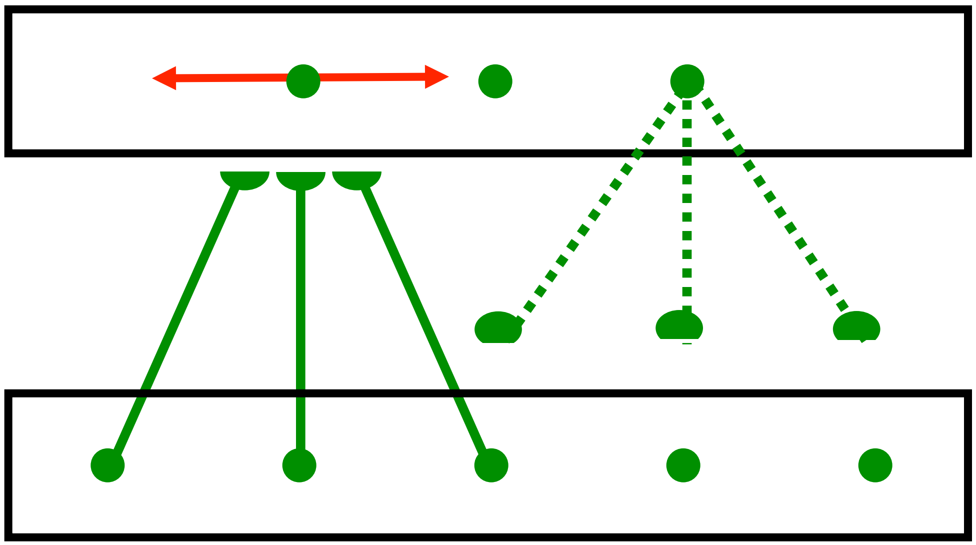


TD learned expectations (LTM)

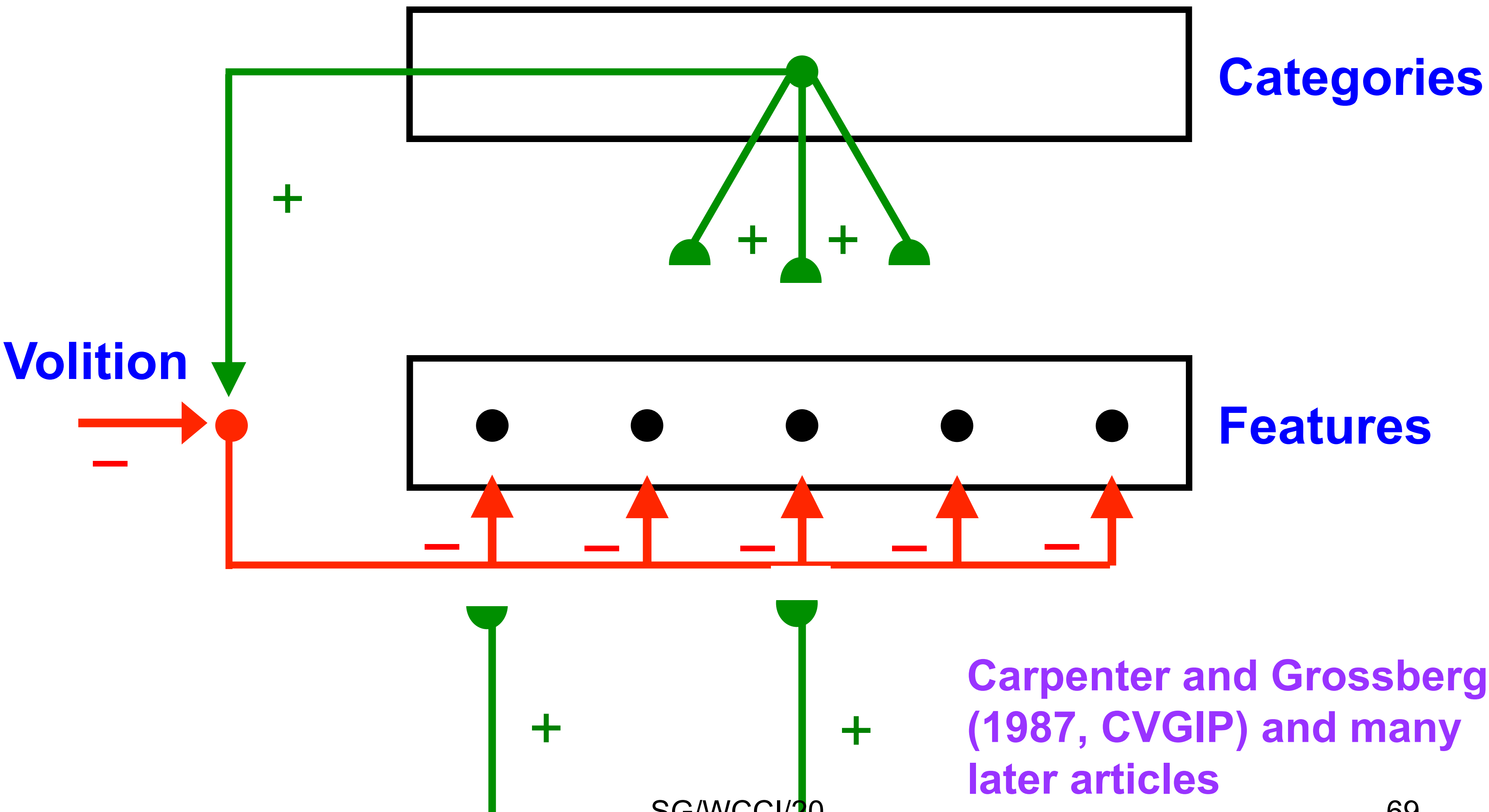
Cf. experiments of C. Gilbert, E. Kandel, M. Merzenich, etc.

HOW do expectations focus attention and stabilize learning?

ART MATCHING RULE FOR OBJECT ATTENTION

Stabilizes Learning

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



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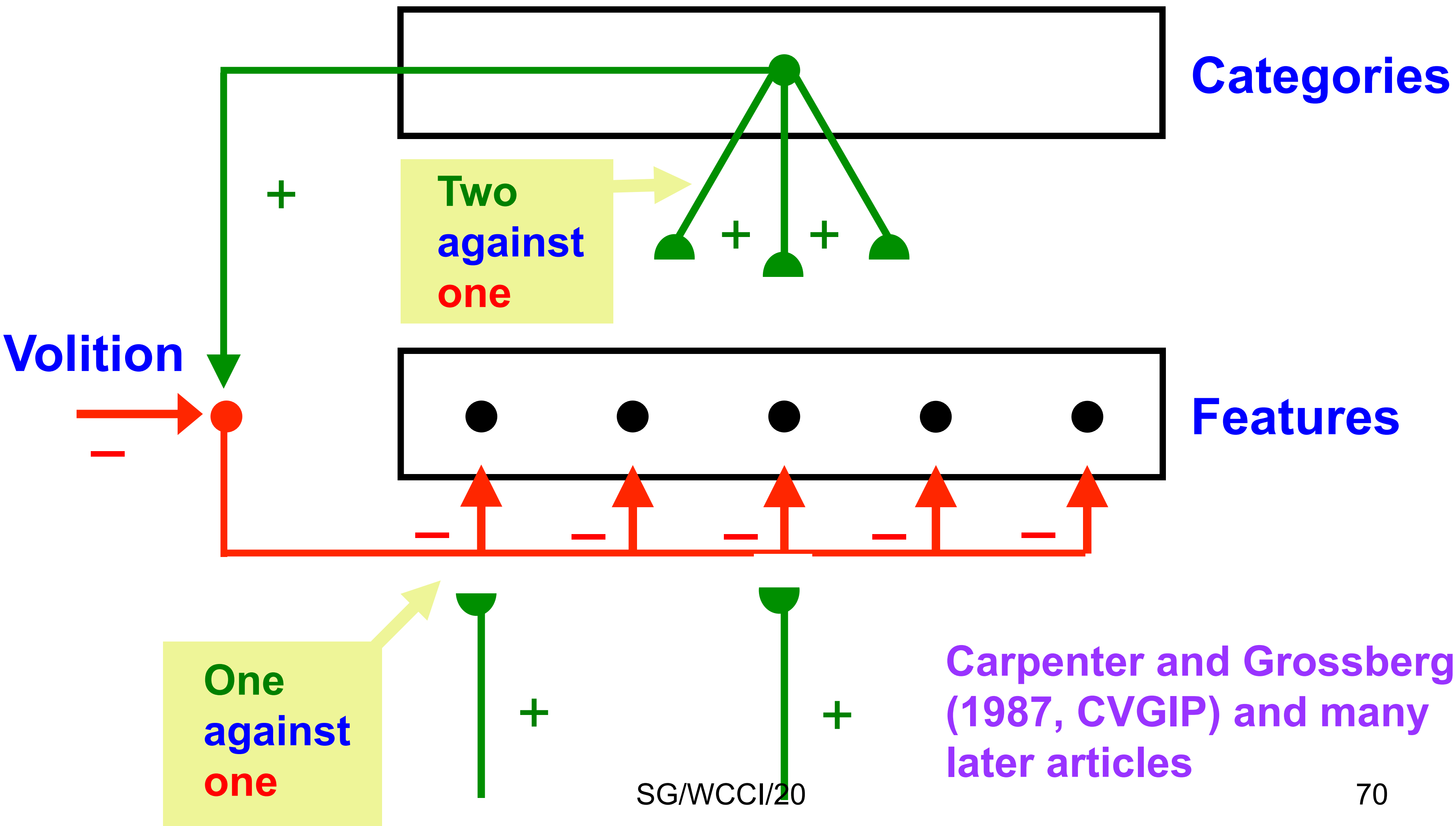
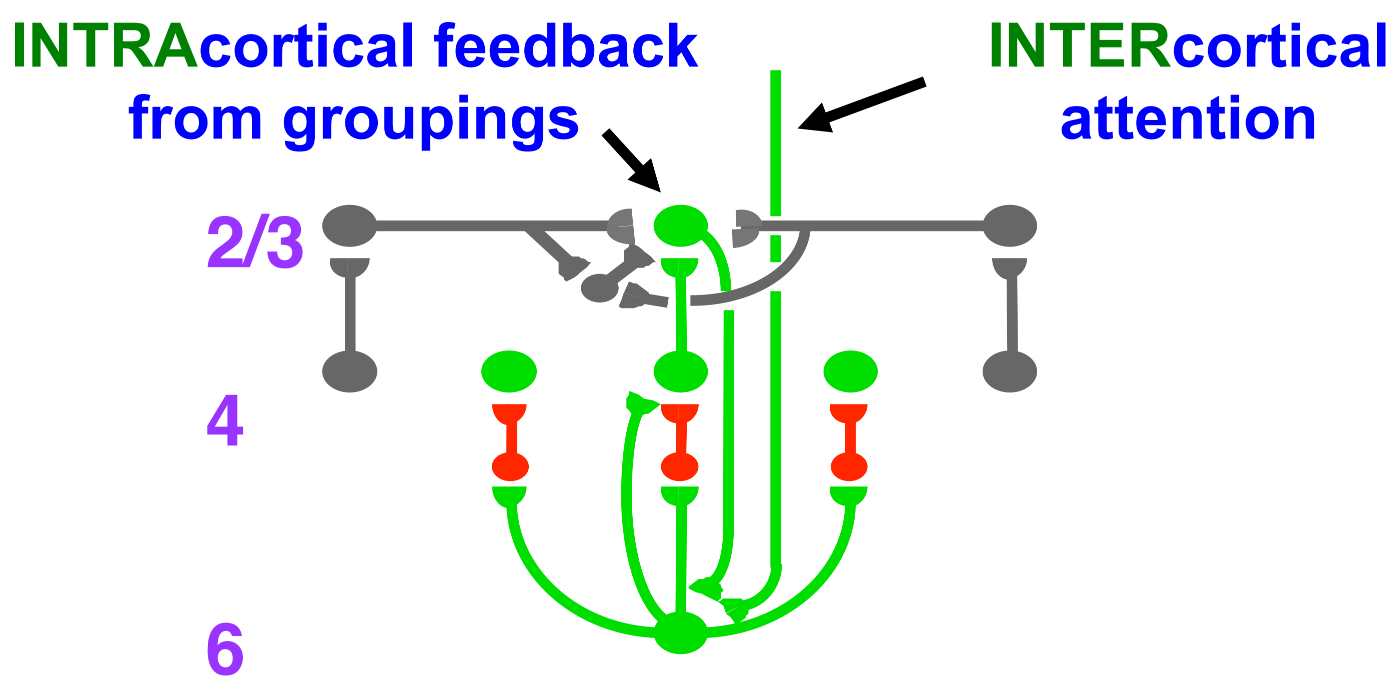


Carpenter and Grossberg (1987, CVGIP) and many later articles

LAMINAR CORTICAL CIRCUIT FOR OBJECT ATTENTION

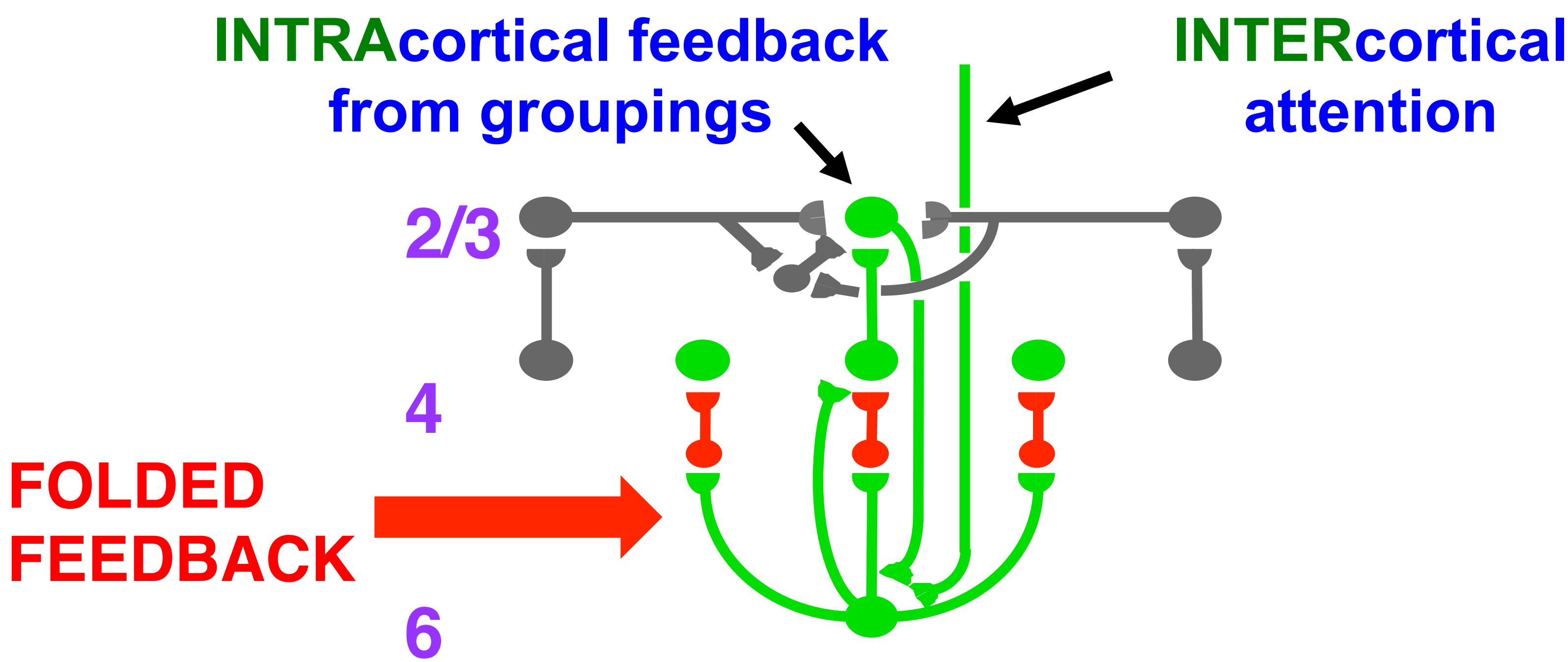
Grossberg (1999, Spatial Vision)



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

LAMINAR CORTICAL CIRCUIT FOR OBJECT ATTENTION

Grossberg (1999, Spatial Vision)



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

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

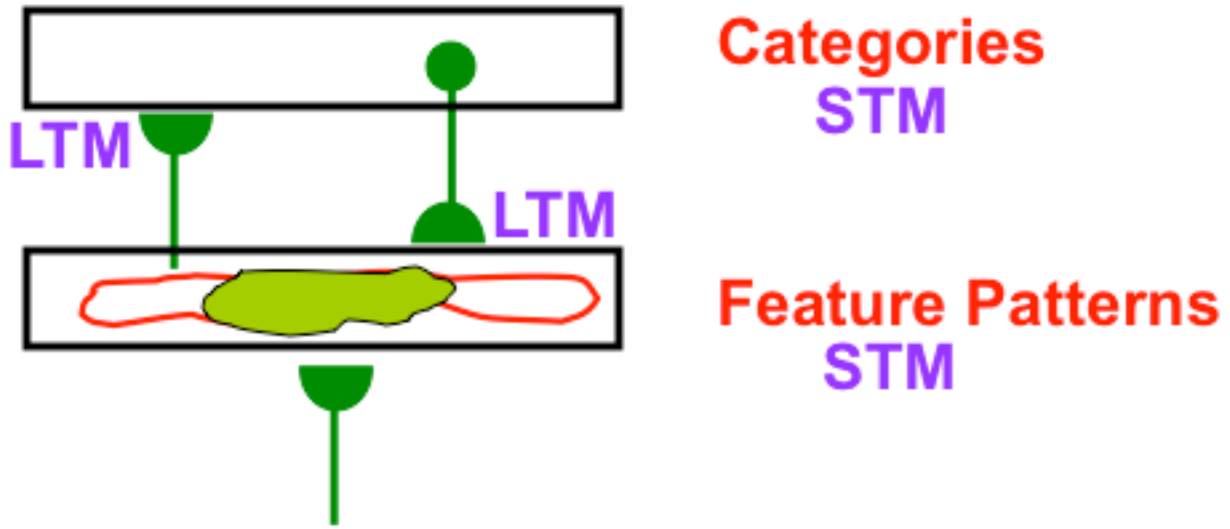
Rao and Ballard, 1999

Bayesian Explaining Away

ADAPTIVE RESONANCE

Attended feature clusters reactivate bottom-up pathways

Activated categories reactivate their top-down pathways



Feature-Category resonance synchronizes
amplifies
prolongs system response

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

ALL THE KEY ART PREDICTIONS HAVE BEHAVIORAL AND NEUROBIOLOGICAL SUPPORT

ALL CONSCIOUS STATES ARE RESONANT STATES

Grossberg, 1976

Resonant states in neural models match parametric properties of psychological data about conscious percepts

Growing neurophysiological support for predicted connections between:

Consciousness
Learning
Expectation
Attention
Resonance
Synchrony

e.g., experiments by J. Bullier, E. Miller, R. Desimone, C. Gilbert, V. Lamme, J. Reynolds, P. Roelfsema, W. Singer, N. Suga, etc.

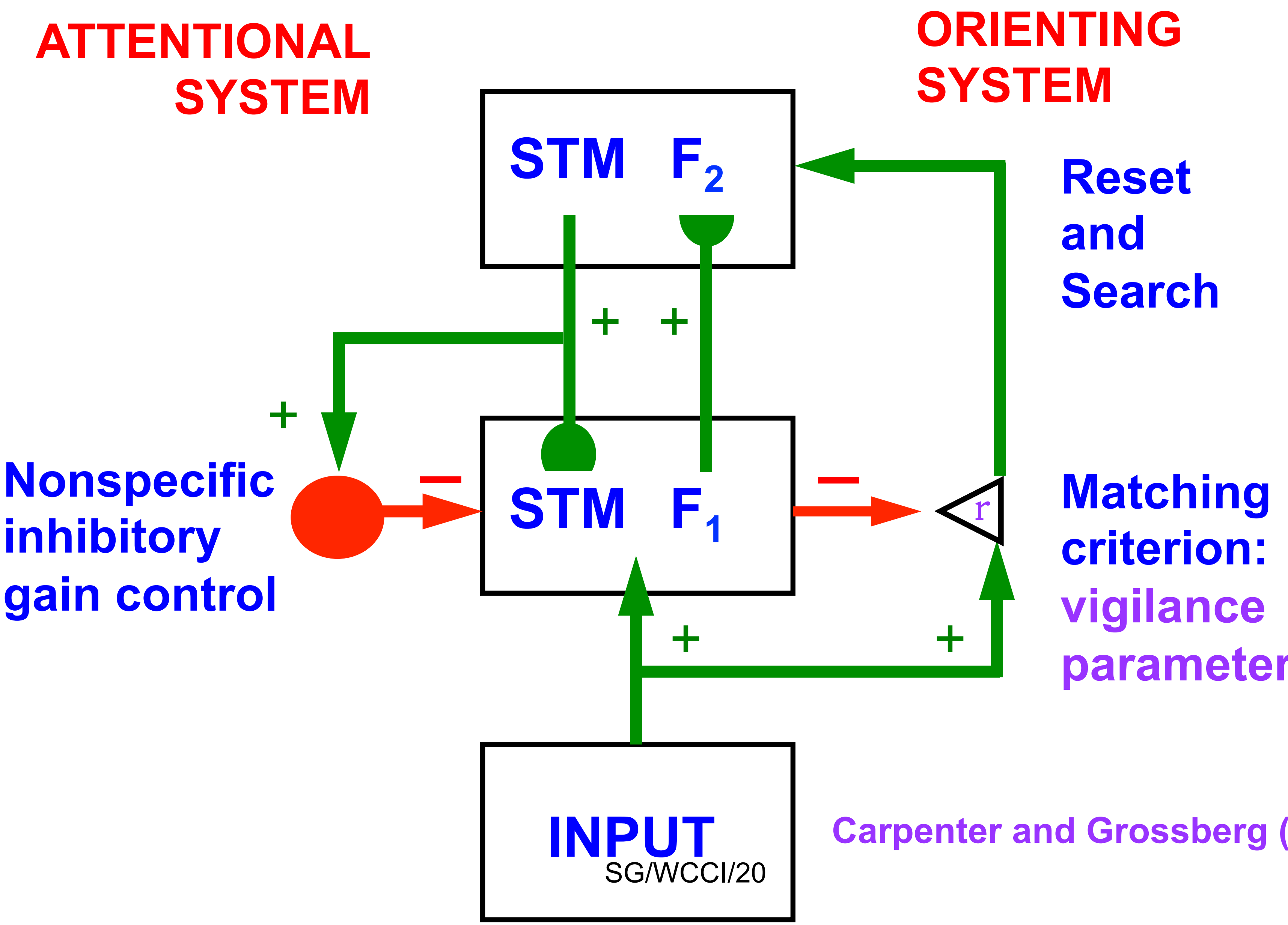
ART

How we balance between expected and unexpected events

Interactions between COMPLEMENTARY SYSTEMS

Attentional System ⟷	Orienting System
Expected Events	Unexpected Events
Familiar Events	Unfamiliar Events
Resonance	Reset
Attention	Memory Search
Learning	Hypothesis Testing
Recognition	
Temporal cortex Prefrontal cortex	Hippocampal system Nonspecific thalamus

ART 1 MODEL



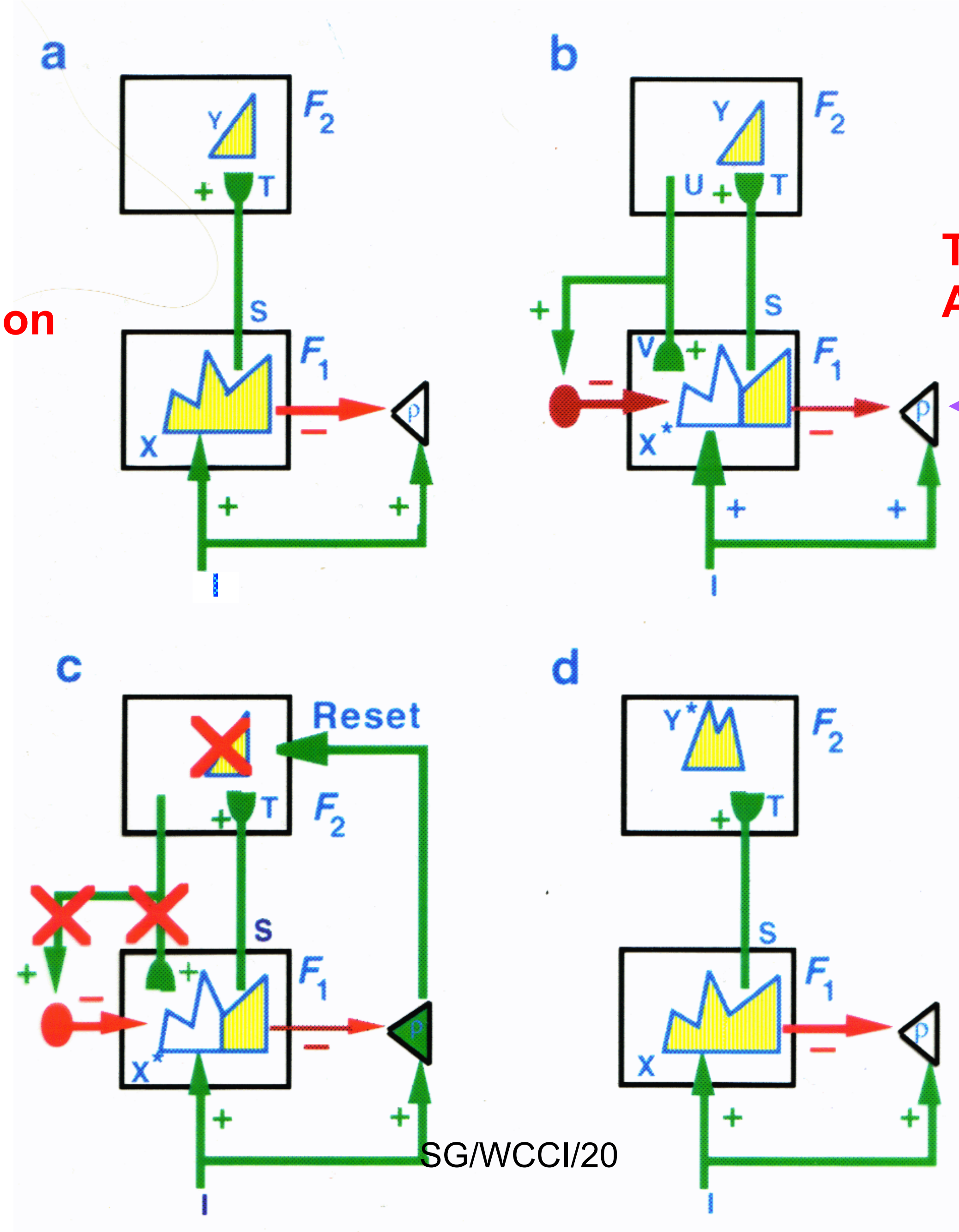
Carpenter and Grossberg (1987)

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

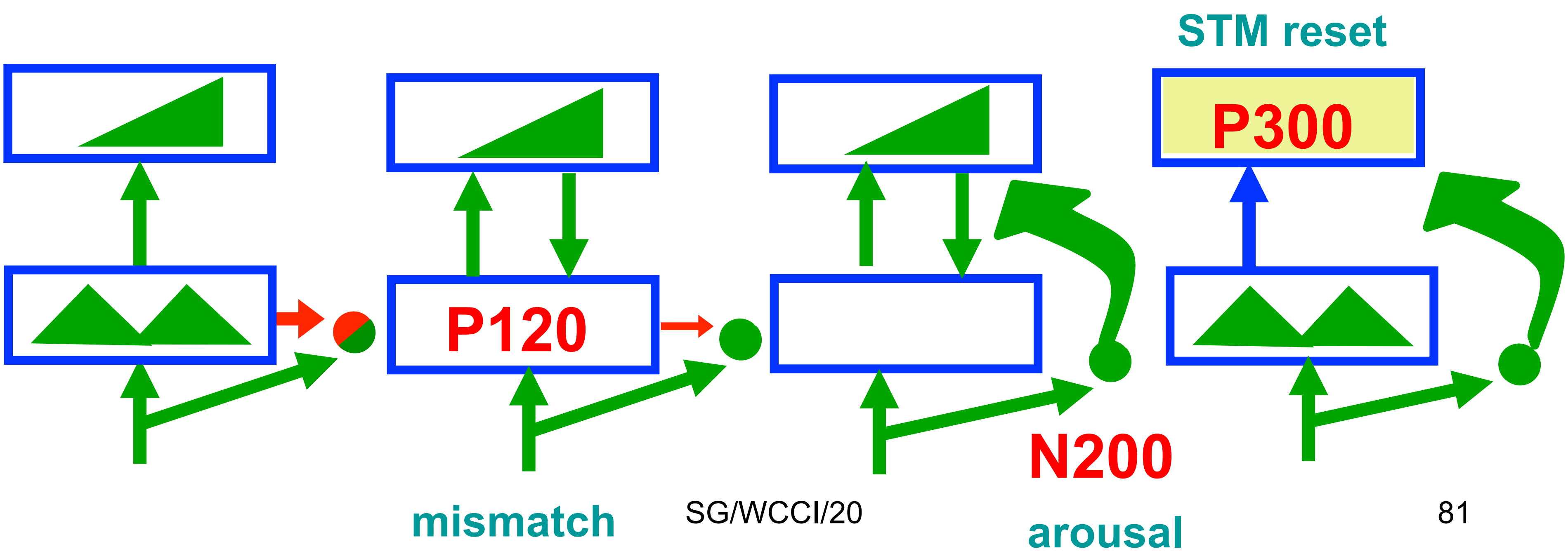
Event-Related Potentials: Human Scalp Potentials

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



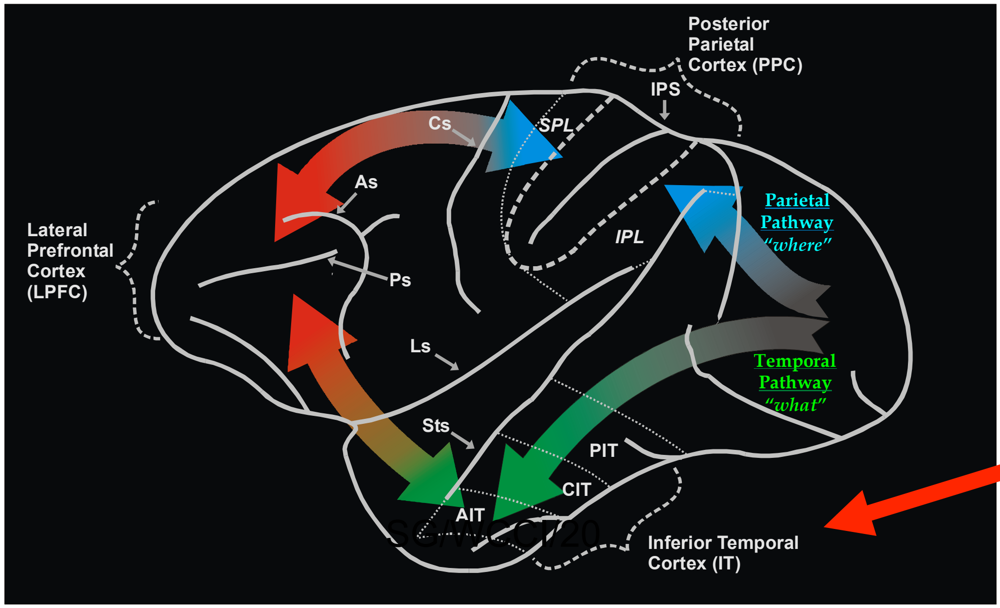
NEUROPHYSIOLOGICAL SUPPORT FOR HYPOTHESIS TESTING CYCLE

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

SG/MLC/20

NEUROPHYSIOLOGICAL SUPPORT FOR HYPOTHESIS TESTING CYCLE

Classical data about hippocampus mismatch dynamics:
Novelty potentials subside as learning proceeds
e.g., Deadwyler et al., 1979, 1981; Otto and Eichenbaum, 1992; Sokolov, 1968; Vinogradova, 1975

More recent data from prefrontal cortex (PFC) and hippocampus (HPC) when monkeys learn object-pair associations:

"Rapid object associative learning may occur in PFC, while HPC may guide neocortical plasticity by signaling success or failure…"
Brincat and Miller, 2015

FROM CONCRETE TO ABSTRACT: TASK-SENSITIVE VIGILANCE CONTROL

Pay Attention!!!

How do our cognitive categories learn

from our uniquely different experiences?

How do our brains learn CONCRETE knowledge for some

tasks and ABSTRACT knowledge for others?

Bridging between DISTRIBUTED PATTERN and SYMBOL

High Vigilance – Narrow Categories; CONCRETE

Mom's face

Low Vigilance – Broad Categories; ABSTRACT

A face

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!

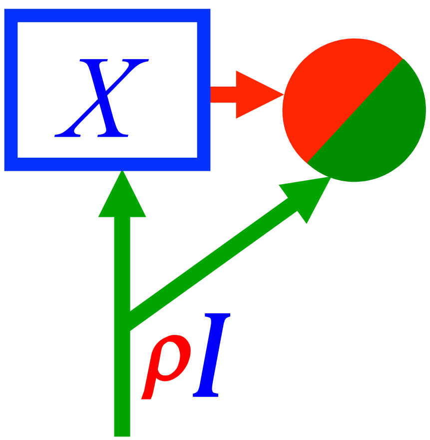
"In the difficult condition the animals adopted a stricter internal criterion for discriminating matching from non-matching stimuli… The animal's internal representations of the stimuli were better separated … increased effort appeared to cause enhancement of the responses and sharpened selectivity for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

Spitzer, Desimone, and Moran, 1988

VIGILANCE CONTROL

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

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



ρ **is a sensitivity or gain parameter**

MINIMAX LEARNING PRINCIPLE

How to conjointly

minimize predictive error

and

maximize generalization

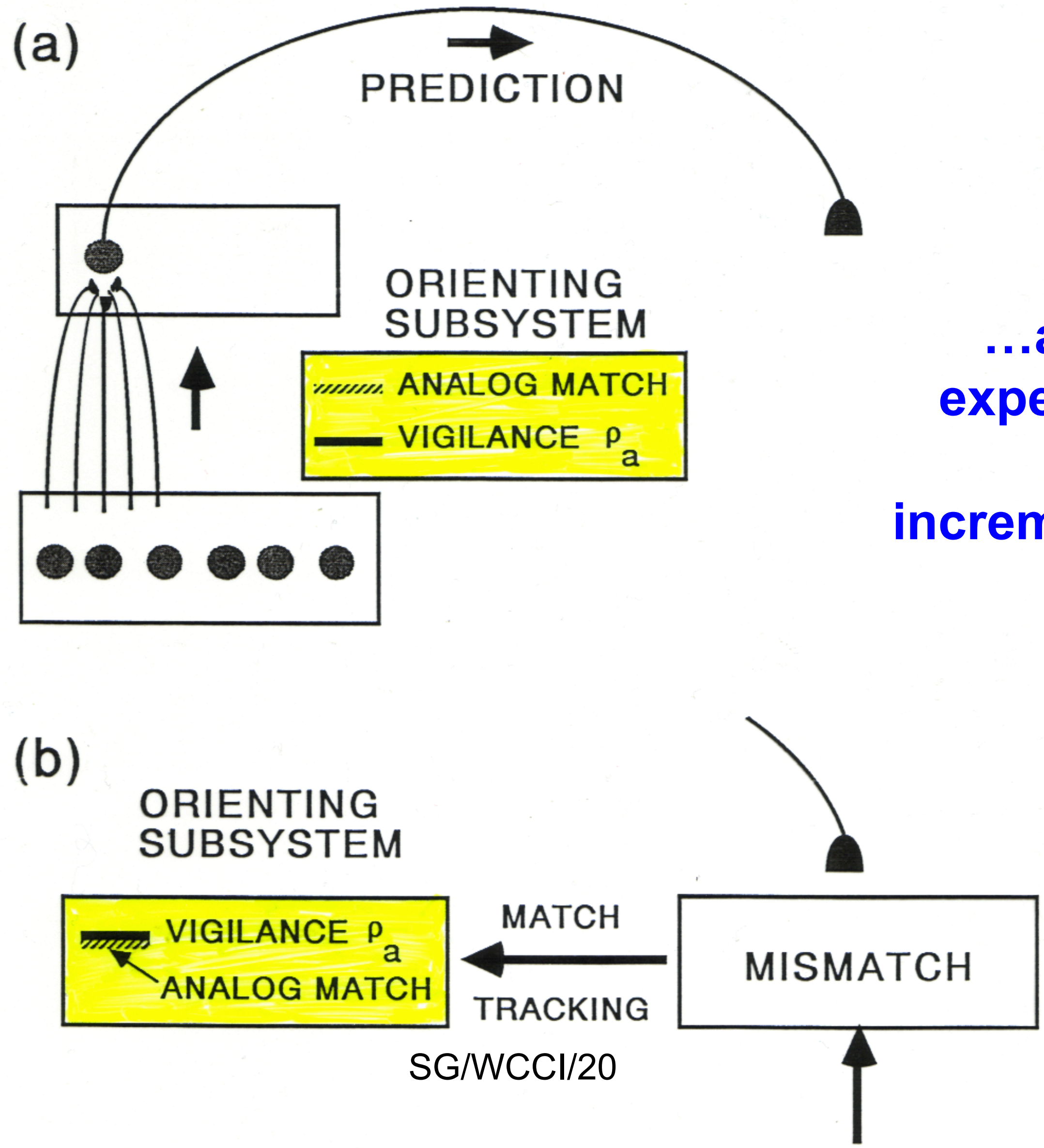
using error feedback

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 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**

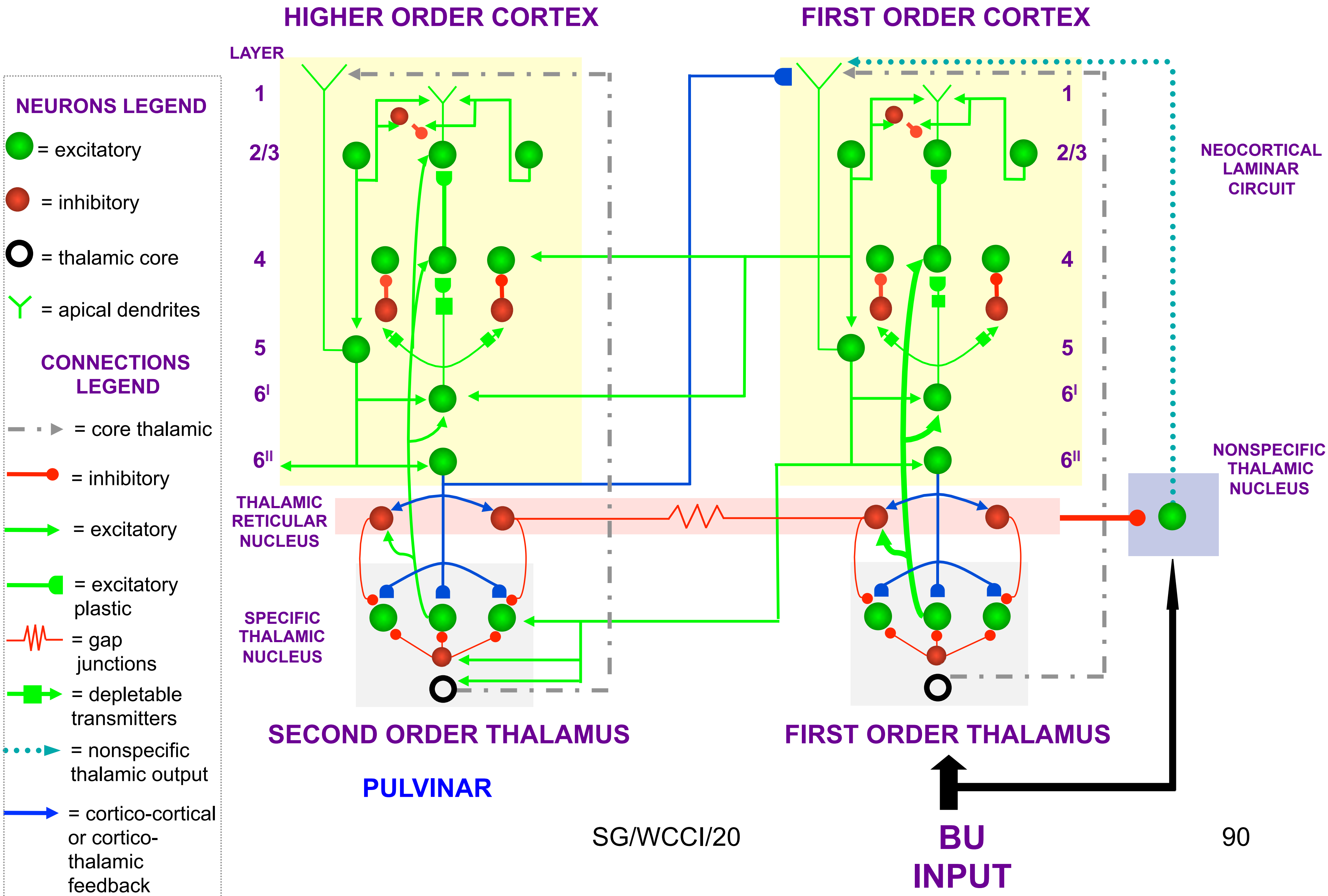
coordinated to

regulate stable category learning and attention

during cognitive information processing via

- **laminar cortical circuits**
- **specific and nonspecific thalamic nuclei?**

SMART: MODEL MACROCIRCUIT



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

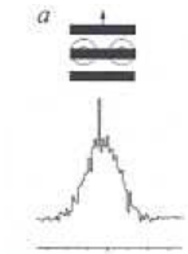
Connections	Type	Functional interpretation	References
5 A → thalamic core B	D	Feedforward connections from Area A to Area B through secondary thalamic relay neurons.	Rockland (1999); Sherman and Guillery (2001)
5 A → 6^{I} A	D	Delivers feedback to the 6 → 4 circuit from higher cortical areas, sensed 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



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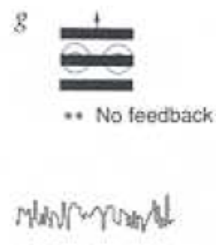

SIMULATION

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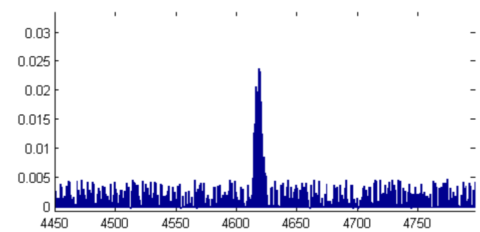

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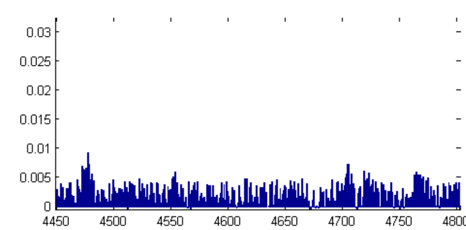
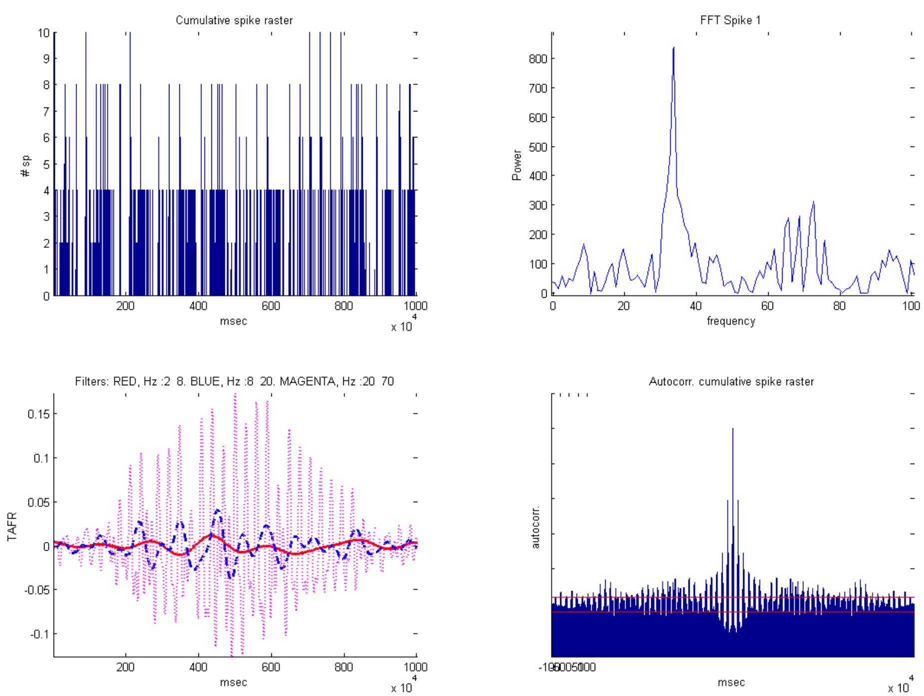
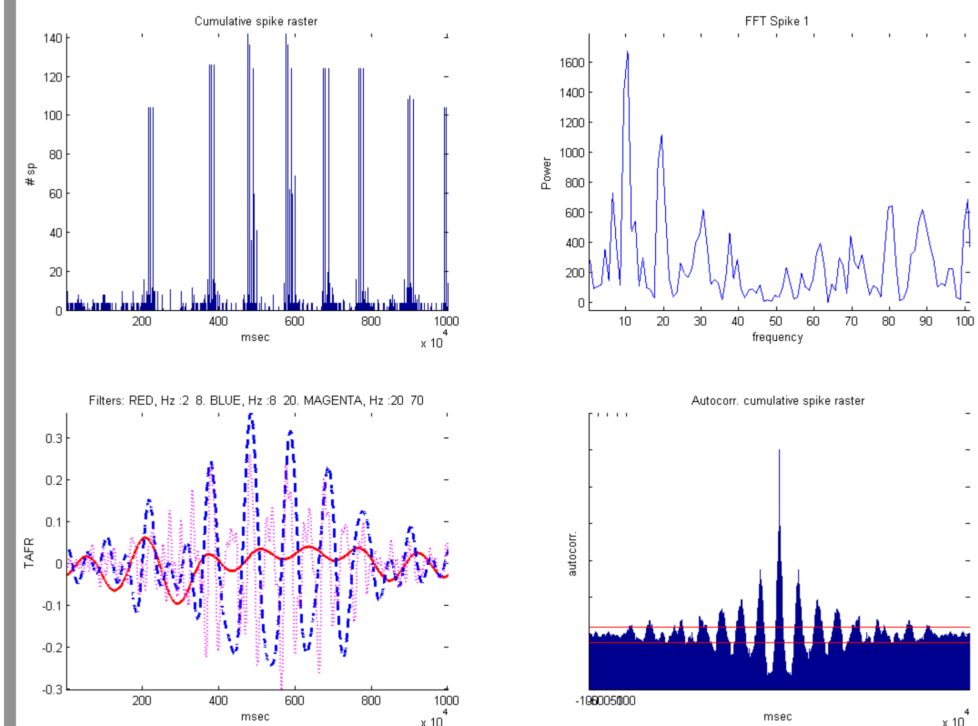


(a) TD CORTICOTHALAMIC FEEDBACK increases SYNCHRONY Sillito *et al.*, 1994



(b) MATCH
Increases γ oscillations

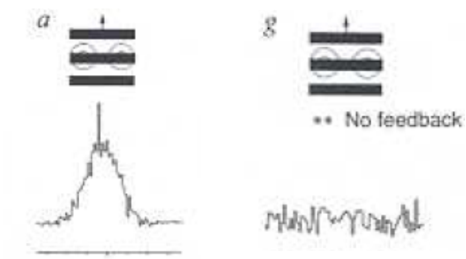


(c) MISMATCH
increases *θ*, *β* oscillations

BRAIN OSCILLATIONS DURING MATCH/MISMATCH

DATA | **SIMULATION**

FB ON **FB OFF**



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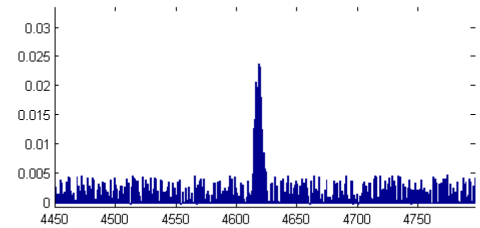

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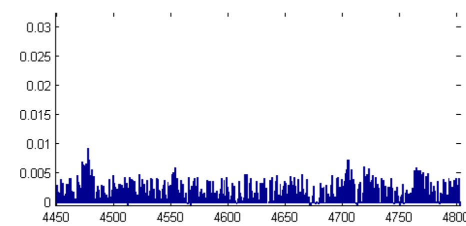

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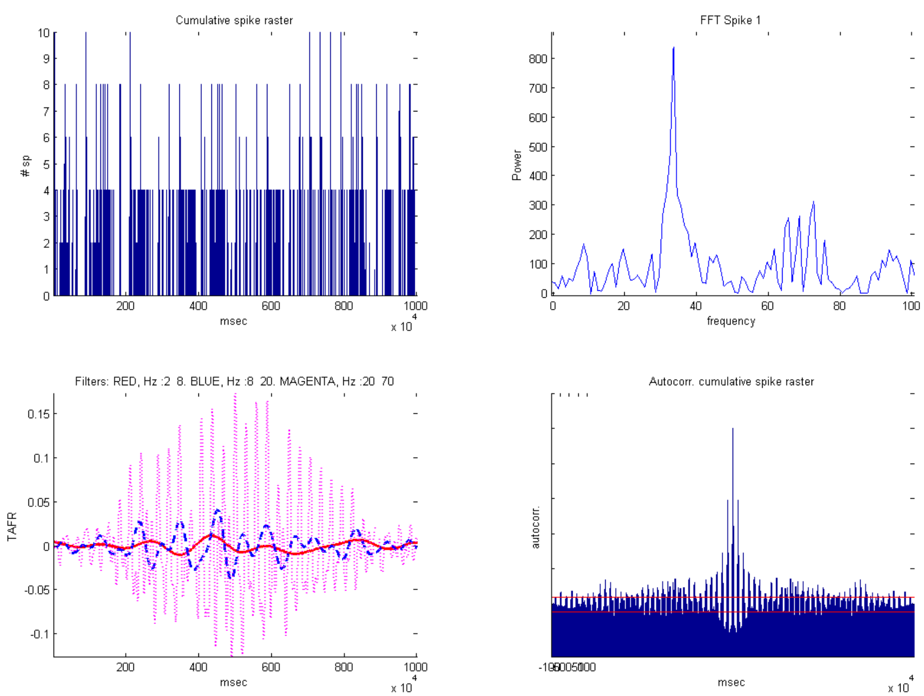

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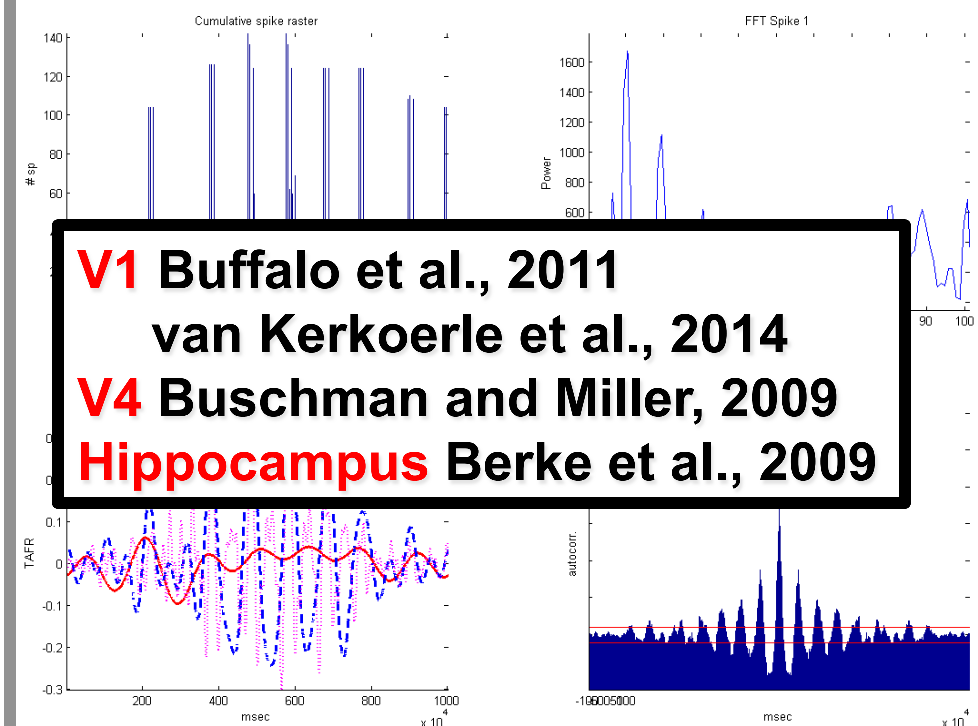


V1 **Buffalo et al., 2011**
van Kerkoerle et al., 2014
V4 **Buschman and Miller, 2009**
Hippocampus **Berke et al., 2009**

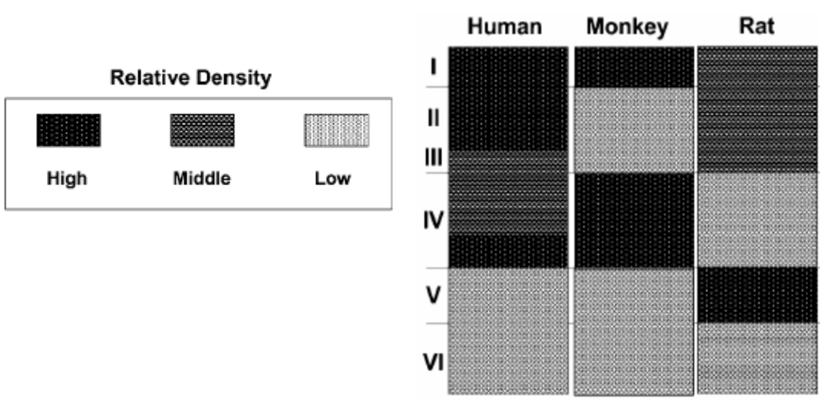
(c) MISMATCH
increases *θ*, *β* oscillations

VIGILANCE CONTROL: MISMATCH-MEDIATED ACETYLCHOLINE RELEASE

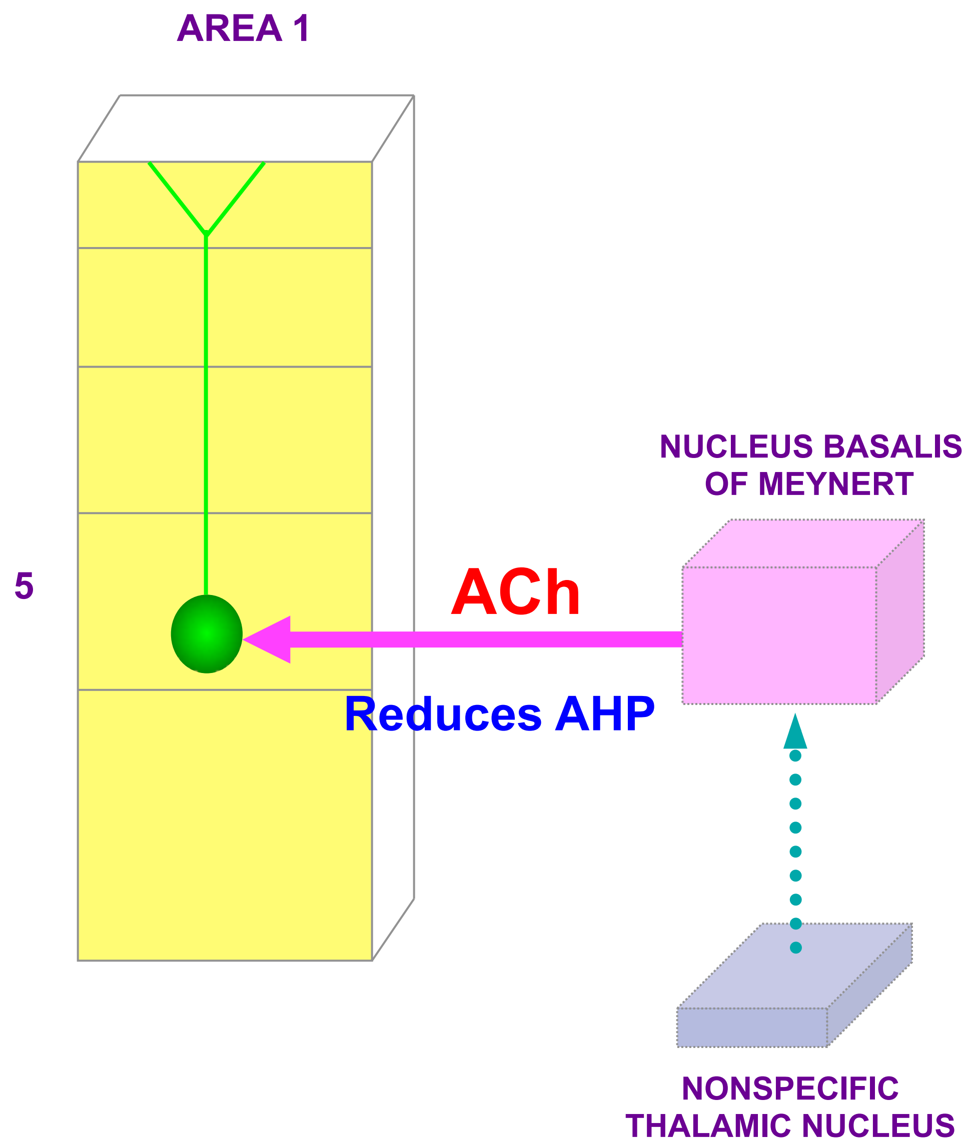
Acetylcholine (Ach) regulation by NONSPECIFIC THALAMIC NUCLEI via NUCLEUS BASALIS OF MEYNERT reduces AHP in layer 5

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)



If ACh dynamics collapse, then:

New category learning is undermined

Cortical layers
cannot resonate to recognize incoming information
and, in the limit,
cannot become conscious

WHAT DOES VIGILANCE HAVE TO DO WITH SLEEP

Fast rhythms (20-60 Hz) occur during awake states, accompanied by increased release of ACh in thalamus and cerebral cortex
Also occur during depolarizing phases of slow oscillation (0.5-1 Hz) in non-REM (NREM) sleep
Steriade, 2004

NREM sleep has a cortical origin
and multiple functions; e.g., metabolic clearance, memory consolidation
Crunelli and Hughes, 2010, Sanchez-Vives and Mattia, 2014; Xie et al, 2013

Stimulation of nucleus basalis elicits EEG activation
and behavioral arousal
from slow oscillations during sleep to fast oscillations during waking
via ACh actions on layer 5 pyramidal neurons
Metherate, Coex, and Ashe, 1992

Loss of basal forebrain ACh neurons contributes to
sleep disruption and cognitive deficits
Kalinchuk et al., 2015; Nair et al., 2016; Vazaquez and Beghdoyan, 2001

SLEEP, UP AND DOWN STATES, AND ACh

Slow wave generation in layer 5 synchronizes activity across neocortex
Ball et al., 1977; Calvet et al, 1973; Chagnac-Amitai and Connors, 1989

UP and DOWN states occur during slow wave sleep
All cells, excitatory and inhibitory, shut off during the DOWN state
including cells that generated silencing discharge
Layer 5 cells initiate this activity cycle
Fast-spiking inhibitory interneurons have an early onset
Steriade and Timofeev, 2003; Steriade et al., 1993; Volgushev et al., 2006

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HOW ARE UP AND DOWN STATES CAUSED?

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HOW ARE UP AND DOWN STATES CAUSED?

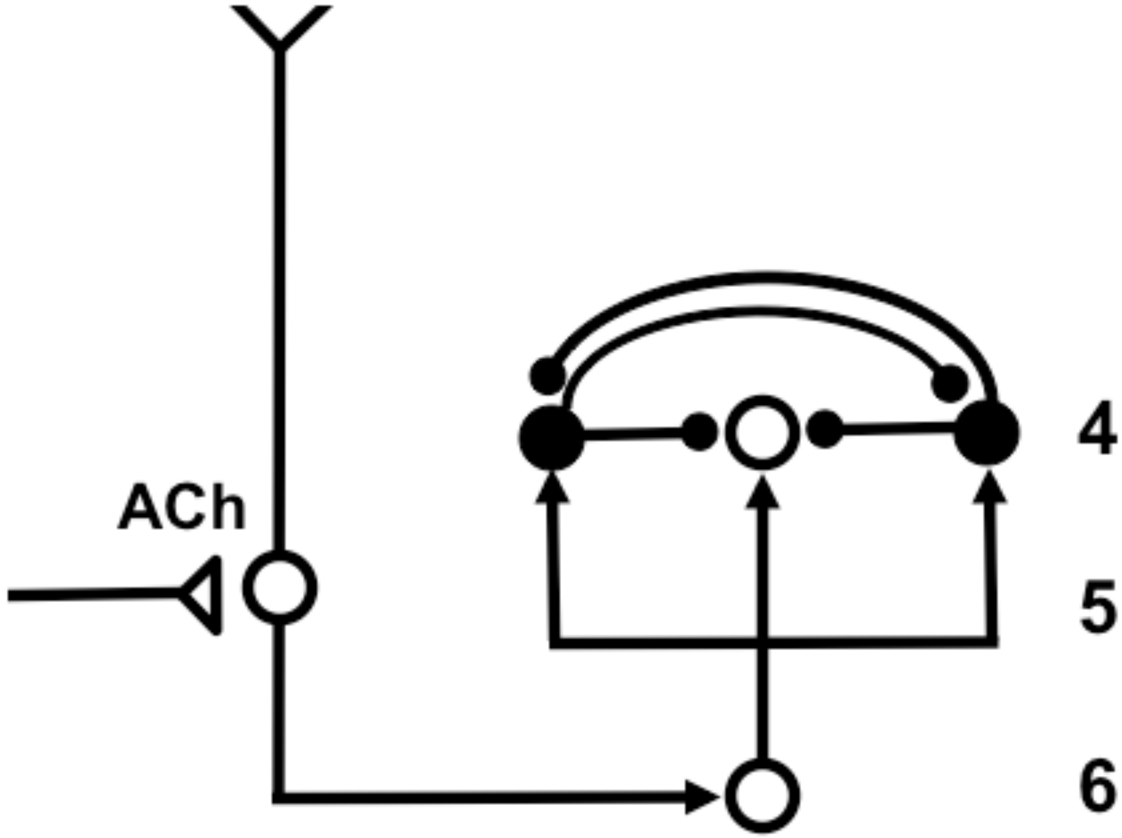
An emergent property of LAMINART cortical model!

Grossberg, 1999; Grossberg and Raizada, 2000;…

Helps to explain both waking and sleep dynamics!

SLEEP, UP AND DOWN STATES, AND ACh

Here is the circuit:



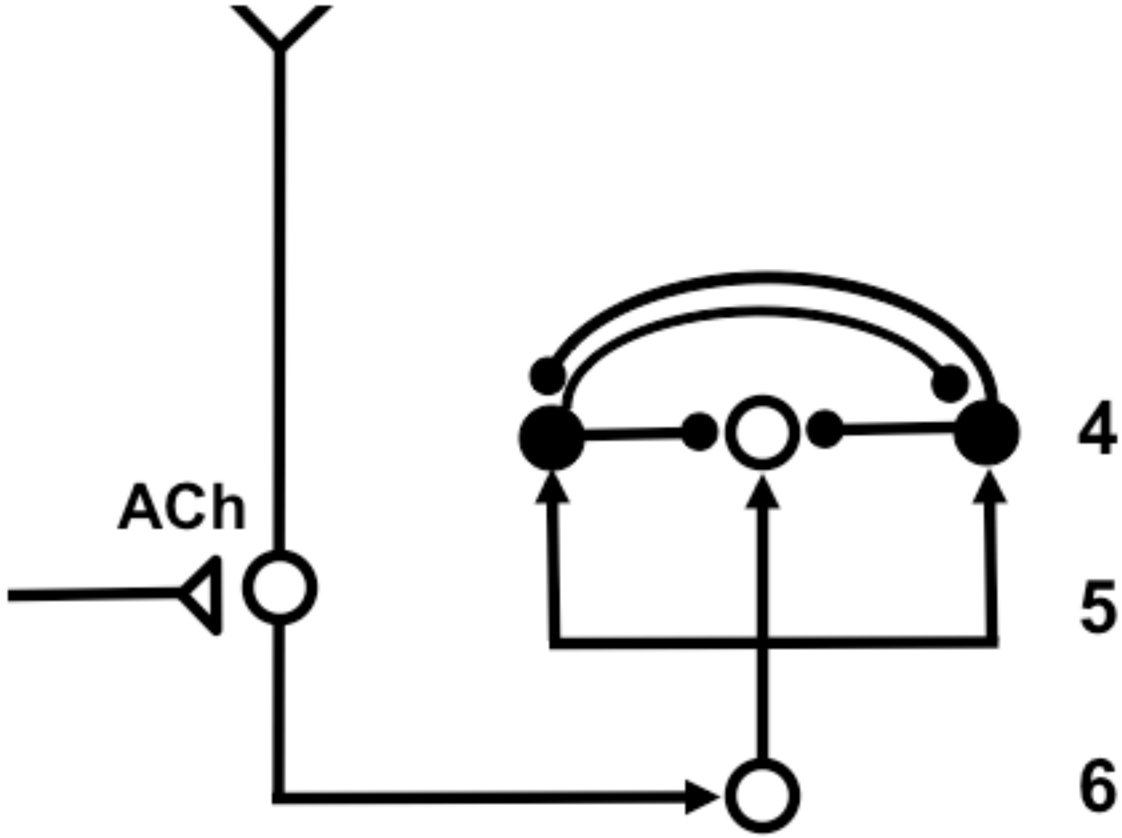
Uses its properties of

Balanced excitation and inhibition

Contrast normalization

RELATES SLEEP DISORDERS IN ALZHEIMER'S & AUTISM

to problems with ACh-mediated VIGILANCE CONTROL in layer 5



RELATES SLEEP DISORDERS IN ALZHEIMER'S & AUTISM
to problems with ACh-mediated VIGILANCE CONTROL in layer 5

A VICIOUS CYCLE

β-amyloid peptide concentration increases due to sleep deprivation, leading to more plaque formation
Ju et al., 2013, 2014, 2017; Spira et al., 2013

More plaques in layer 5 can disrupt ACh-mediated UP and DOWN sleep states, thereby further disrupting sleep

WHAT DOES VIGILANCE HAVE TO DO WITH AUTISM?

Prediction that many individuals with autism have
TONIC vigilance stuck at high values

Leads to
Hyperconcrete categorization and recognition
Narrow focus of attention

Grossberg and Seidman, 2006, *Psychological Review*, 113, 483-525.

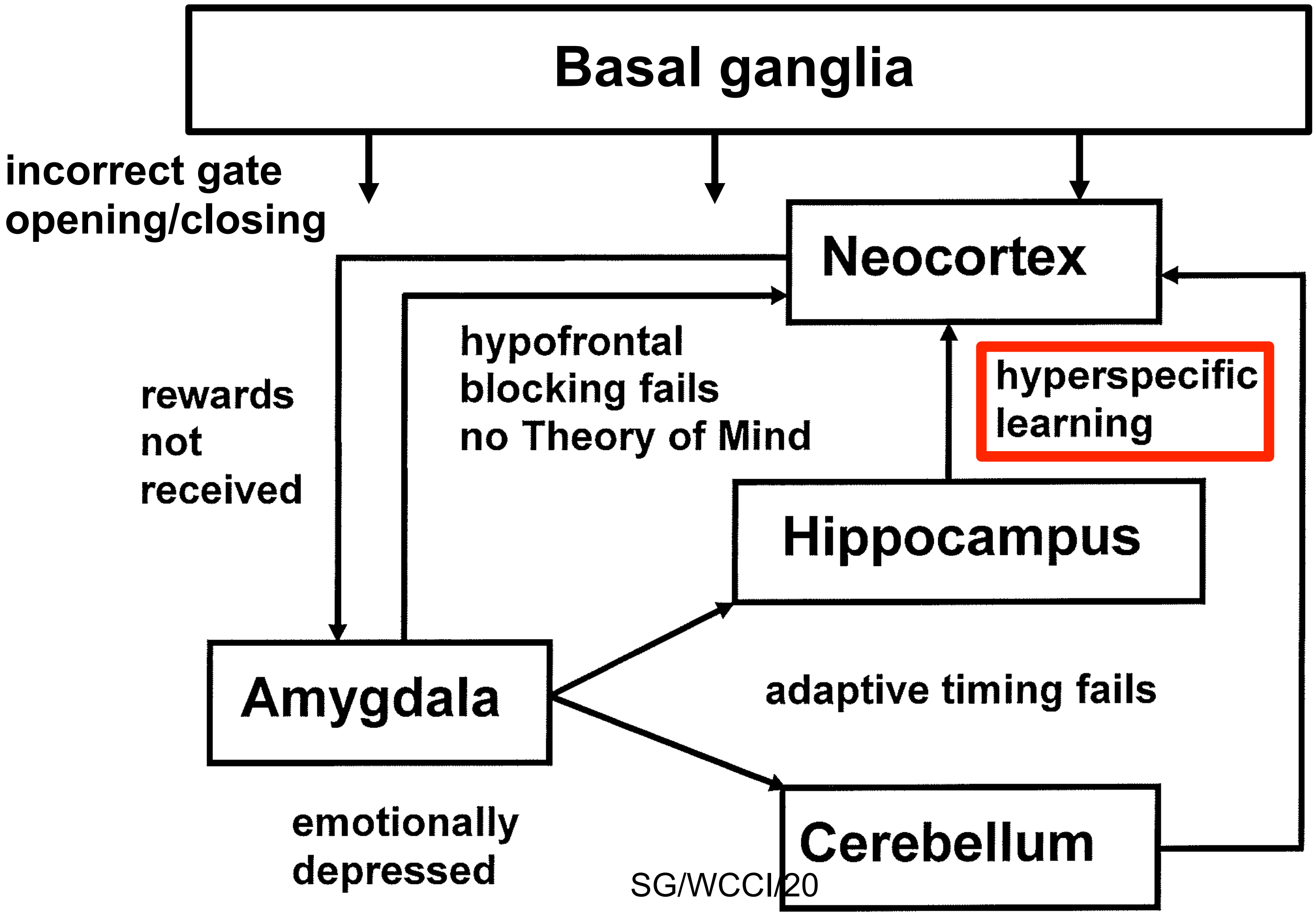
Supportive psychophysical data from high-functioning autistic individuals
Church et al. (2010). *Psychonomic Bulletin and Review*, 17, 862-868.
Vladusich et al. (2010). *Autism Research*, 3, 226-236.

Neuron pathology, morphological abnormalities,
and abnormalities of *ACh dynamics*
***in cerebral cortex and nucleus basalis* of autistic individuals**
Kemper and Bauman (1998). *J. Neurophy. & Exp. Neurol.*, 57, 645-652
Perry et al. (2001). *American Journal of Psychiatry*, 158, 1058-1066
Riva et al. (2011). *American Journal of Neuroradiology*, 32, 1430-1435.

NOT THE ONLY PROBLEM DURING AUTISM

multiple genes are affected

cf. Grossberg and Seidman, 2006; Grossberg and Kishan, 2018



THIS IS A TALK IN TWO PARTS

The second part:

HOW DO WE CONSCIOUSLY SEE?
and
HOW DOES A BREAKDOWN IN THIS PROCESS LEAD TO VISUAL NEGLECT?

HOW DO WE CONSCIOUSLY SEE?
and
HOW DOES A BREAKDOWN IN THIS PROCESS LEAD TO VISUAL NEGLECT?

Grossberg, S. (2017). Towards solving the hard problem of consciousness: The varieties of brain resonances and the conscious experiences that they support. *Neural Networks*, 87, 38-95.

Published Open Access; also on my web page
sites.bu.edu/steveg

HOW DO WE CONSCIOUSLY SEE?
and
HOW DOES A BREAKDOWN IN THIS PROCESS LEAD TO VISUAL NEGLECT?

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…very briefly…

What is the
Hard Problem of Consciousness?

Wikipedia

"…is the problem of explaining how and why we have qualia or phenomenal experiences…"

Chalmers (1995):
"The really hard problem of consciousness is the problem of *experience.* When we think and perceive, there is a whir of information-processing, but there is also a subjective aspect…"

What is the
Hard Problem of Consciousness?

Internet Encyclopedia of Philosophy

"The hard problem of consciousness is the problem of explaining
why any physical state is conscious rather than unconscious…
It is the problem of explaining why…conscious mental states
"light up"
and directly appear to the subject….
we can still meaningfully ask the question,
***Why is it conscious?*..."**

Before jumping in, it is fair to ask:

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What kind of event occurs in the brain that is anything more than a "whir of information processing"

What happens when conscious mental states "light up" and directly appear to a subject?

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Our brains sometimes go into a context-sensitive RESONANT STATE that can involve multiple brain regions

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Our brains sometimes go into a
context-sensitive RESONANT STATE
that can involve multiple brain regions

ALL CONSCIOUS STATES ARE RESONANT STATES

Before jumping in, it is fair to ask:

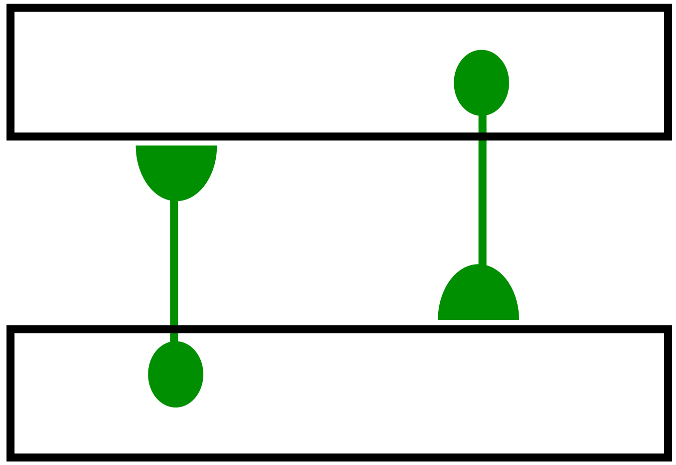
What kind of event occurs in the brain
that is anything more than a
"whir of information processing"

What happens when conscious mental states
"light up"
and directly appear to a subject?

Our brains sometimes go into a
context-sensitive RESONANT STATE
that can involve multiple brain regions

ALL CONSCIOUS STATES ARE RESONANT STATES
Not all brain dynamics are resonant, so
consciousness is not just a "whir of information processing"

WHAT IS A RESONANT BRAIN STATE?



A dynamical state during which neuronal firings across a brain network are amplified and synchronized when they interact via reciprocal excitatory feedback signals during a matching process that occurs between bottom-up and top-down pathways

CENTRAL CLAIM

Conscious states are part of larger adaptive behavioral capabilities that help us to adapt to a changing world

Resonances for conscious

seeing help to ensure effective reaching

hearing help to ensure effective speaking

feeling help to ensure effective goal-oriented action

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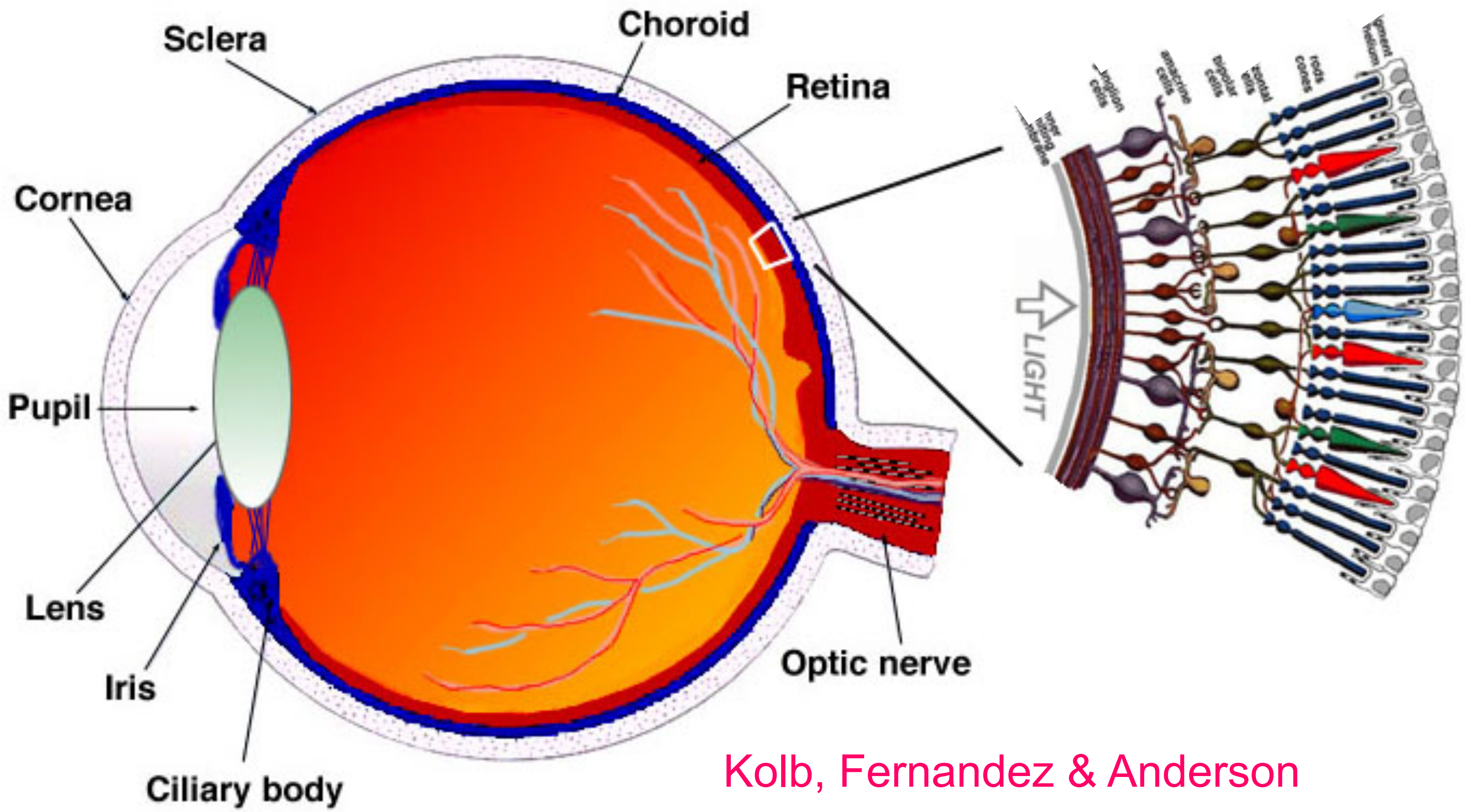
WHY DID EVOLUTION INVENT CONSCIOUSNESS?

Visual inputs to the retina are ambiguous, noisy, and incomplete

BLIND SPOT AND RETINAL VEINS

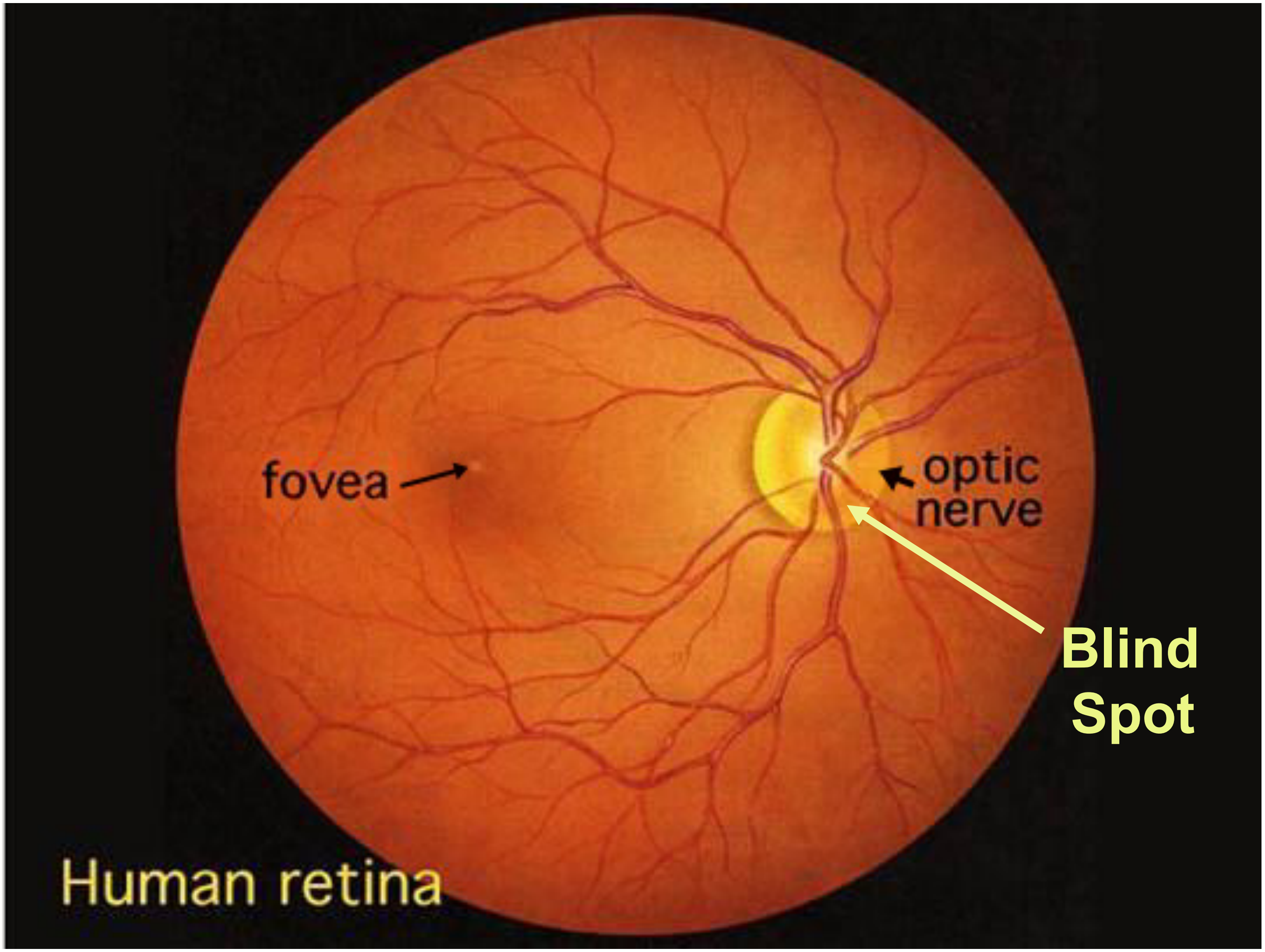
another reason for boundary completion and surface filling-in



Kolb, Fernandez & Anderson

http://retina.umh.es/Webvision/sretina.html

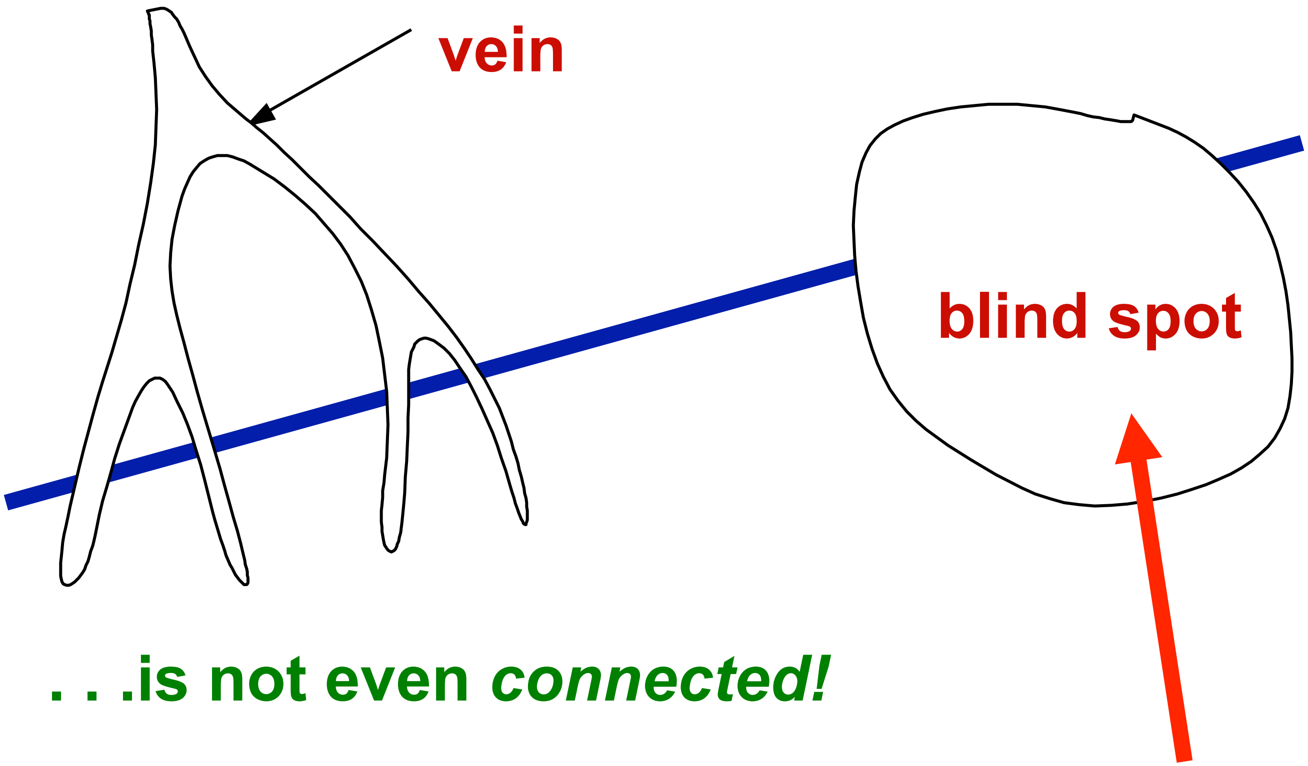
TOP-DOWN VIEW OF THE RETINA



Blind spot, retinal veins, and layers all interfere

VISUAL IMAGES ARE OCCLUDED BY THE BLIND SPOT AND RETINAL VEINS

The pattern formed on a retina by a **dark line**



. . .is not even *connected!*

HOW COULD YOU REACH TO THE LINE HERE?

WHY DID EVOLUTION INVENT CONSCIOUSNESS?

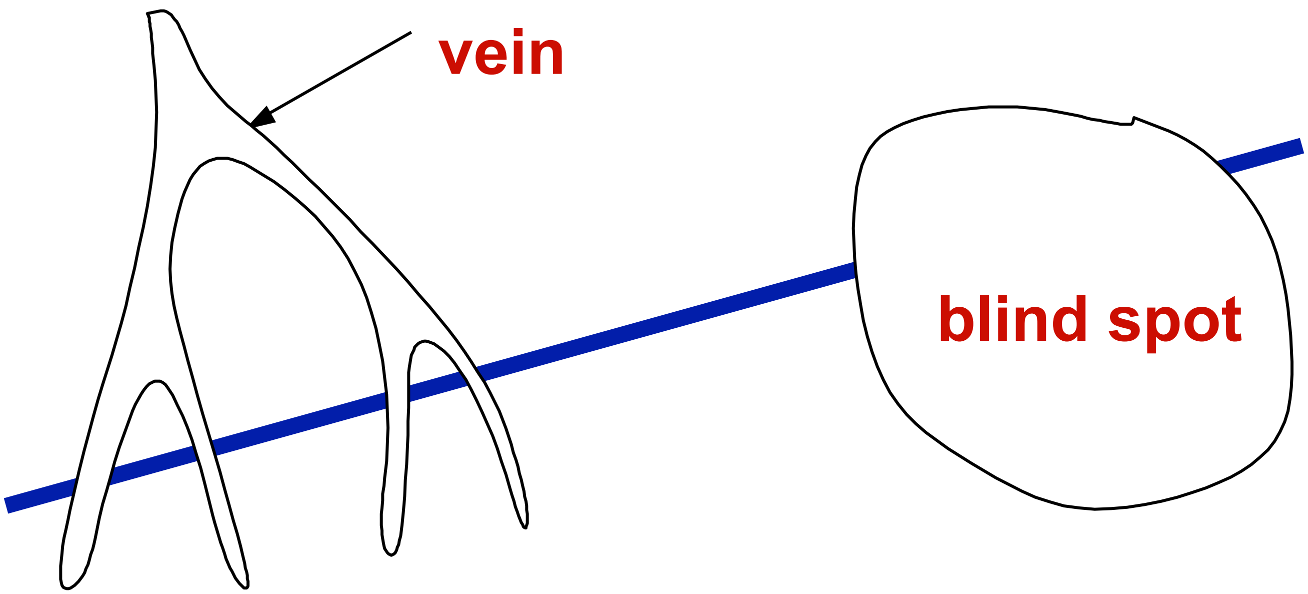
**Visual inputs to the retina are
ambiguous, noisy, and incomplete**

**Multiple processing stages are needed to generate
a sufficiently complete and stable surface representation
that can control effective looking and reaching**

HIERARCHICAL RESOLUTION OF UNCERTAINTY

WHY DON'T WE SEE BLIND SPOT AND RETINAL VEINS?!

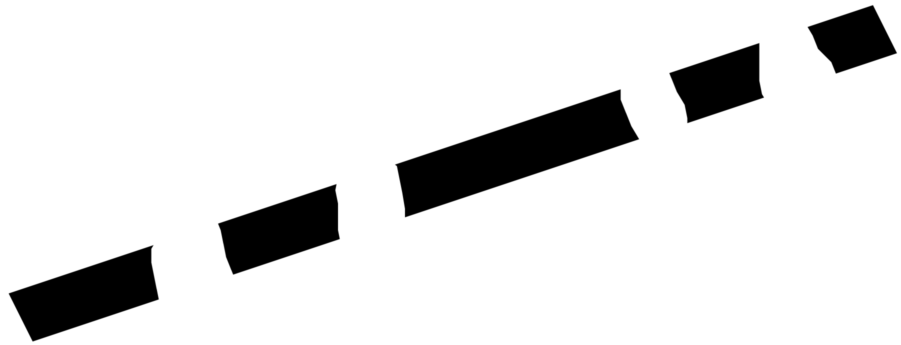
***The pattern formed on a retina* by a dark line**



. . .is not even *connected!*

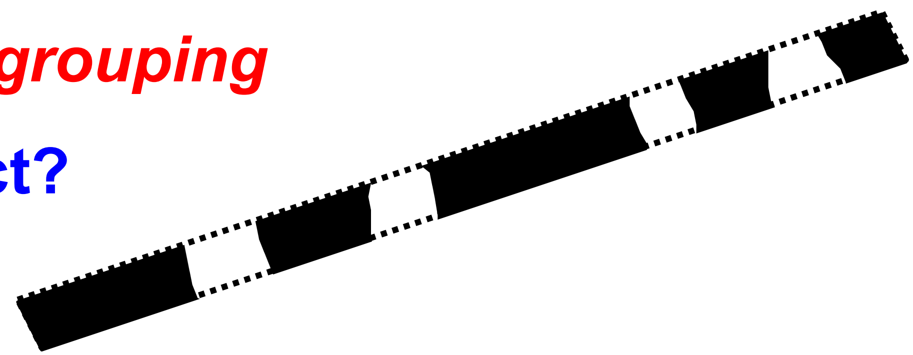
Eye jiggles in its orbit
Stabilized images fade

EVERY LINE IS AN ILLUSION!



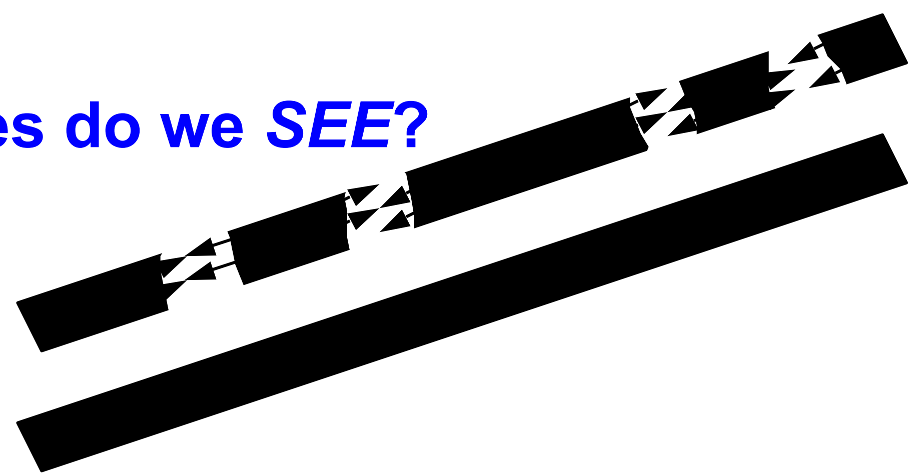
Boundary completion and grouping

Which boundaries to connect?



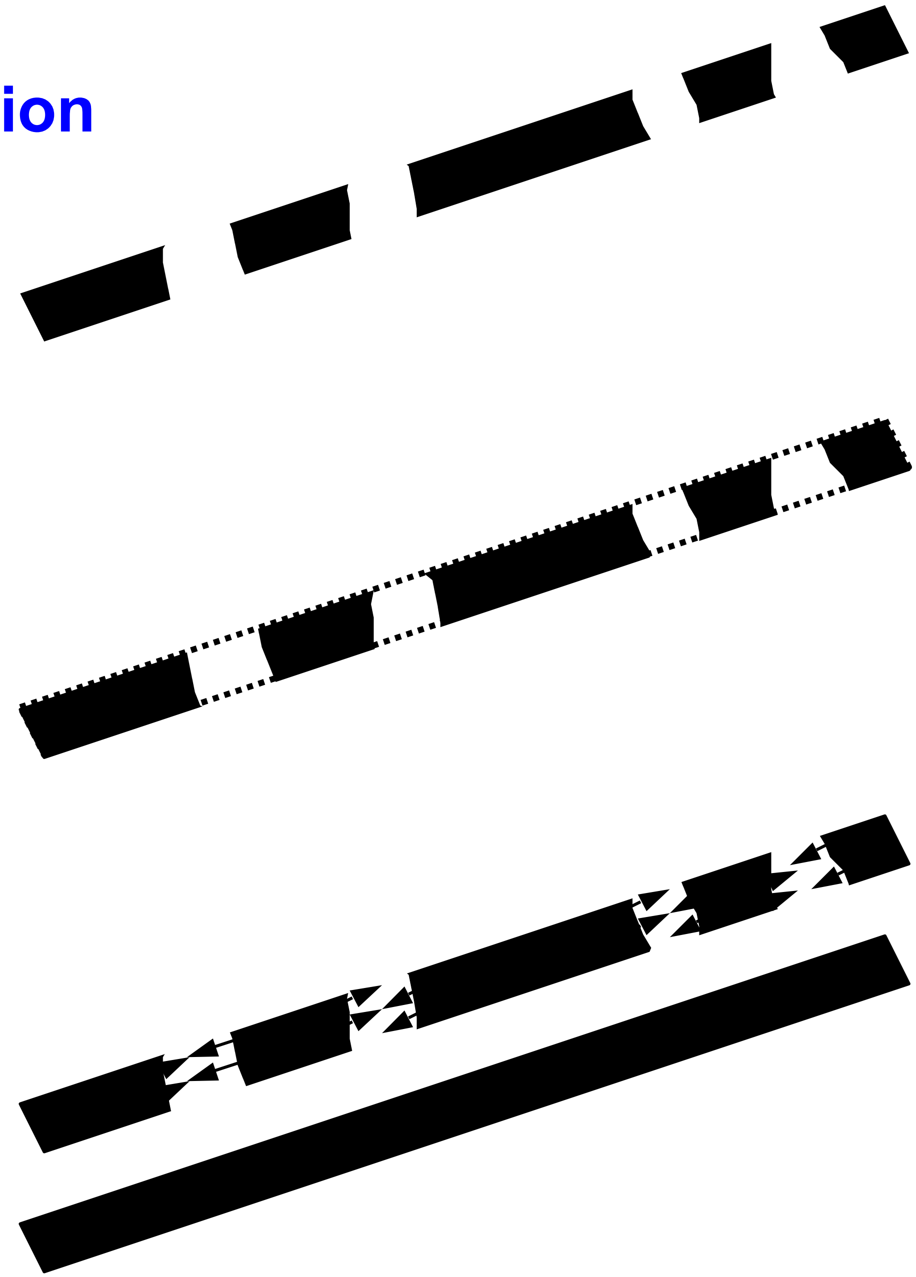
Surface filling-in

What colors and brightnesses do we *SEE*?



WHAT DO WE *CALL* AN ILLUSION?

…an unexpected combination of boundary completion and surface filling-in



WHY DID EVOLUTION INVENT CONSCIOUSNESS?

Visual inputs to the retina are ambiguous, noisy, and incomplete

Multiple processing stages are needed to generate a sufficiently complete and stable surface representation that can control effective looking and reaching

This surface representation is predicted to occur in V4

A SURFACE-SHROUD RESONANCE
between V4 and PPC
“lights up” the V4 surface representation
with an extra degree of freedom
CONSCIOUS AWARENESS!
and uses IT to control
LOOKING at and REACHING to
unoccluded surface regions

WHY ARE MULTIPLE PROCESSING STAGES NEEDED TO COMPUTE A GOOD ENOUGH REPRESENTATION WITH WHICH TO CONTROL MOVEMENTS?

Because of the way that our brains compute

COMPLEMENTARY COMPUTING

Boundaries and Surfaces are complementary

HIERARCHICAL RESOLUTION OF UNCERTAINTY

e.g., boundary completion

Visual consciousness "lights up"
surface representations
that can safely be used to look and reach

WHY DID EVOLUTION INVENT CONSCIOUSNESS?

The SURFACE-SHROUD RESONANCE
between V4 and PPC
can also propagate
TOP-DOWN to V2 and V1
and resonate with representations that are
consistent with the V4 surface representation
and suppress those that are not
using the ART Matching Rule
for top-down attention
only data consistent with the action are selected

and also
BOTTOM-UP to prefrontal cortex

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

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WHAT KIND OF RESONANCE SUPPORTS VISIBLE SURFACE QUALIA?

How do we see?!

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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+)

CLASSIFICATION OF RESONANCES

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:

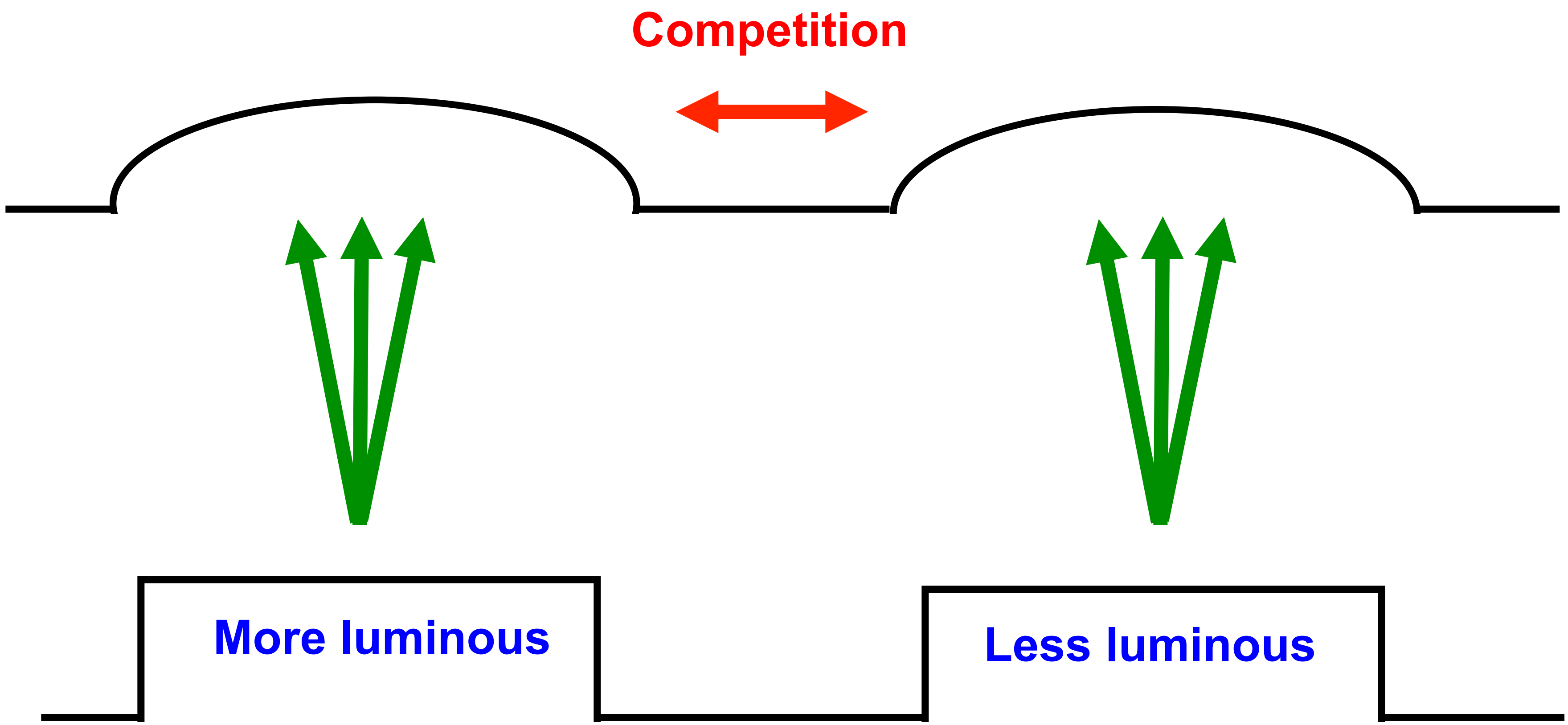
Shrouds enable learning of invariant object categories

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)

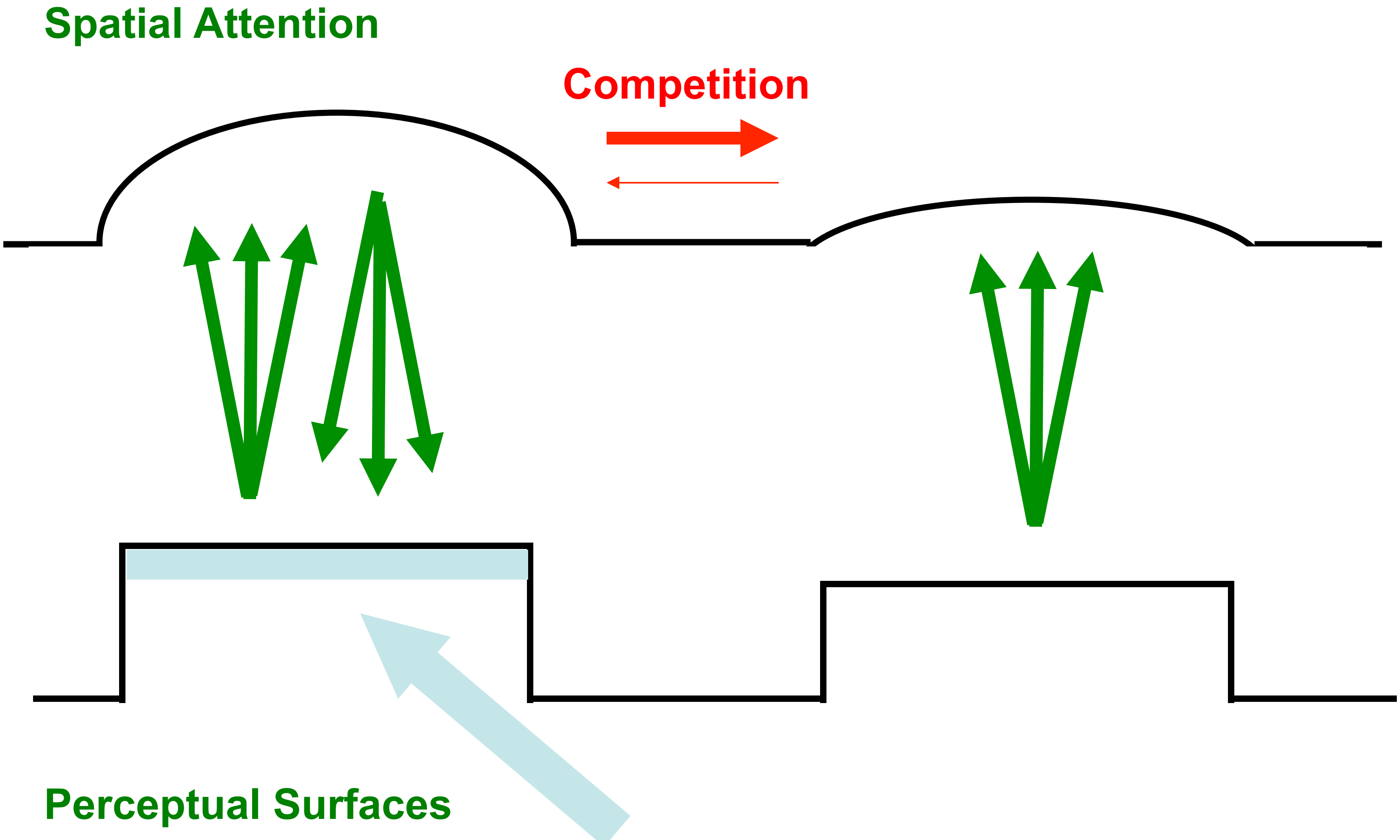
BOTTOM-UP SPATIAL ATTENTIONAL COMPETITION

Spatial Attention



Perceptual Surfaces

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

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A SURFACE-SHROUD RESONANCE ALSO SUPPORTS
CONSCIOUS SEEING
OF AN ATTENDED OBJECT

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OF AN ATTENDED OBJECT

WHY SHOULD YOU BELIEVE THIS?

FACADE AND 3D LAMINART simulations explain a lot of psychophysical and neurobiological data with these model hypotheses

e.g., psychophysics, anatomy, and neurophysiology about:
random-dot stereograms Fang and Grossberg (2009)
Panum's limiting case, dichoptic masking, Venetian blind illusion,
da Vinci stereopsis Cao and Grossberg (2005, 2012)
slanted surfaces, Necker cubes Grossberg and Swaminathan (2004)
3D neon and transparency Grossberg and Yazdanbakhsh (2005)
texture segregation Bhatt, Carpenter, and Grossberg (2007)
McCullough effect Grossberg, Hwang, and Mingolla (2002)
3D shape-from-texture Grossberg,, Kuhlmann, and Mingolla (2007)
Bregman-Kanizsa figure-ground separation, Kanizsa stratification,
Munker-White, Benary cross, and checkerboard percepts
Kelly and Grossberg (2000)
watercolor illusion Pinna and Grossberg (2005)
border ownership, stereoscopic cues,
and Gestalt grouping rules Grossberg (2016)

They are consistent with many neurophysiological experiments about V2 and V4

e.g., V2:

O'Herron and von der Heydt (2009)
Ziu, Sugihara, and von der Heydt (2007)
Qiu and von der Heydt (2005)
Von der Heydt, Zhou, and Friedman (2000)
Zhang and von der Heydt (2010)
Zhou, Friedman, and von der Heydt (2000)

V4:

Chelazzi, Miller, Duncan, and Desimone (2001)
Desimone and Schein (1987)
Lueck et al. (1989)
Ogawa and Komatsu (2004)
Reynolds, Pasternak, and Desimone (2000)
Schiller and Lee (1991)
Zeki (1983)

NEED MORE FOCUSED EXPERIMENTS!

Explaining clinical data about consciousness with Surface-Shroud Resonances

PARIETAL VISUAL NEGLECT

No parietal cortex, no Surface-Shroud Resonance!

Classical Review of effects of lesions in inferior parietal lobule (IPL)

Driver and Mattingly (1989)

Head-centered shroud coexists with retinotopic surface qualia

Shown by how neglect varies with patient's direction of gaze

Kooistra and Heilman (1989)

Competition for spatial attention across parietal cortex

Shown by how neglect varies with isolated vs. simultaneous cues

Posner et al (1984)

Preserved figure-ground segmentation during neglect

Shown by how grouping can overcome neglect

Mattingley, Davis, and Driver (1997)

Explaining clinical data about consciousness with Surface-Shroud Resonances

PARIETAL VISUAL NEGLECT

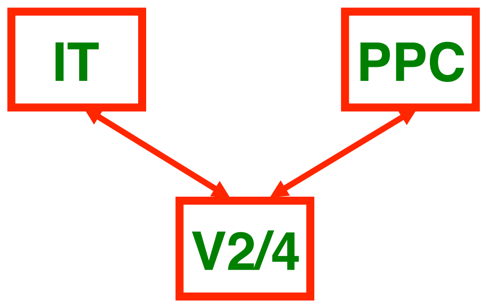
Unconscious processing of neglected object identity:
seeing vs. knowing

Shown by Implicit knowledge of neglected stimuli (color, shape, identity,…)

Mattingley, Bradshaw, and Bradshaw (1995)
McGlinchey-Berroth et al. (1993)

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

Explaining data about consciousness with Surface-Shroud Resonances

PARIETAL VISUAL NEGLECT

A link between visual neglect and motor planning deficits: "seeing to reach"

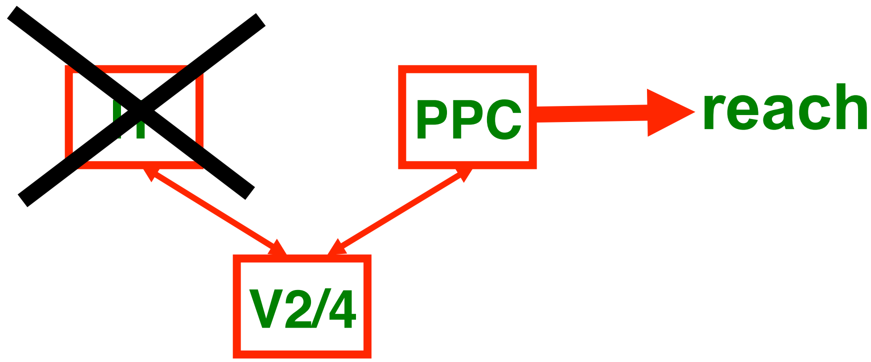
Shown by abnormal motor biases

Heilman et al. (1985)
Mattingley et al. (1998)

IPL lesions lead to deficits in sustained visual attention:
no Surface-Shroud Resonance to maintain attention
Rueckert and Grafman (1998)

WHAT KINDS OF RESONANCES SUPPORT KNOWING VS. SEEING?

What Stream **Where Stream**



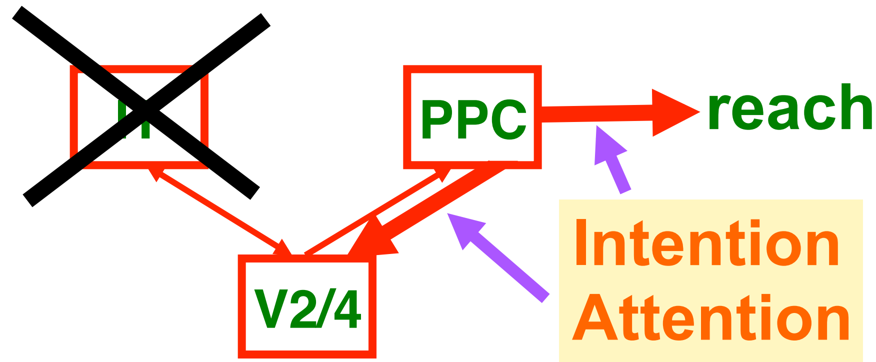
KNOWING
Feature-Category Resonance

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

Brain dynamics of normal and abnormal learning, cognition, and consciousness
with applications to
Alzheimer's disease, autism, amnesia, sleep, neglect, and memory consolidation

The key role of
BRAIN RESONANCES
in conscious seeing and recognition
notably of Adaptive Resonance Theory
hypothesis testing and category learning dynamics
in LAMINAR CORTICAL CIRCUITS
in response to properly pre-processed perceptual data

Lots more to do, including roles of basal ganglia and prefrontal cortex…

ART CURRENTLY HAS AN UNRIVALLED RANGE

"The gift that keeps on giving"

It has explained and predicted much more data than competing cognitive and neural theories

That range extends to helping to provide emerging neural explanations of mental disorder symptoms that afflict millions of people

Alzheimer's disease
Autism
Fragile X syndrome
ADHD
Schizophrenia
Sleep disorders

and how brain lesions cause problems with

Medial temporal amnesia
Memory consolidation
Visual and auditory neglect

I hope some of you will help to advance this theory in either its biological or technological incarnations!