ANTICIPATORY BRAIN DYNAMICS IN PERCEPTION, COGNITION, AND ACTION

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THEMES

What is the role of anticipatory mechanisms with respect to reactive ones?

How do we pay attention to appropriate features using expectations and goals?

What is the relation between anticipatory processes and symbol formation?

How are emotions related to anticipatory representations?
How are emotions such as fear and relief built and exploited?

How do different anticipatory mechanisms integrate and interact?

THEMES

A great deal of recent interest in these themes

Almost 50 years of behavioral and neural modeling have been developing them!

My talk will give a (necessarily) selective overview

Many relevant articles from my work with my colleagues can be downloaded from http://www.cns.bu.edu/Profiles/Grossberg

A TALK IN THREE PARTS

COGNITIVE INFORMATION PROCESSING

Show link between

- working memory in STM
- learning and categorization (symbol formation) in LTM
- expectation
- attention
- resonance
- hypothesis testing and memory search
- consciousness

sensory cortex
temporal cortex
prefrontal cortex
hippocampal system

A TALK IN THREE PARTS

BALANCING REACTIVE AND PLANNED MOVEMENTS

how reactive movements are made rapidly to urgent environmental challenges

how reactive movements may be suppressed when more slowly developing plans are selected

how the brain knows that a plan is being selected before it is selected

how the brain uses reactive movements to learn planned movements

sensory cortex	motor cortex
temporal cortex	prefrontal cortex
basal ganglia	cerebellum
superior colliculus	reticular formation

A TALK IN THREE PARTS

COGNITIVE-EMOTIONAL INTERACTIONS

classical and instrumental conditioning
attentional blocking
opponent emotions; e.g., fear vs. relief (hope)
how expectations influence emotions
adaptively timed learning and attention
how unexpected rewards generate reinforcing signals

sensory cortex
temporal cortex
prefrontal cortex
sensory thalamus
amygdala
basal ganglia
cerebellum

Let’s start with a basic question:

HOW DOES THE BRAIN CONTROL BEHAVIOR?

Mind-Body Problem

Many groups study BRAIN OR BEHAVIOR

BRAIN provides MECHANISMS

BEHAVIOR provides FUNCTIONS

Without a link between them

BRAIN MECHANISMS have no FUNCTION

BEHAVIORAL FUNCTIONS have no MECHANISM

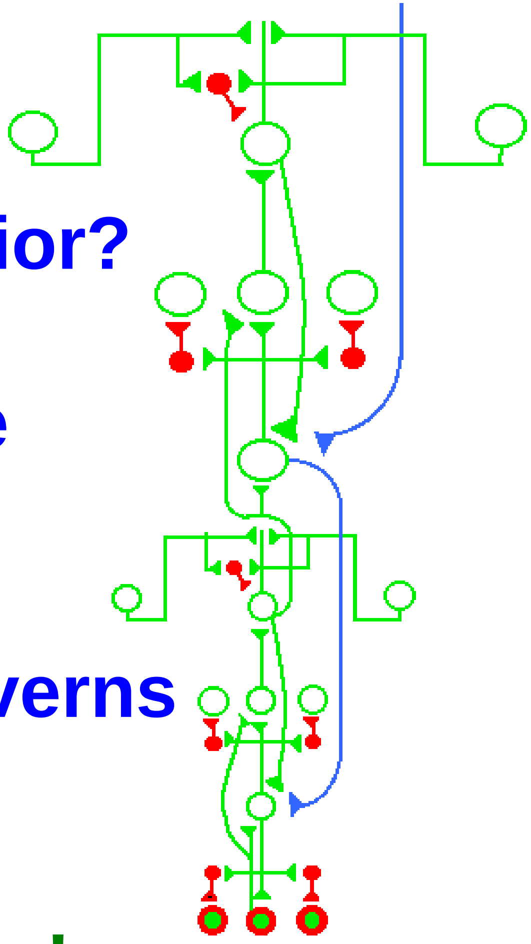
HOW DOES THE BRAIN CONTROL BEHAVIOR?

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!



How does BEHAVIOR arise as EMERGENT PROPERTIES OF NEURAL NETWORKS?

Does this mean that individual neurons are unimportant?

Not at all!

How are individual NEURONS designed and connected so that the NETWORKS they comprise generate emergent properties that govern successful BEHAVIORS?

Need to simultaneously describe 3 levels (at least):

BEHAVIOR

NETWORK

NEURON

and a MODELING language to link them

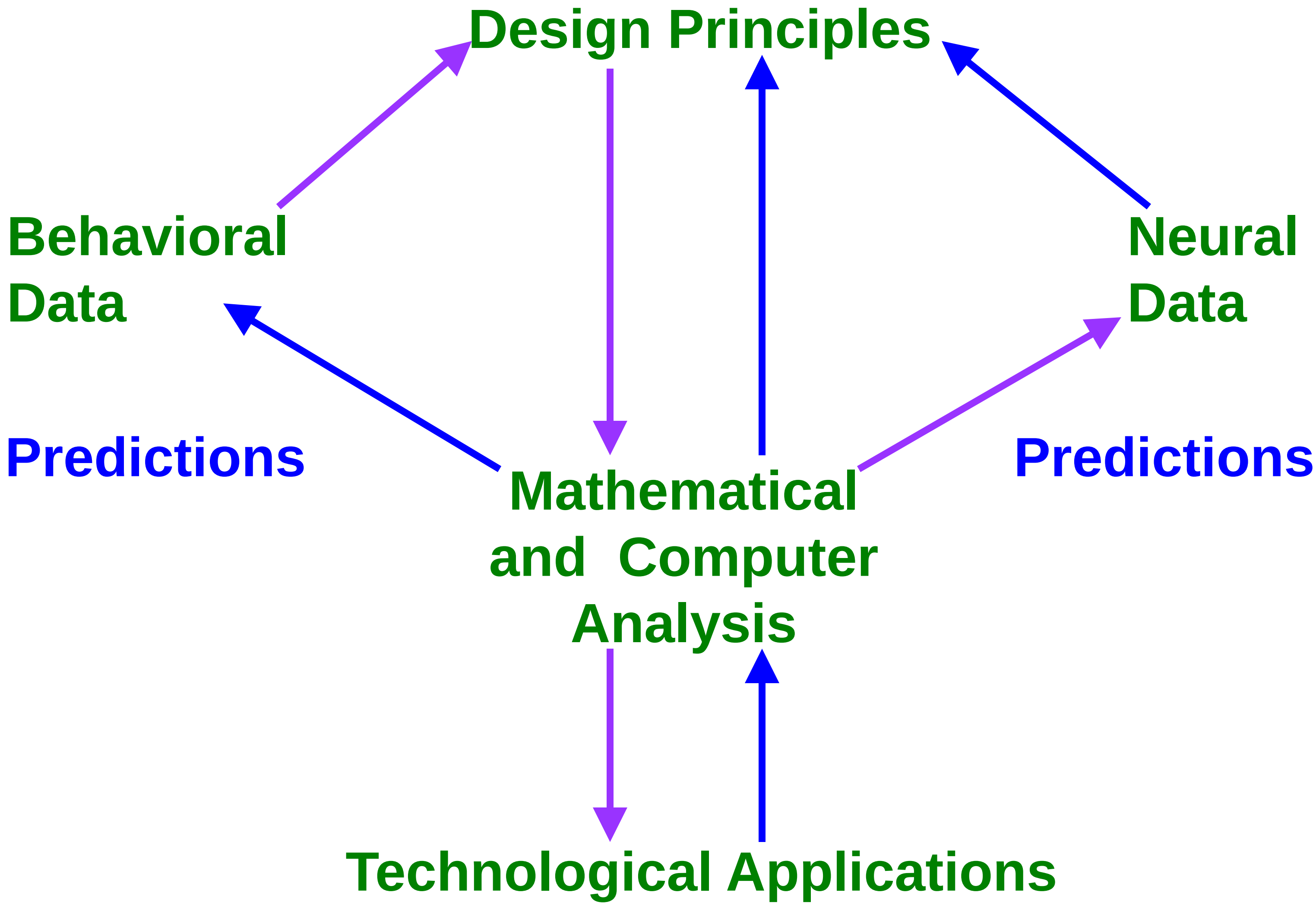
A KEY MODELING THEME has unified these levels during forty years of modeling:

HOW AN INDIVIDUAL
ADAPTS
ON ITS OWN
IN REAL TIME
TO A COMPLEX AND CHANGING WORLD

AUTONOMOUS ADAPTATION TO A NON-STATIONARY ENVIRONMENT

This theme is realized in a modeling cycle that leads to models of brain and behavior with surprising explanations and predictions:

MODELING CYCLE



TWO KEY CONCLUSIONS

1. Advanced brains look like they do to enable

REAL-TIME AUTONOMOUS LEARNING

Lesson: The Architecture is the Algorithm

2. Recent models show how the brain's ability to DEVELOP and LEARN greatly constrain the laws of

ADULT INFORMATION PROCESSING

Lesson: You cannot fully understand adult neural information processing without studying how the brain LEARNS

TECHNOLOGICAL TAKE HOME LESSON

The brain is designed to
AUTONOMOUSLY ADAPT TO A CHANGING WORLD

Engineering and Technology need this competence to solve urgent societal problems

Both FUNCTION AND MECHANISM are needed to solve technological problems

FUNCTION = What it is for
MECHANISM = How it works

This explains how
BEHAVIOR AND BRAIN modeling can inspire
NEUROMORPHIC TECHNOLOGY

A CENTRAL QUESTION OF BOTH BIOLOGICAL AND ARTIFICIAL INTELLIGENCE

How does an INDIVIDUAL

ADAPT

ON ITS OWN

IN REAL TIME

TO A CHANGING WORLD?

Autonomous adaptation to a nonstationary environment

Answers to different aspects of this question have led to…

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

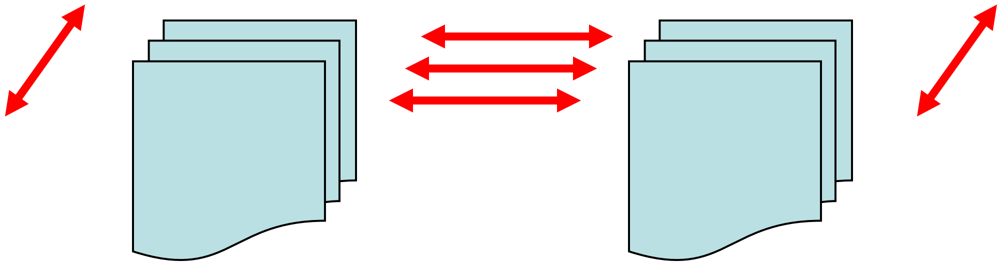
COMPLEMENTARY COMPUTING
Brain as part of the physical world

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

Principles of

UNCERTAINTY and COMPLEMENTARITY

Multiple Parallel Processing Streams Exist



HIERARCHICAL INTRASTREAM INTERACTIONS

UNCERTAINTY PRINCIPLES operate at individual levels

Hierarchical interactions resolve uncertainty

PARALLEL INTERSTREAM INTERACTIONS

Each stream computes COMPLEMENTARY properties

Parallel interactions overcome complementary weaknesses

ADAPTIVE BEHAVIOR = EMERGENT PROPERTIES

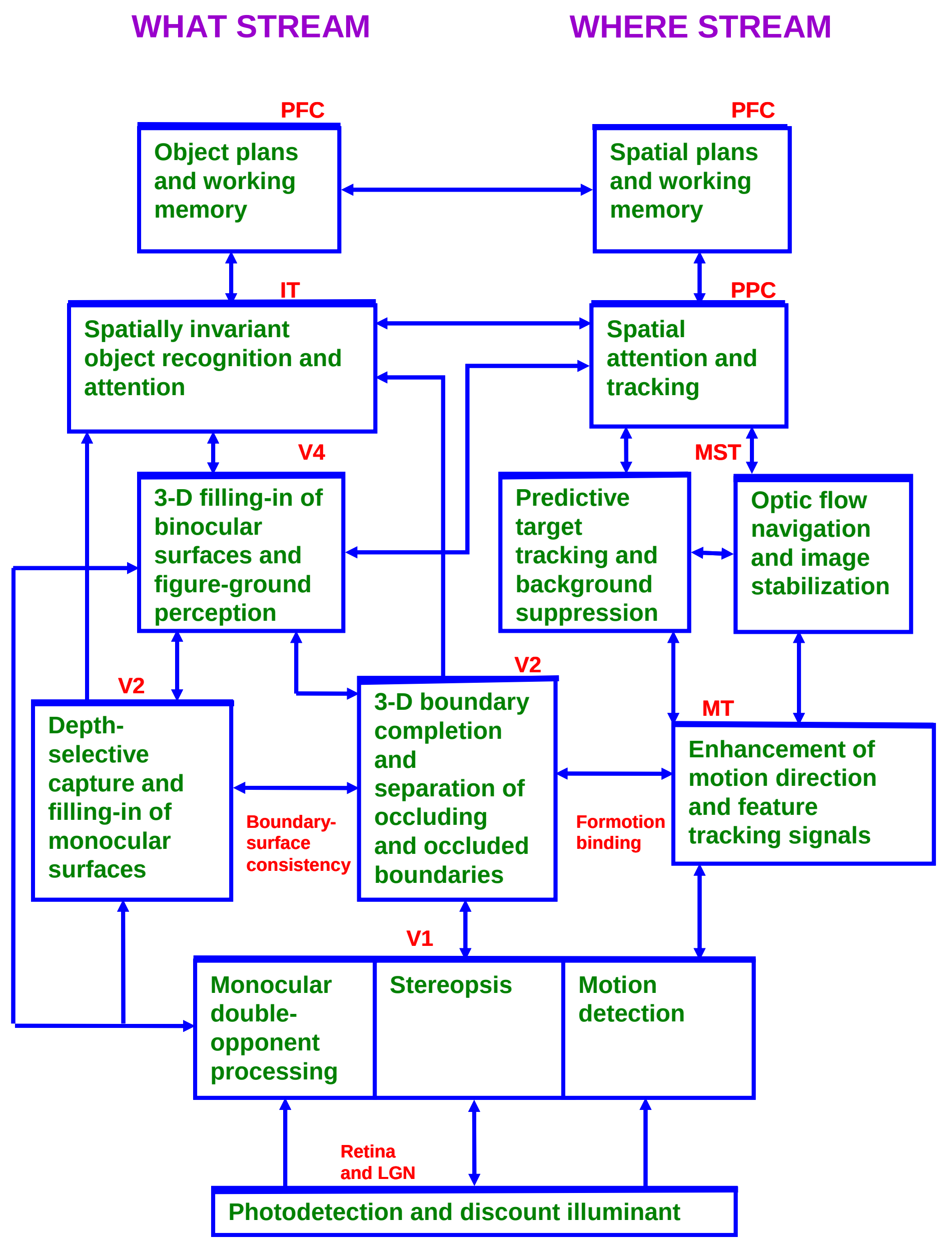
SOME COMPLEMENTARY PROCESSES

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 learning/ Matching **Inferotemporal and Prefrontal areas**	**WHERE learning/ Matching** **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**

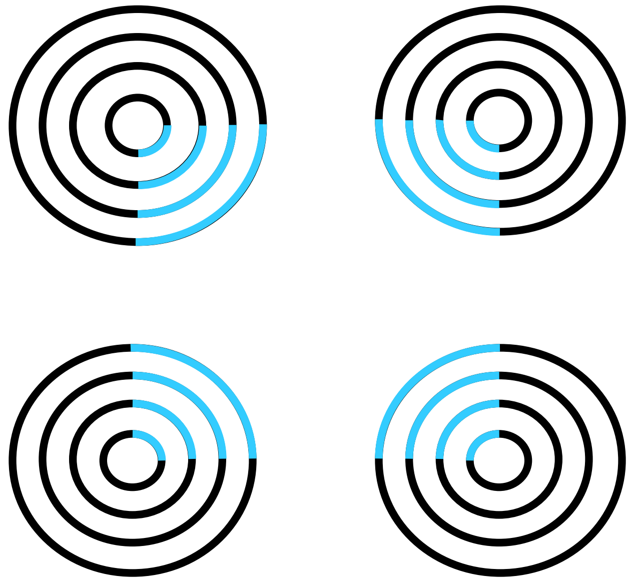
PROJECTS IN CNS TO DEVELOP UNIFIED MODEL OF HOW VISUAL CORTEX SEES

BOTTOM-UP
TOP-DOWN
HORIZONTAL
interactions
everywhere to
overcome
COMPLEMENTARY
WEAKNESSES

Not independent modules



BOUNDARY AND SURFACE COMPUTATIONS ARE COMPLEMENTARY



neon color spreading

BOUNDARY COMPLETION

oriented
inward
insensitive to
direction-of-contrast

SURFACE FILLING-IN

unoriented
outward
sensitive to
direction-of-contrast

BIOLOGICAL TAKE HOME LESSON

Need to model

PAIRS OF
COMPLEMENTARY CORTICAL STREAMS

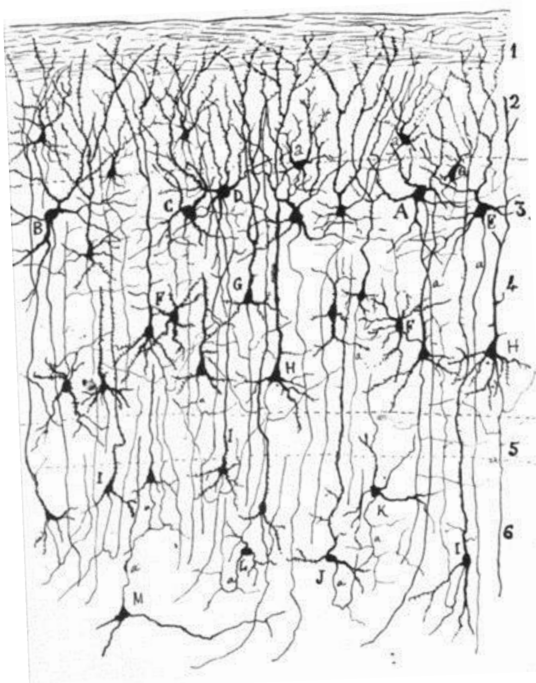
to compute

COMPLETE INFORMATION

about a changing world

HOW DOES THE CEREBRAL CORTEX WORK?

It supports the highest levels of biological intelligence in all modalities



VISION, SPEECH, COGNITION, ACTION

Why does the cortex have LAYERS?

How does LAMINAR COMPUTING give rise to biological intelligence?

1. How does visual cortex stably DEVELOP and LEARN to optimize its structure to process different environments?

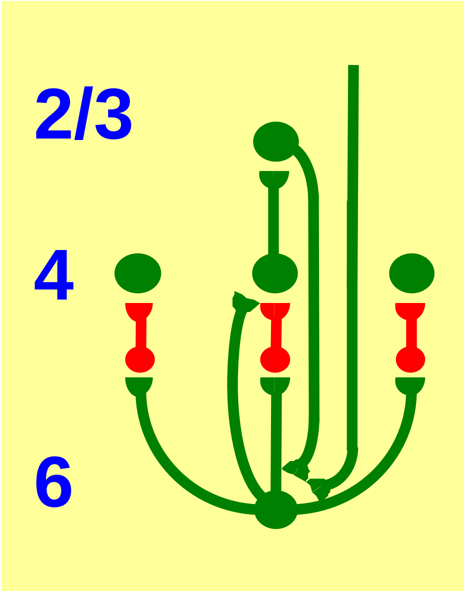
2. How does visual cortex GROUP distributed information?

3. How does top-down ATTENTION bias visual processing?

A CNS breakthrough shows how 1 implies 2 and 3!

WHAT DOES LAMINAR COMPUTING ACHIEVE?

1. SELF-STABILIZING DEVELOPMENT AND LEARNING



2. Seamless fusion of

    PRE-ATTENTIVE AUTOMATIC
    BOTTOM-UP PROCESSING

  and

    ATTENTIVE TASK-SELECTIVE
    TOP-DOWN PROCESSING

3. ANALOG COHERENCE: Solution of the BINDING
    PROBLEM without a loss of analog sensitivity

Even the earliest cortical stages carry out active adaptive information processing:
LEARNING, GROUPING, ATTENTION

LAMINAR COMPUTING: A NEW WAY TO COMPUTE

1. FEEDFORWARD AND FEEDBACK

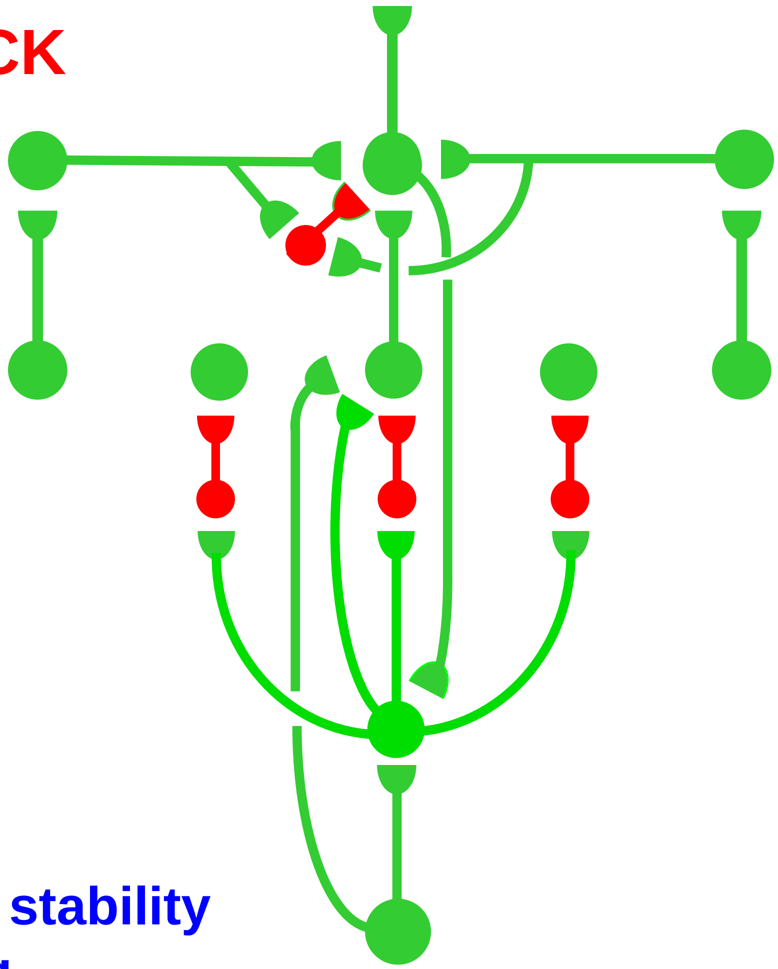
Rapid feedforward processing when data are unambiguous

Feedback is automatically engaged to choose among ambiguous alternatives:

self-normalizing competition

A self-organizing system that trades certainty against speed

Goes beyond Bayesian models



2. ANALOG AND DIGITAL

ANALOG COHERENCE combines the stability of digital with the sensitivity of analog

3. PRE-ATTENTIVE AND ATTENTIVE LEARNING

A pre-attentive grouping is its own “attentional” prime!

A TALK IN THREE PARTS: PART 1

COGNITIVE INFORMATION PROCESSING

Show link between

- **working memory in STM**
- **learning and categorization (symbols) in LTM**
- **expectation**
- **attention**
- **resonance**
- **hypothesis testing and memory search**
- **consciousness**

sensory cortex
temporal cortex
prefrontal cortex
hippocampal system

SEVERAL TYPES OF LEARNING

Recognition	Identify	What
Reinforcement	Evaluate	Why
Timing	Synchronize	When
Spatial	Locate	Where
Motor Control	Act	How

…and they Interact!

How to unravel this complexity?

TWO APPROACHES TO HUMAN LEARNING, CATEGORIZATION, AND MEMORY

MY face vs. A face

EXEMPLAR MODELS

- **Memory**
  - store each event
- **Categorization**
  - compare items to each stored exemplar
  - assign item to category with nearest exemplar

PROTOTYPE MODELS

- **Memory**
  - store abstraction of multiple exemplars
- **Categorization**
  - compare items to each stored prototype
  - assign item to category with nearest prototype

PROBLEMS OF EXEMPLAR AND PROTOTYPE MODELS

EXEMPLAR MODELS

How to:

- abstract from individual events?
- recognize novel events?
- search such a large memory?

PROTOTYPE MODELS

How to:

- determine proper level of abstraction?
- code individual events?
- learn prototypes on line when only exemplars are ever experienced?

PROBLEMS OF EXEMPLAR AND PROTOTYPE MODELS

ALL MODELS

- **How do:**
  - **NEW items degrade memory of OLD items**
    - **during recognition trials?**
      - **I.e., How to FORGET?**

INFEROTEMPORAL CORTEX

- **Learns to encode both**
  - **specific and general information**
- **Forgets**

COGNITIVE MODELS

CONTEXT MODEL

Medin & Shaffer, 1978; Medin & Smith, 1981;
Medin, Dewey & Murphy, 1984

Early successful exemplar model
Shows weaknesses of prototype models

RULE–PLUS-EXCEPTIONS MODEL

Nosofsky, 1984, 1987; Nosofsky, Kruschke & McKinley, 1992; Palmeri & Nosofsky, 1995

Hybrid model
Mixes prototypes and exemplars

COGNITIVE MODELS

RETURN OF PROTOTYPE MODELS

Smith & Minda, 1998; Smith, Murray & Minda,1997;
Smith & Minda, 2000

Trace exemplar model success to differential processing of OLD and NEW items

Prototype models do better when designed to process OLD and NEW items separately

But see Nosofsky (2000) and Nosofsky and Zaki (2002)

5-4 CATEGORY STIMULI IN 30 EXPERIMENTS

Smith & Minda, 2000

Geometric Shapes

Verbal Descriptions

Brunswick Faces

Rocket Ship Drawings

Yearbook Photos

Data set	Reference	Physical Stimuli	Instruction-Condition
1	Medin & Shaffer (1978)	Geometric Shapes	Neutral
2		Brunswick Faces	Neutral
3	Medin & Smith (1981)	Brunswick Faces	Neutral
4		Brunswick Faces	Rule-plus-exception
5		Brunswick Faces	Prototype instructions
6	Medin, Dewey, & Murphy (1984)	Yearbook photos	Neutral
7		Yearbook photos	Neutral
8		Yearbook photos	Learn first-last name
9		Yearbook photos	Learn first name
10	Medin, Altom, & Murphy (1992)	Geometric Shapes	Neutral
11		Geometric Shapes	Prototype facts given concurrently
12		Geometric Shapes	Prototype facts given first
13		Geometric Shapes	Neutral
14		Geometric Shapes	Prototype facts given concurrently
15		Geometric Shapes	Prototype facts given first
16			Neutral
17			Prototype facts given concurrently
18			Prototype facts given first
19	Nosofsky, Kruschke, & McKinley (1992)	Geometric Shapes	Neutral
20		Geometric Shapes	Neutral
21		Geometric Shapes	Neutral
22		Geometric Shapes	Neutral
23		Geometric Shapes	Neutral
24	Nosofsky, Kruschke, & McKinley (1994)	Rocket Ships	Neutral
25	Palmeri & Nosofsky (1995)	Rocket Ships	Rule-plus-exception
26		Rocket Ships	Neutral
27	Lamberts (1995)	Brunswick Faces	Neutral-speeded
28		Brunswick Faces	Neutral-speeded
29		Brunswick Faces	Neutral-speeded
30		Brunswick Faces	Neutral

5-4 CATEGORY STRUCTURE

	Type and Stimulus	Dimension (D)			
		D1	D2	D3	D4
TRAINING (OLD) ITEMS	Category A				
	A1	1	1	1	0
	A2	1	0	1	0
	A3	1	0	1	1
	A4	1	1	0	1
	A5	0	1	1	1
	Category B				
	B1	1	1	0	0
	B2	0	1	1	0
	B3	0	0	0	1
	B4	0	0	0	0
NEW TEST ITEMS	Transfer (T)				
	T10	1	0	0	1
	T11	1	0	0	0
	T12	1	1	1	1
	T13	0	0	1	0
	T14	0	1	0	1
	T15	0	0	1	1
	T16	0	1	0	0

A1-A5: closer to the (1 1 1 1) prototype B1-B4: closer to (0 0 0 0) prototype

5-4 CATEGORY STRUCTURE PROPERTIES

Within-category similarity: **2.4**

average number of features that exemplars within a category share

Between-category similarity: **1.6**

average number of features that exemplars across categories share

Structural ratio (s.r.) **1.5**

ratio of within-category similarity to between-category similarity

measure of within-category coherence & between-category differentiation

s.r. = 1.5 implies poor differentiation

s.r. = 1.0 ⇨ no differentiation

s.r. > 3.0 ⇨ easy differentiation

5-4 CATEGORY STRUCTURE PROPERTIES

Classes are linearly separable

Predictive power of each dimension

percent correct using only one feature in training

Dimension:

1	78 %
2	56 %
3	78 %
4	67 %

Ideal Rule:

Subjects should use dimensions 1 & 3 and not 2

PROBLEMS OF COGNITIVE MODELS

None of these models actually learns its exemplars or prototypes

None of them explains how information is stored or retrieved in real time

They define prototypes a priori, not by what prototypes humans may actually learn

They all use combinations of exemplars, not just individual exemplars

EXEMPLAR MODELS IMPLICITLY USE PROTOTYPE KNOWLEDGE

Probability of a category A response equals
sum of similarities between the test item i and stored exemplars of A

divided by the

sum of similarities between the test item i and ALL stored exemplars:

$$P_{iA} = \frac{\sum_{j \in A} S_{ij}}{\sum_{j \in A} S_{ij} + \sum_{j \in B} S_{ij}}$$

HOW DOES THE MODEL KNOW WHICH EXEMPLARS ARE IN CATEGORY A?

It must know this to compare ONLY these exemplars with the test item to compute their similarity

BOTTOM-UP LEARNING:

Every exemplar, including the test item, is associated during learning with a "prototype"

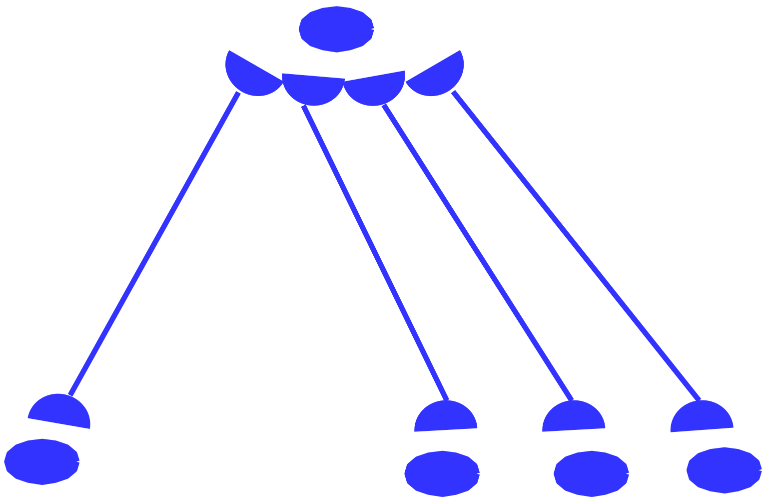
TOP-DOWN LEARNING:

When activated by a test item, the prototype feeds back to selectively activate ALL its exemplars

Although these exemplars are simultaneously activated, the similarity of the test item to EACH one can be computed and then summed. How is this done?!

HOW DOES THE MODEL KNOW WHICH EXEMPLARS ARE IN CATEGORY A?

CATEGORY A



BOTTOM-UP

AND

TOP-DOWN

LEARNING

TEST ITEM

OLD ITEMS

EXEMPLARS

How does a NOVEL test item access the “category” A?

ADAPTIVE RESONANCE THEORY

ART Grossberg, 1976

An ART model autonomously learns

CRITICAL FEATURE PATTERNS

of relevant features to which the model pays attention

Some patterns represent general information

PROTOTYPES

Other patterns represent specific information

EXEMPLARS

Together they represent

RULES-PLUS-EXCEPTIONS

ADAPTIVE RESONANCE THEORY

INTRODUCED

Grossberg, 1976

UNSUPERVISED ART

Carpenter & Grossberg, 1987

SUPERVISED ARTMAP

Carpenter, Grossberg, & Reynolds, 1991

SUPERVISED DISTRIBUTED ARTMAP:

Carpenter, Milenova, & Noeske, 1998

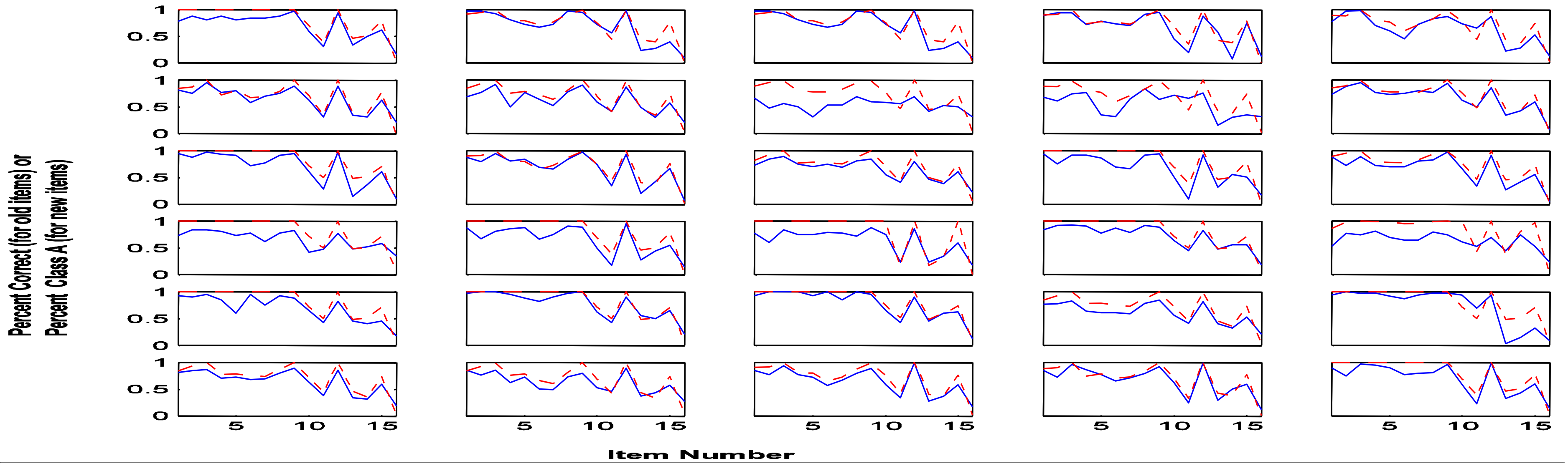
DISTRIBUTED ARTMAP:

- Fits the data as well as the E & P models after LEARNING these categories
- Proposes a new definition of PROTOTYPE
- Clarifies the E & P controversy and provides a way out of the E & P impasse

SIMULATION OF 5-4 DATA

Carpenter, Ersoy, and Grossberg, 2005

Best fits to 30 experiments

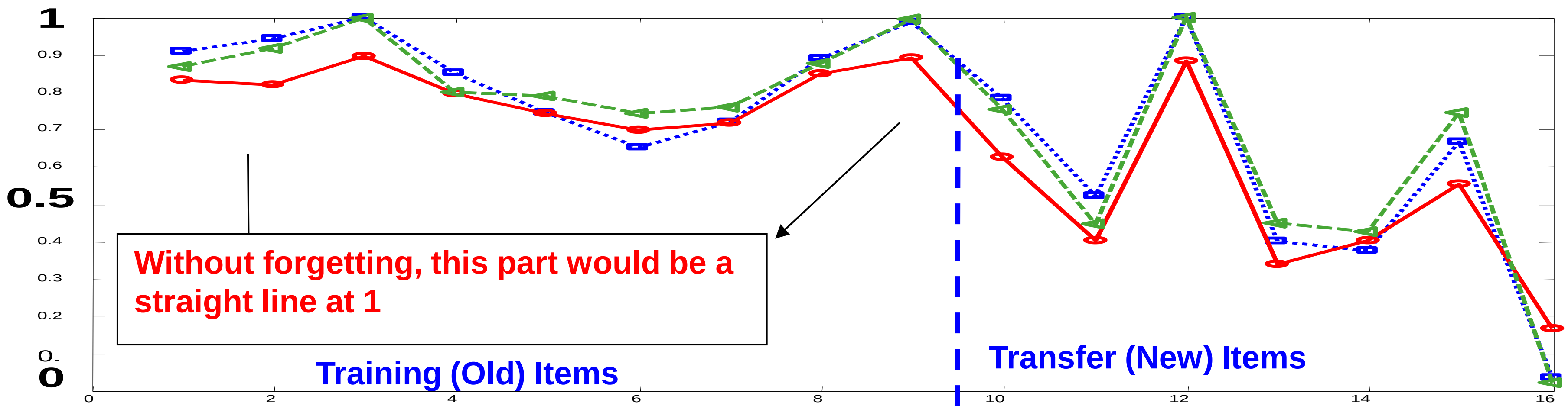


solid: experimental data

dash: best simulation fits

SIMULATION OF 5-4 DATA

Best fits to mean of 30 experiments



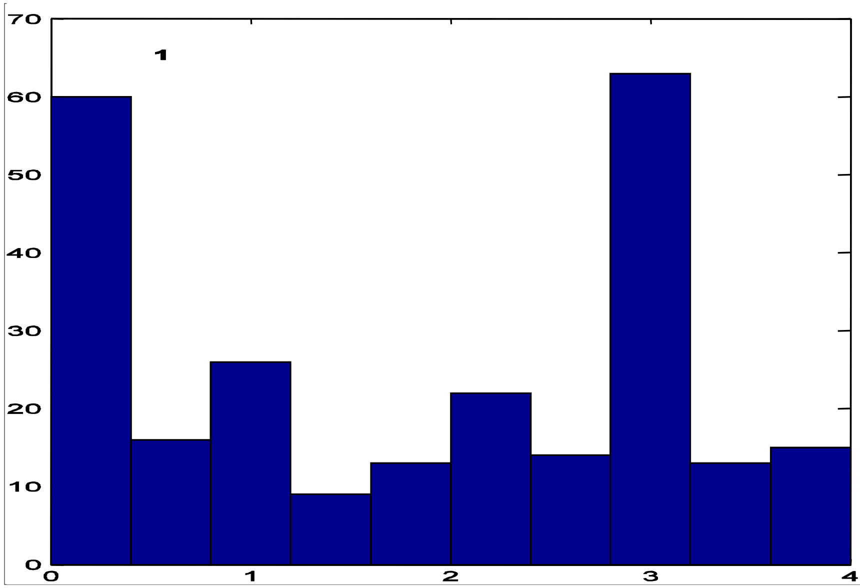
solid (circles): average of 30 experimental results

dash (triangles): average of 30 fits to individual data

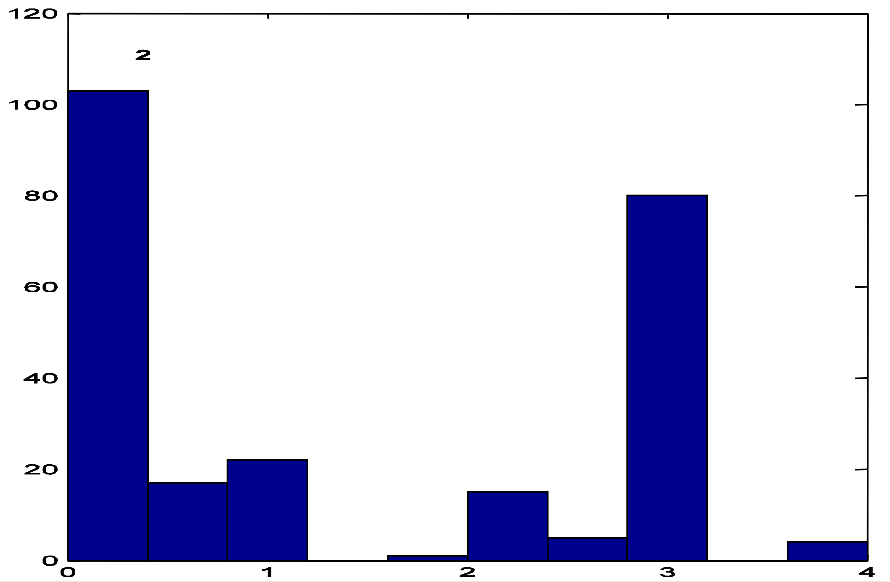
dot (squares): fit to average of data

LEARNED PROTOTYPES AND EXEMPLARS

BOXES: Geometric representation of memories



Histogram of box sizes labeled Class A



Histogram of box sizes labeled Class B

PROTOTYPES: big boxes

EXEMPLARS: small boxes

Learns RULES-PLUS-EXCEPTIONS

WHAT ART SHOWS

How and why the following processes work together:

- working memory in STM
- learning and categorization (symbols) in LTM
- expectation
- attention
- resonance
- hypothesis testing and memory search
- consciousness

sensory cortex
temporal cortex
prefrontal cortex
hippocampal system

ADAPTIVE RESONANCE THEORY

Grossberg, 1976

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?

STABILITY-PLASTICITY DILEMMA

Key design trade-off

How does a brain dynamically switch between its STABLE and PLASTIC modes without an external teacher?

Too Stable	**Too Plastic**
↓	↓
Rigid	**Chaotic**

Dynamic Balance

ART MATCHING AND RESONANCE RULES

BOTTOM-UP ACTIVATION

by itself can activate target nodes

(automatic activation)

TOP-DOWN EXPECTATIONS

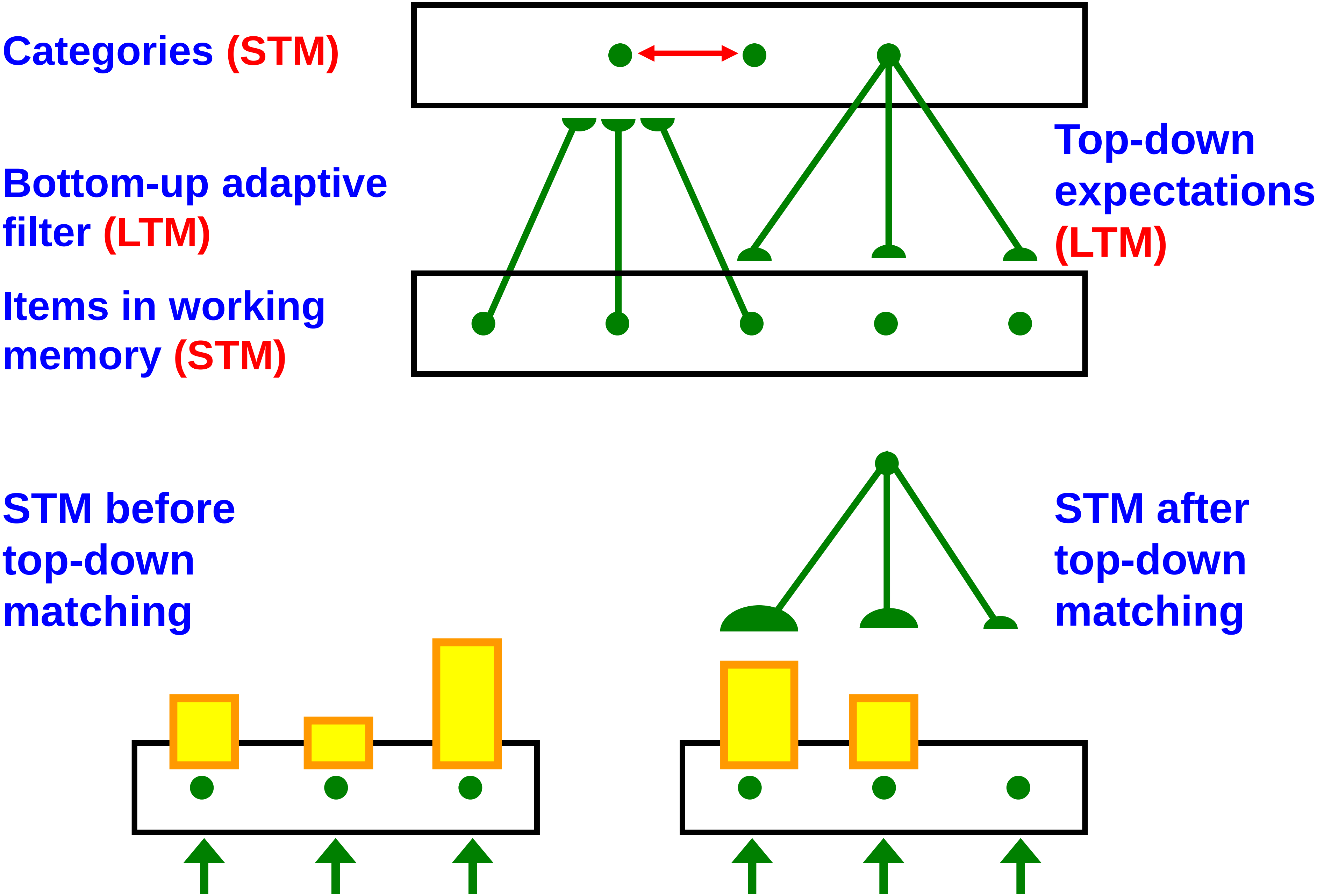
learn prototypes that

select consistent bottom-up signals

suppress inconsistent bottom-up signals (attentional focusing)

cannot by themselves fully activate target nodes (modulation, priming)

EXPECTATIONS FOCUS ATTENTION



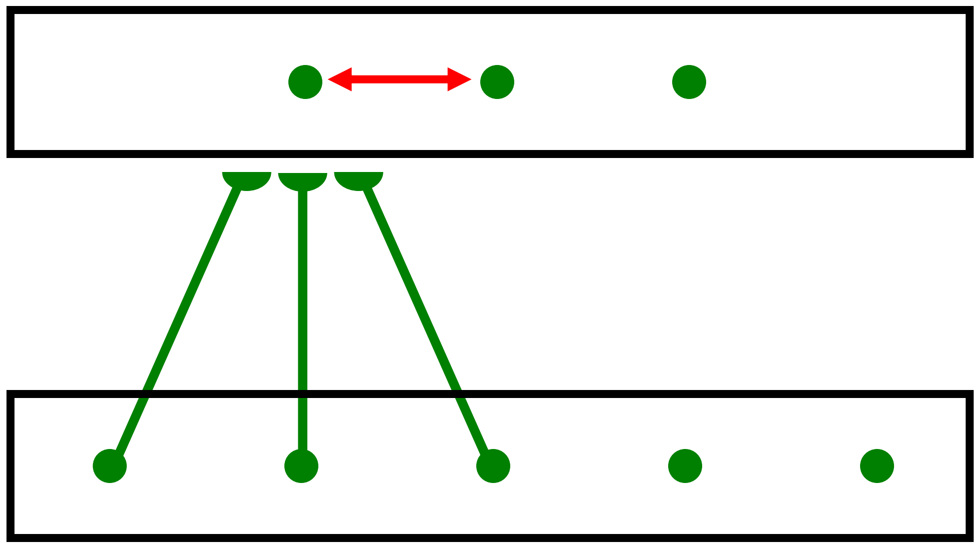
COMPETITIVE LEARNING
AND
SELF-ORGANIZING MAPS

Grossberg (1972, 1976), von der Malsburg (1973), Kohonen (1982)

List categories (STM)

Bottom-up adaptive filter (LTM)

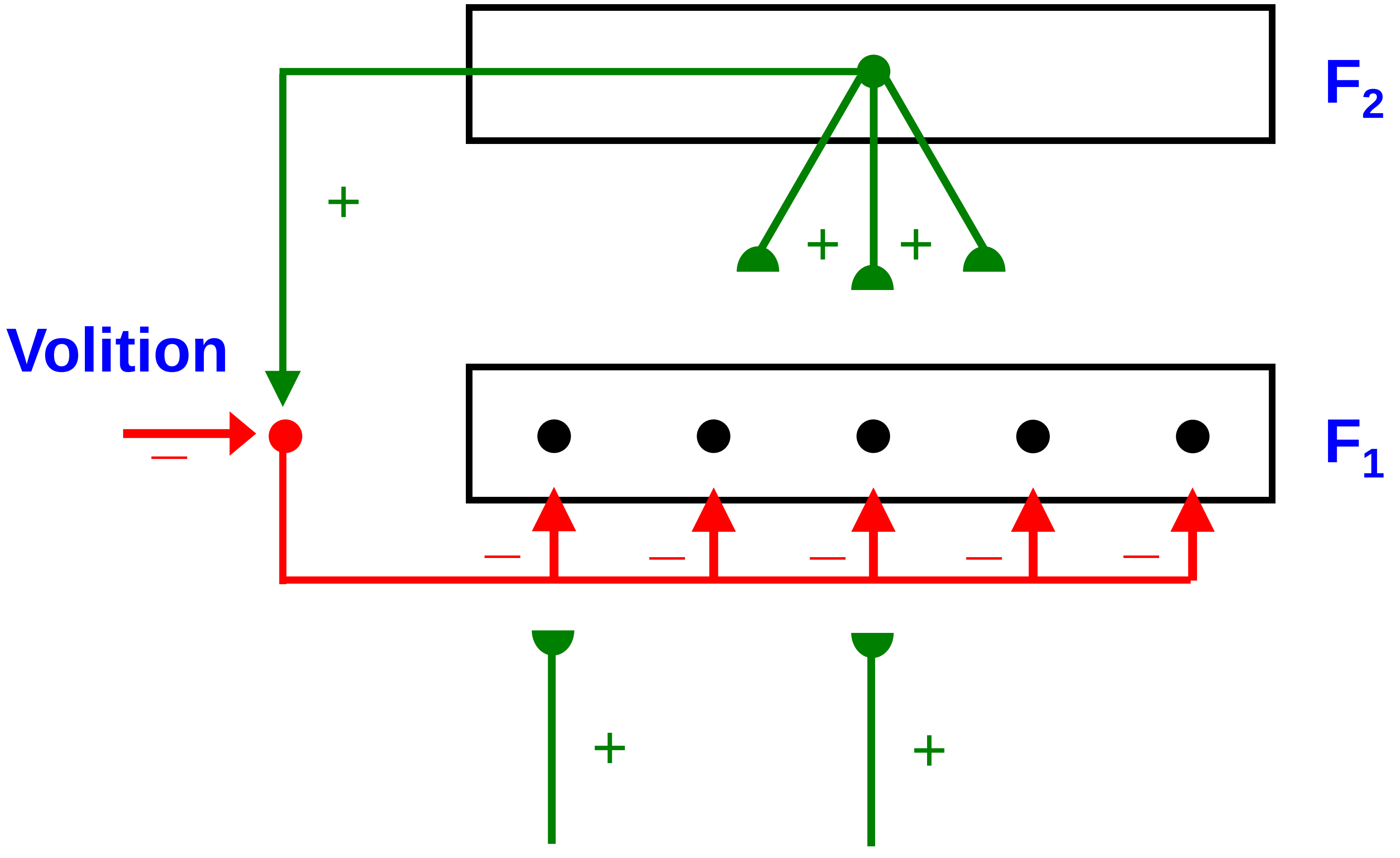
Items in working memory (STM)



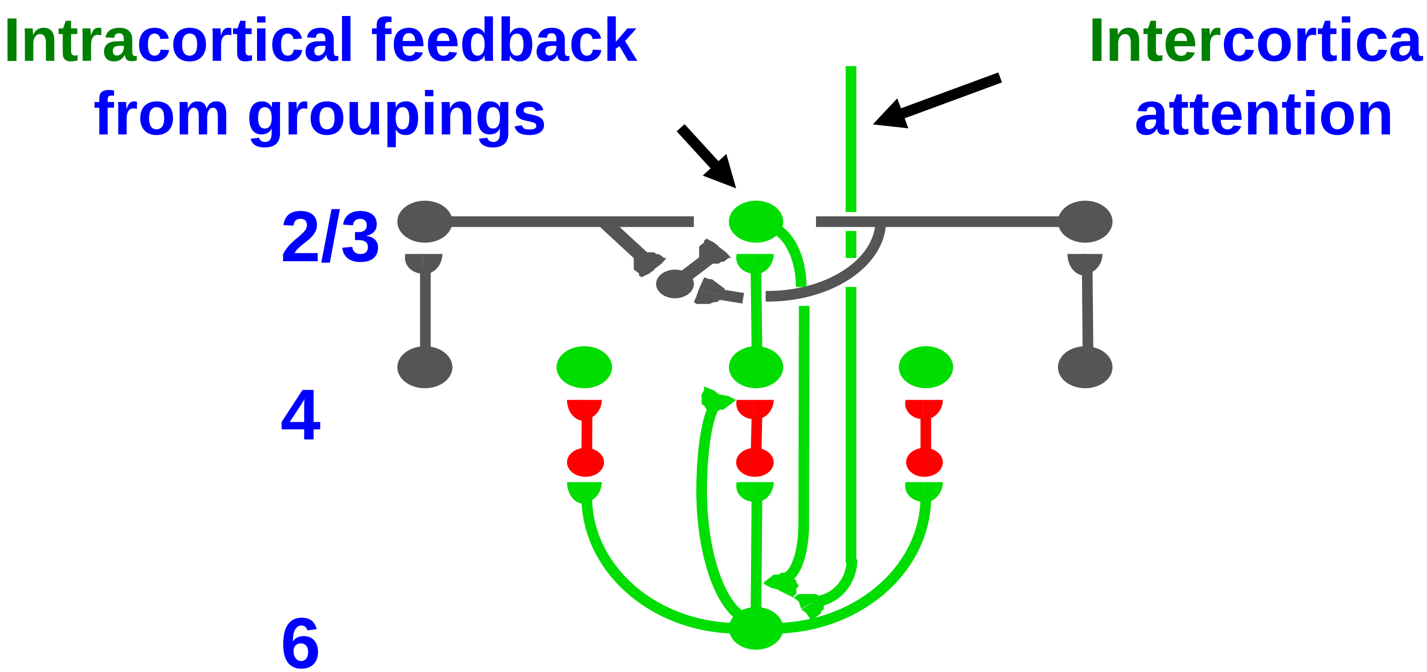
ART was introduced in 1976 to self-stabilize CL and SOM learning using top-down EXPECTATIONS and ATTENTION

ART MATCHING RULE

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



LAMINAR COMPUTING: GROUPING AND ATTENTION SHARE THE SAME MODULATORY CIRCUIT



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

INTRAcortical loop
pre-attentively stabilizes learning
INTERcortical loop
attentively stabilizes learning

SUPPORT FOR ART PREDICTION:
EXPECTATION, MATCHING, AND ATTENTION

There is a link between

TOP-DOWN EXPECTATION

COOPERATIVE-COMPETITIVE MATCHING

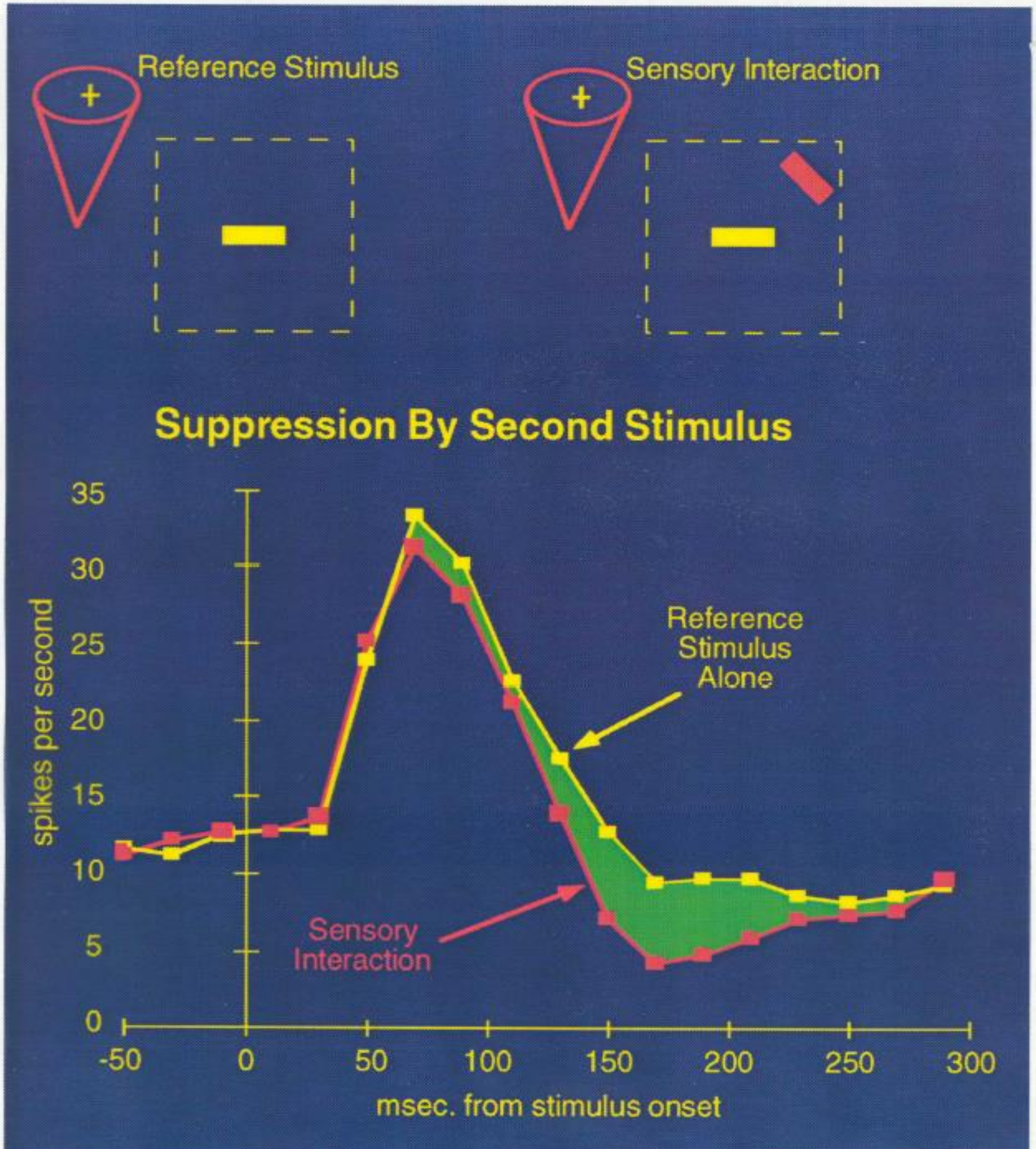
ATTENTION

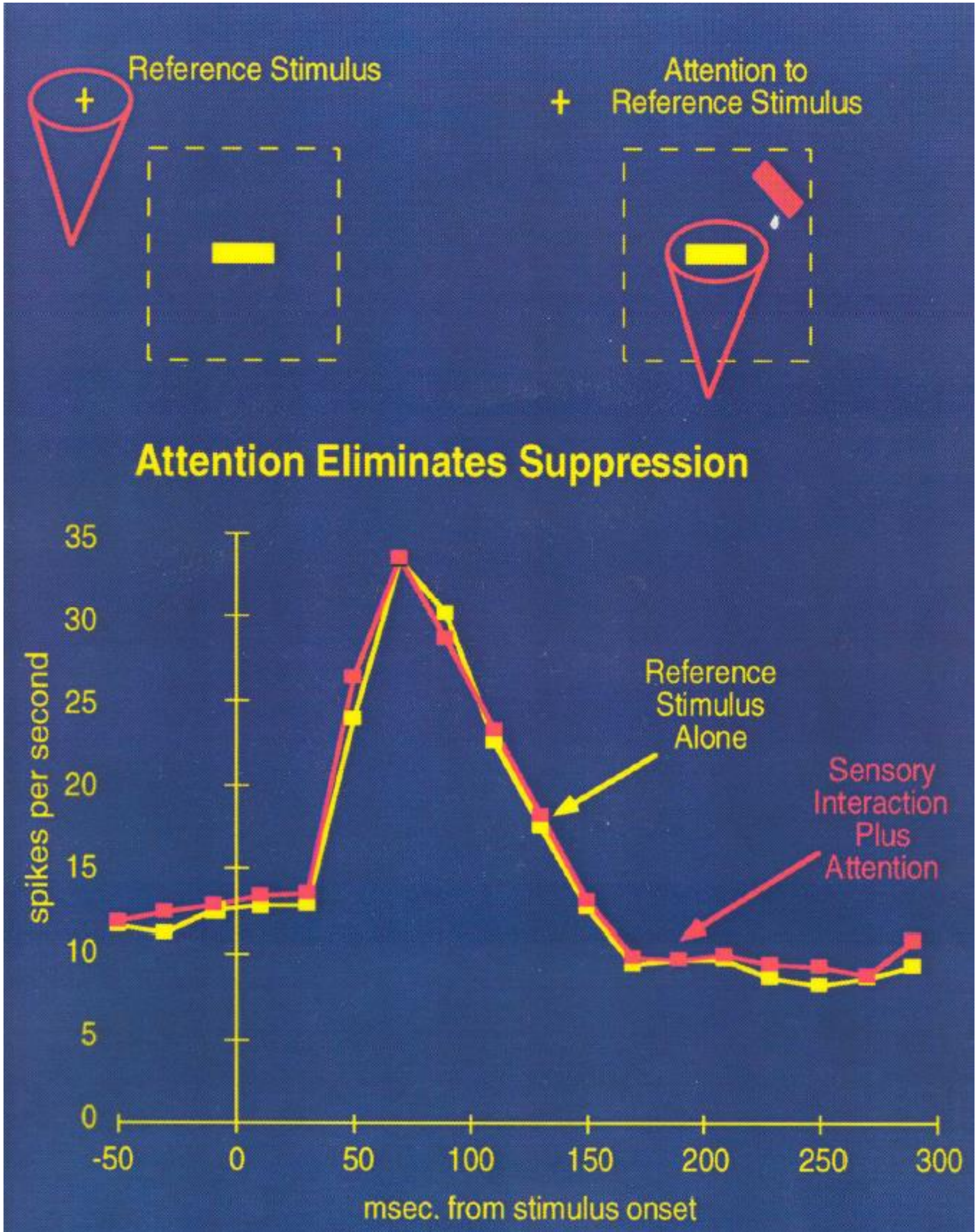
ART MATCHING IN PRESTRIATE VISUAL CORTEX

Reynolds, J., Nicholas, J., Chelazzi, L., & Desimone, R. (1995)

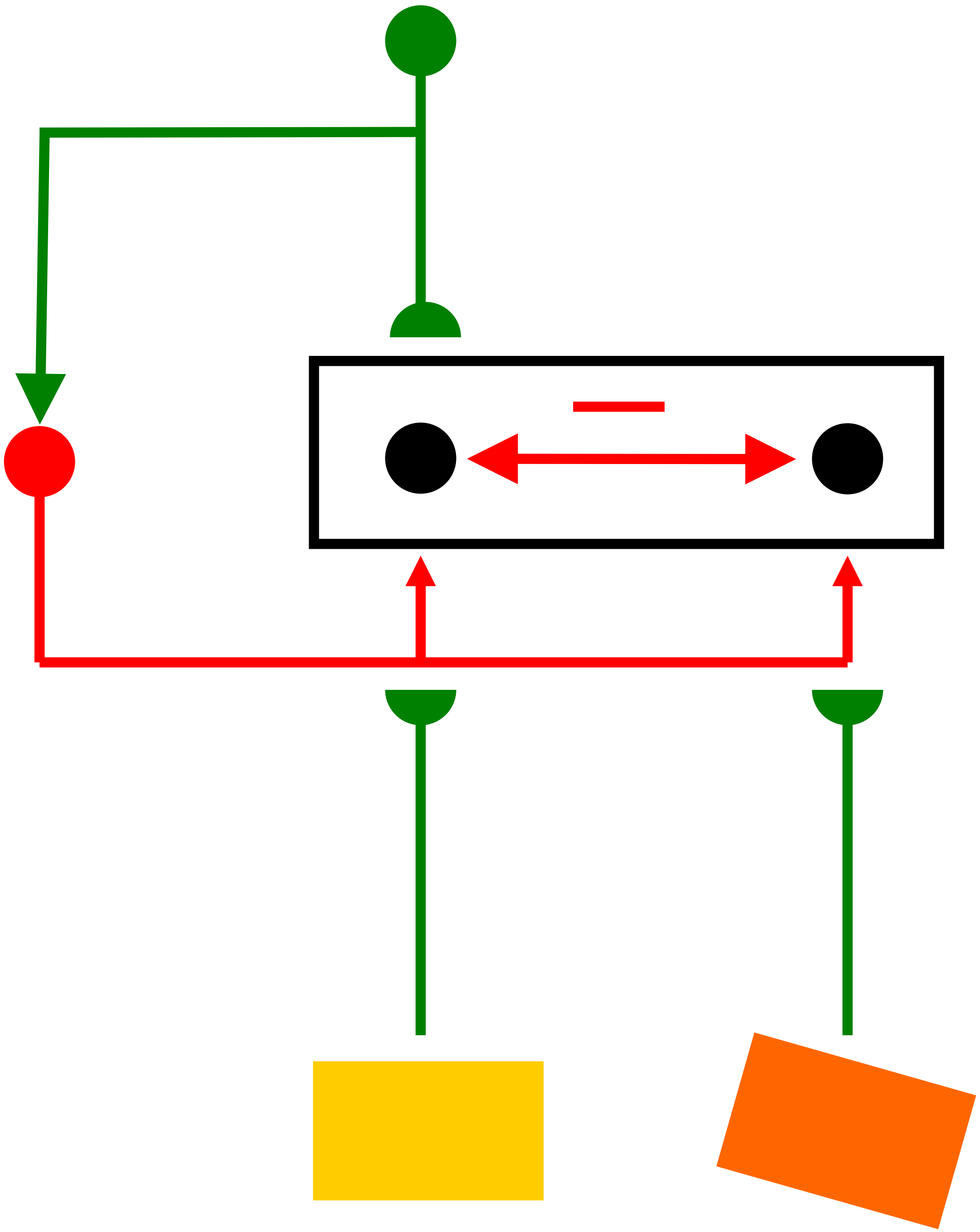
Spatial attention protects macaque V2 and V4 cells from the influence of non-attended stimuli

Society for Neuroscience Abstracts, 1995, 693.1, page 356

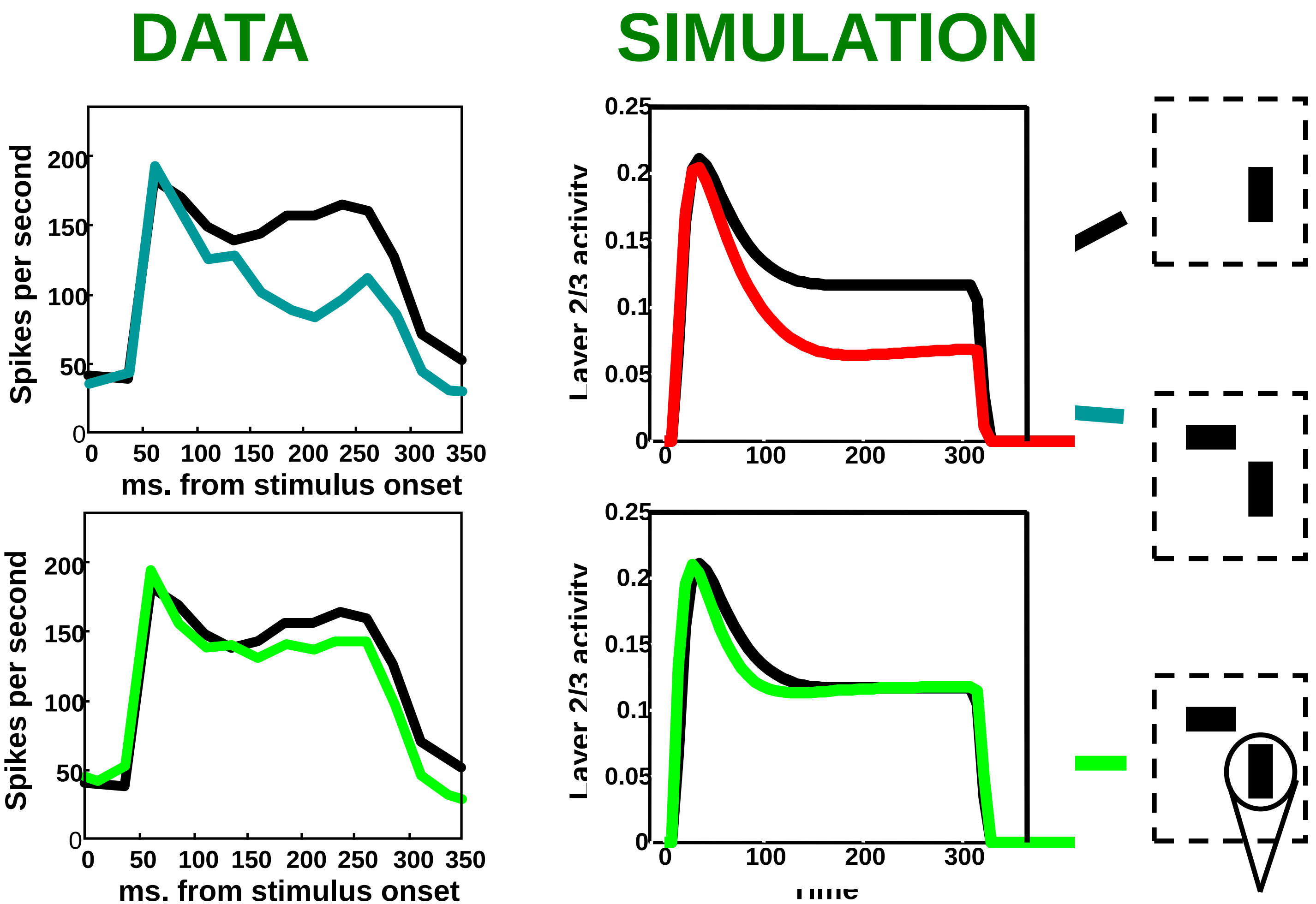

Reference Stimulus
Sensory Interaction
Suppression By Second Stimulus
spikes per second
35
30
25
20
15
10
5
0
-50
0
50
100
150
200
250
300
msec. from stimulus onset
Reference Stimulus Alone
Sensory Interaction


Reference Stimulus
Attention to
Reference Stimulus
Attention Eliminates Suppression
35
30
25
20
15
10
5
0
spikes per second
-50
0
50
100
150
200
250
300
msec. from stimulus onset
Reference
Stimulus
Alone
Sensory
Interaction
Plus
Attention

EXPLANATION OF REYNOLDS ET AL. DATA



SIMULATION OF REYNOLDS ET AL. (1995)

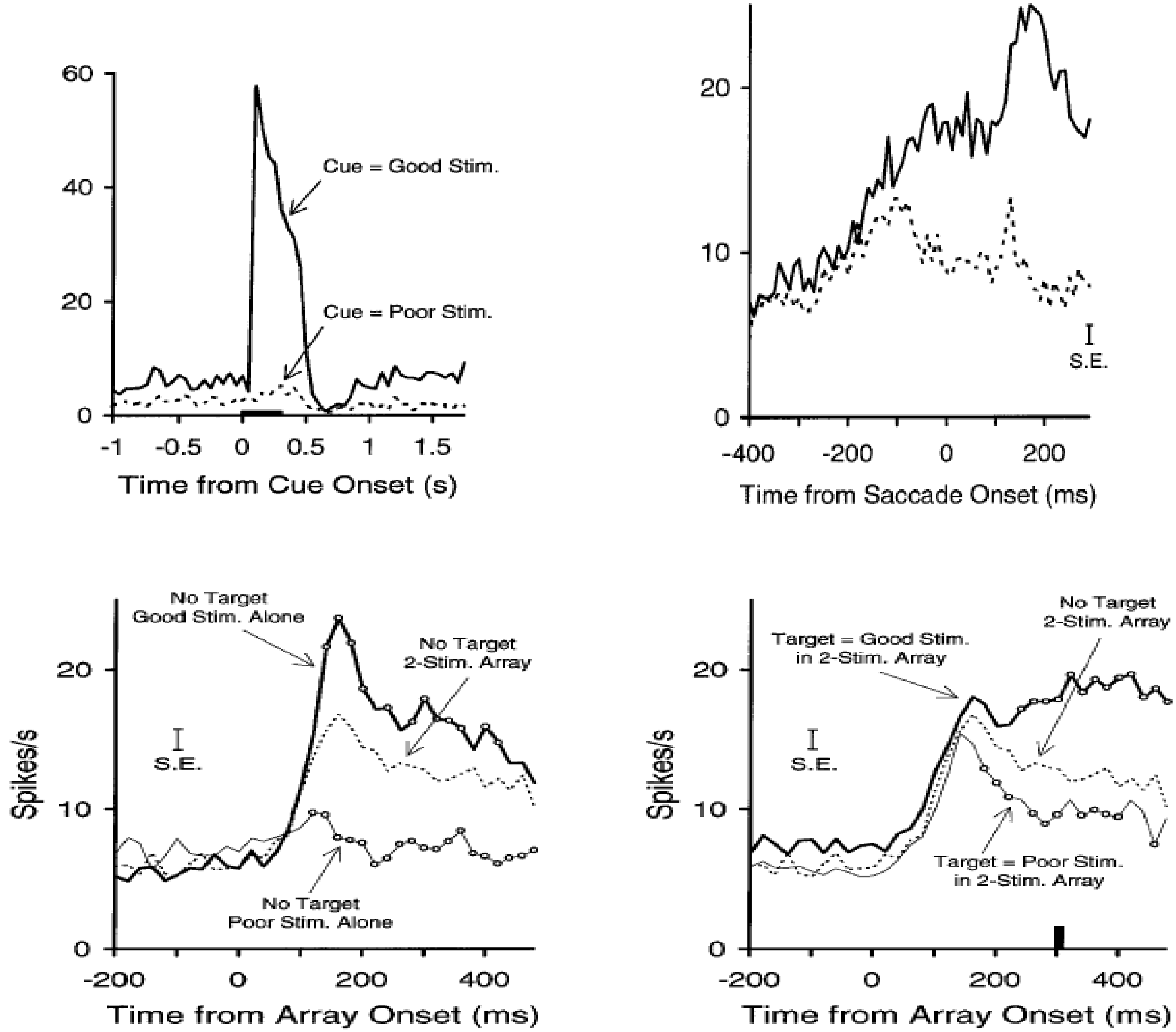


Data plots adapted with permission from Reynolds et al. (submitted)

IT CELLS DURING MEMORY-GUIDED SEARCH

Priming and Competition

Chelazzi, Duncan, Miller, and Desimone, 1998



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…

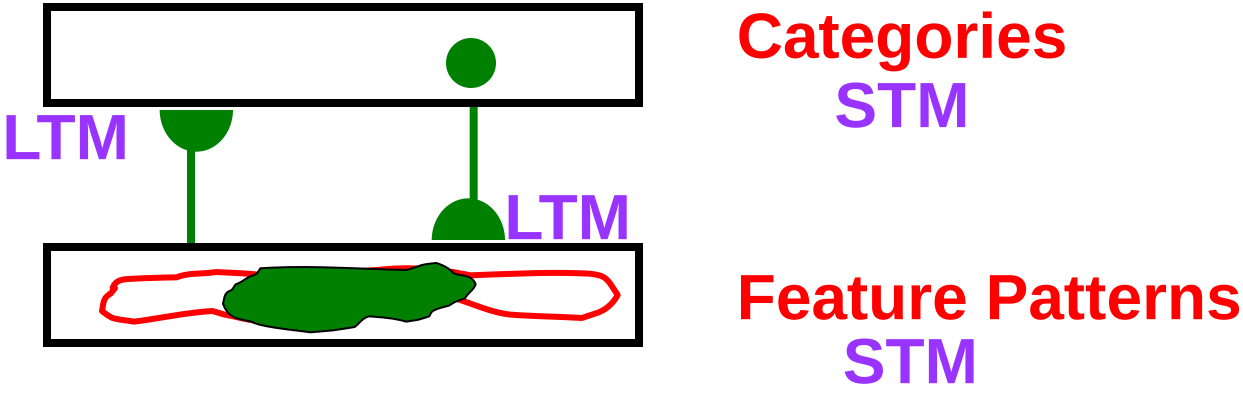
INCONSISTENT WITH MODELS WHERE TOP-DOWN MATCH IS SUPPRESSIVE

Mumford, 1992
Rao and Ballard, 1999

ADAPTIVE RESONANCE

Attended featured clusters reactivate bottom-up pathways

Activated categories reactivate their top-down pathways



Resonance synchronizes
amplifies
prolongs system response

Resonance triggers learning in bottom-up and top-down
adaptive weights

ART RECONCILES COMPLEMENTARY UNCERTAINTIES OF SYMBOLIC AND DISTRIBUTED COMPUTATION

SYMBOLS VS. DISTRIBUTED FEATURES

Individual features are meaningless, just as individual pixels in a picture are meaningless out of context

Each symbol, or compressed category, can selectively represent an event, or prescribed global pattern of features, but it cannot represent the featural contents of the event

Resonance between these two types of information converts the pattern of attended features into a coherent context-sensitive state that is linked to its symbol through feedback. This coherent state binds distributed features and symbolic categories, and can enter consciousness

KEY ART PREDICTION

ALL CONSCIOUS STATES ARE RESONANT STATES

Grossberg, 1976

Growing neurophysiological support during the past several years for the predicted connection between:

LEARNING
EXPECTATION
ATTENTION
RESONANCE
CONSCIOUSNESS

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

SUPPORT FOR ART PREDICTIONS

LINK BETWEEN ATTENTION AND LEARNING

VISUAL PERCEPTUAL LEARNING

Ahissar and Hochstein, 1993

Also clarifies Watanabe et al (2002+) data on when attention is not needed for subliminal learning without consciousness

AUDITORY LEARNING

Gao and Suga, 1998

SOMATOSENSORY LEARNING

Krupa, Ghazanfar, and Nicolelis, 1999
Parker and Dostrovsky, 1999

SUPPORT FOR ART PREDICTIONS

LINK BETWEEN ATTENTION AND SYNCHRONY

Engel, Fries, and Singer, 2001

Fries, Reynolds, Rorie, and Desimone, 2001

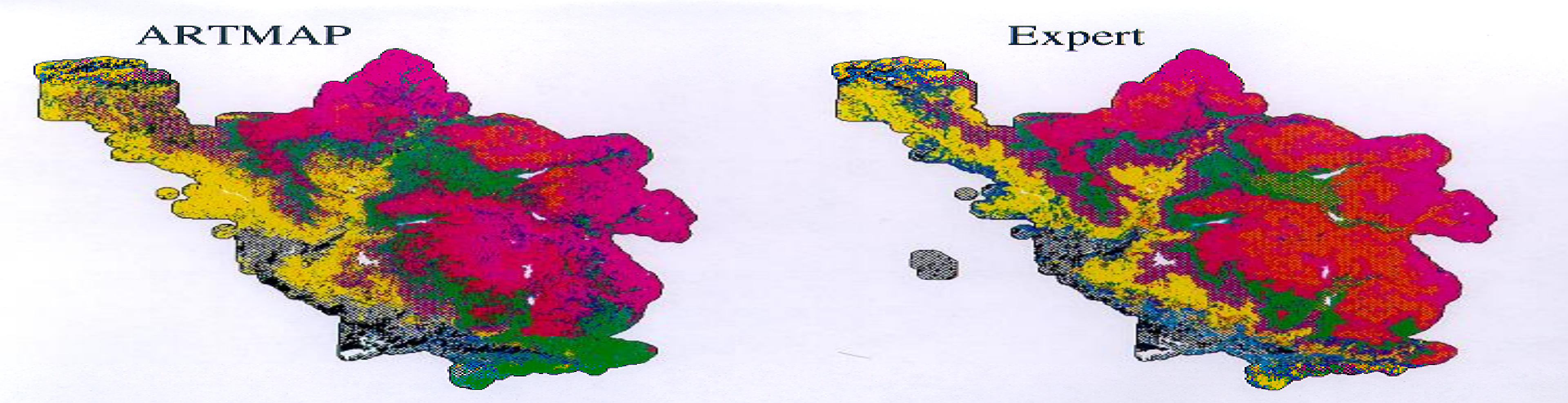
`` Pollen, 1999

ART & ARTMAP APPLICATIONS

Boeing parts design retrieval; used in 777 design
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

ART & ARTMAP APPLICATIONS

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



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

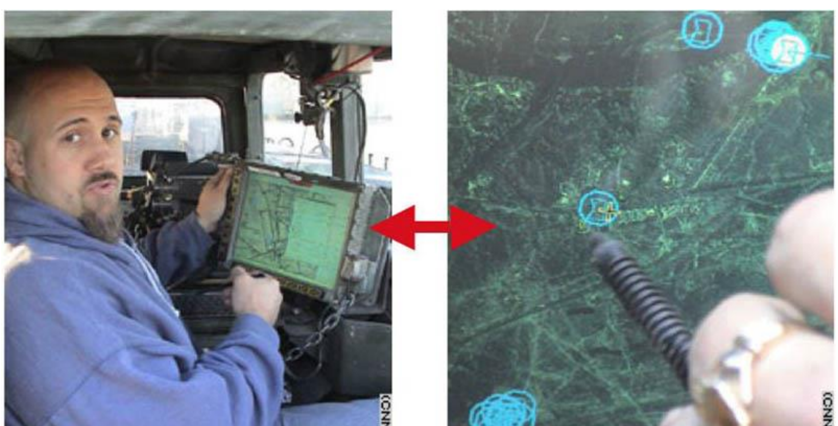
30*m* (pixel–level) scale: can see roads

Equal accuracy at test sites

RECENT MACHINE LEARNING PROJECT: INFORMATION FUSION IN REMOTE SENSING

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

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



Carpenter et al. (2004)

SOURCE 1
GOAL 1
SENSOR 1
TIME 1

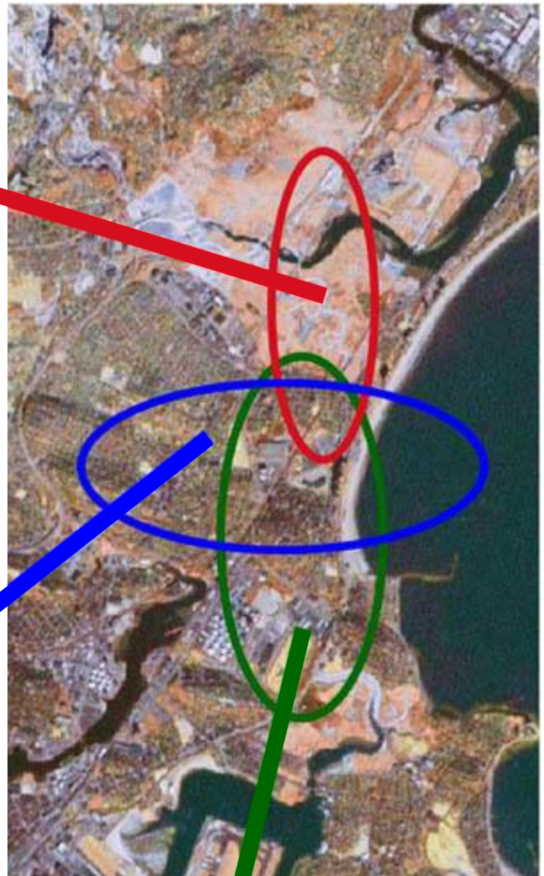
SOURCE 2
GOAL 2
SENSOR 2
TIME 2

SOURCE 3
GOAL 3
SENSOR 3
TIME 3

Boston testbed

CONSISTENT KNOWLEDGE FROM INCONSISTENT DATA

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

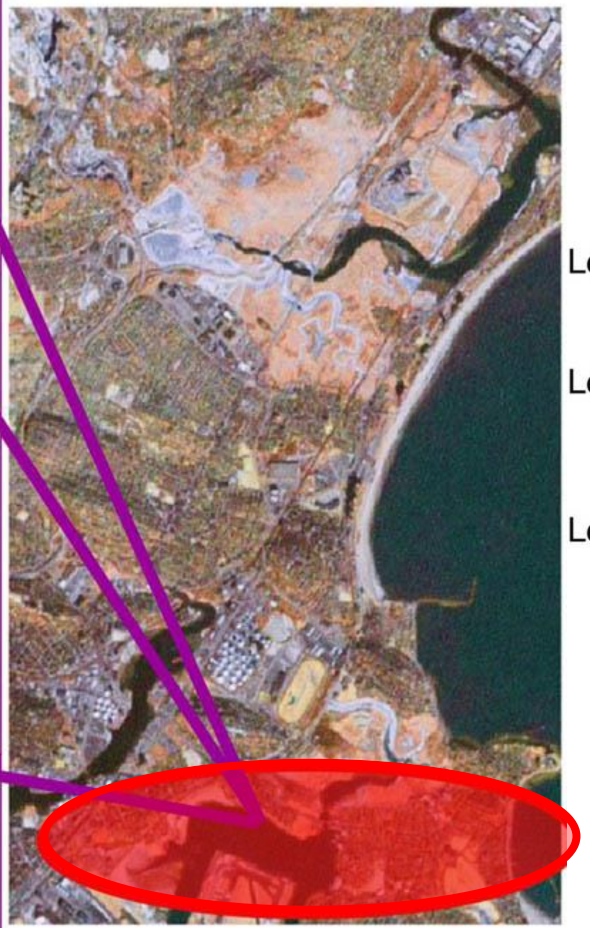
Solution 2:
Distributed ARTMAP MODEL:
Fast, automatic, easy to deploy
NO PRIOR RULES OR DOMAIN KNOWLEDGE

Self-organizing expert system

SELF-ORGANIZED KNOWLEDGE HIERARCHY

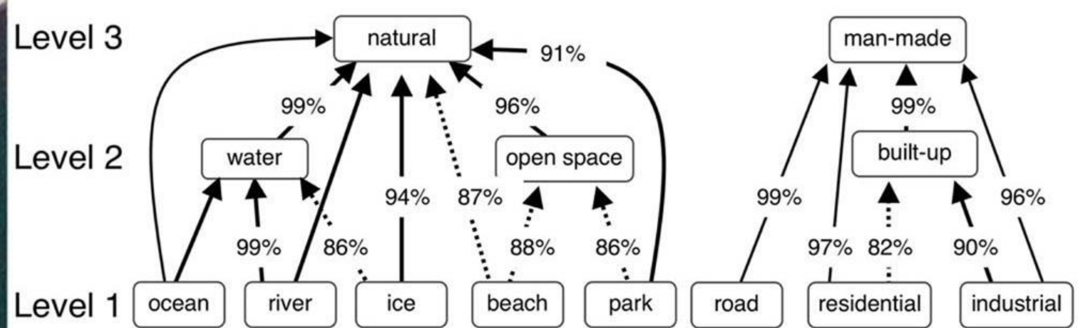
Distributed predictions across test set pixels

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

WHY IS ART USED IN SO MANY APPLICATIONS?
DESIRED LEARNING PROPERTIES

Rare events

need fast learning

Large non-stationary data bases

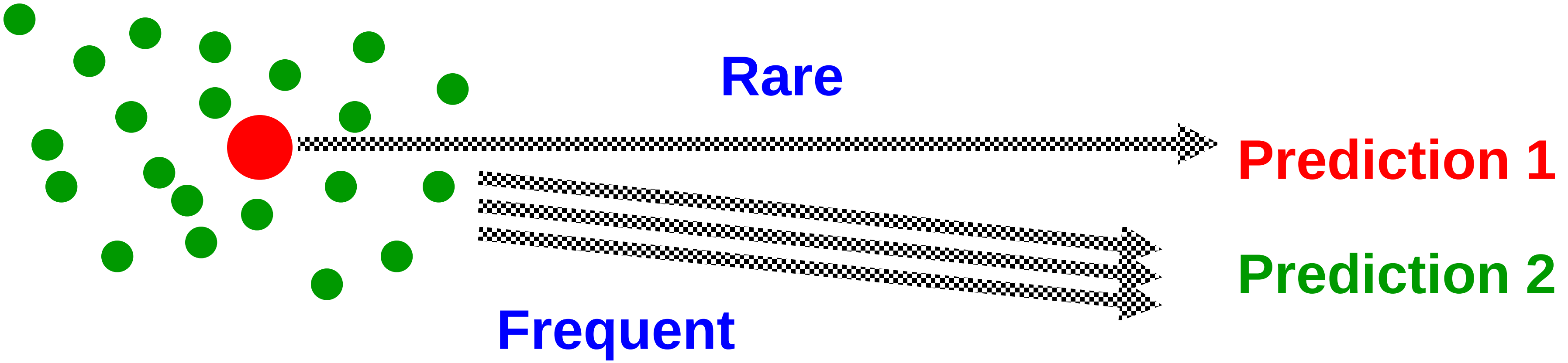
need self-stabilizing learning

Morphologically variable events (fine/coarse)

need multiple scales of generalization

One-to-many and many-to-one relationships

need categorization, naming, and expert knowledge



ARTMAP PROPERTIES

To realize these properties, ARTMAP systems:

Pay attention

- **Ignore masses of irrelevant data**

Test hypotheses

- **Discover predictive constraints hidden in data streams**

Choose best answers

- **Quickly select a globally optimal solution at any stage of learning**

Calibrate confidence

- **Measure on-line how well a hypothesis matches the data**

Discover rules

- **Identify transparent IF-THEN relations at each learning stage**

Scale

- **Preserve all desirable properties in arbitrarily large problems**

KEY ART THEMES

Why do we pay attention?

Why do we learn expectations about the world?

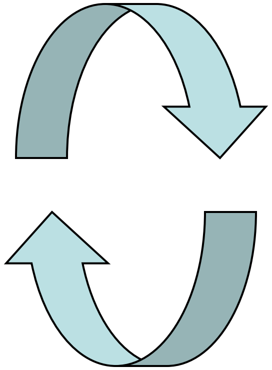
Role of top-down processing

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

ART MAIN IDEA

Top-down attentive feedback
encodes
learned expectations
that
self-stabilize learning
in response to
arbitrary temporal sequences
of input spatial patterns in
real time

Attentive Information Processing



Learning and Memory

FAST

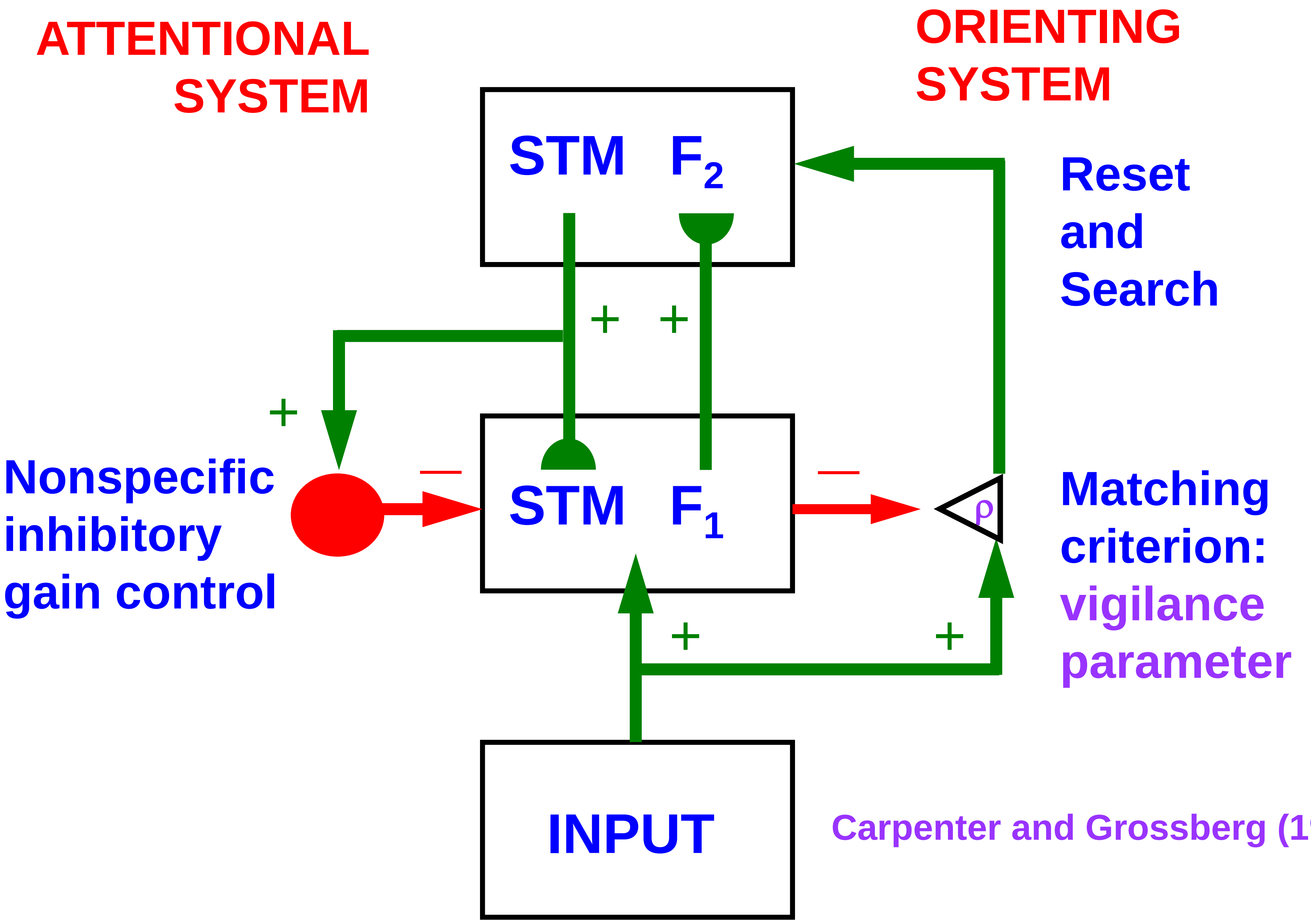
SLOW

ART

COMPLEMENTARY Interacting Systems

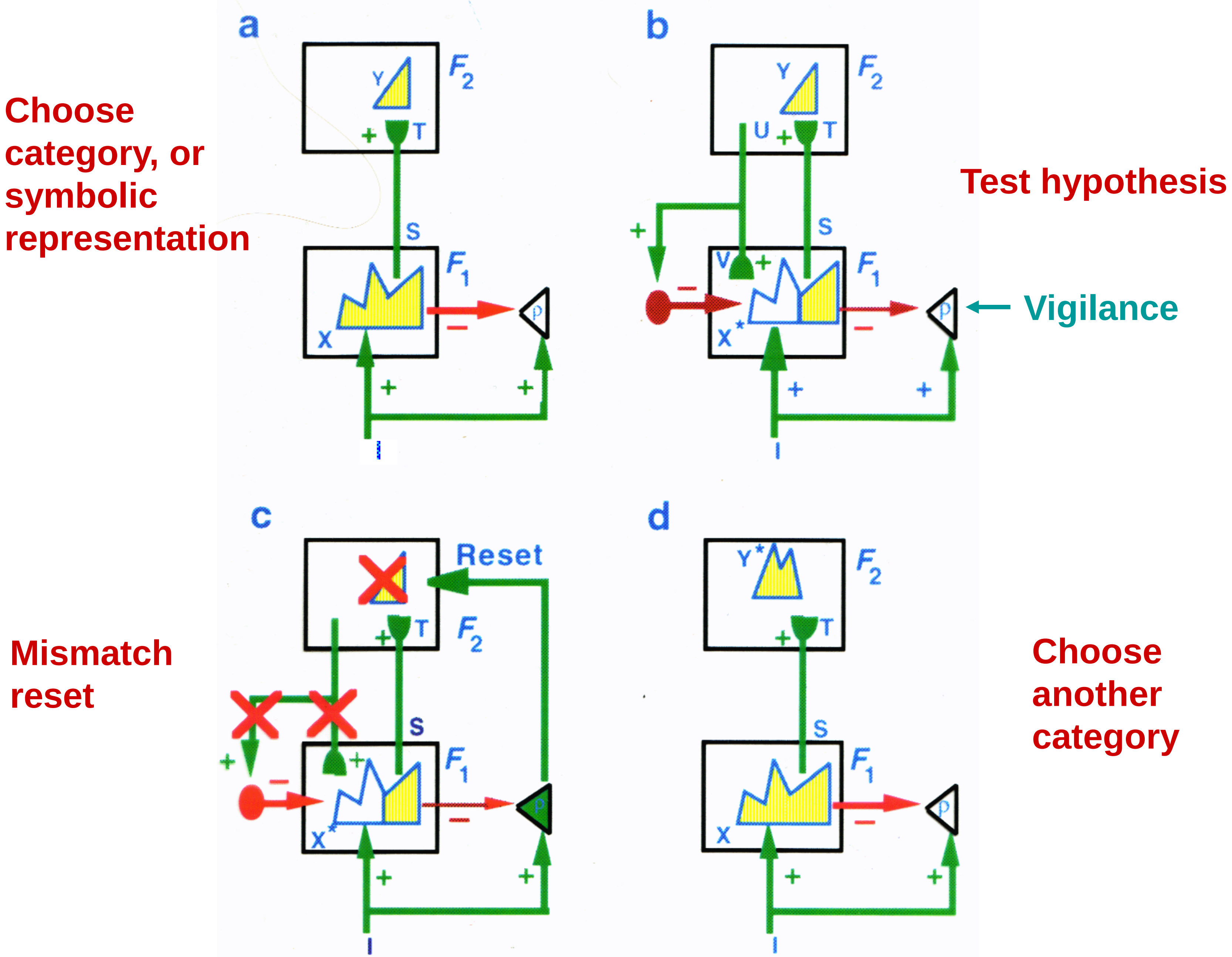
Attentional System ⟷	Orienting System
Expected Events	Unexpected Events
Familiar Events	Unfamiliar Events
Resonance	Reset
Attention	Memory Search
Learning	Hypothesis Testing
Recognition	
Temporal cortex Prefrontal cortex	Hippocampal system

ART 1 MODEL



Carpenter and Grossberg (1987)

ART HYPOTHESIS TESTING AND LEARNING CYCLE



SUPPORT FOR HYPOTHESIS TESTING CYCLE

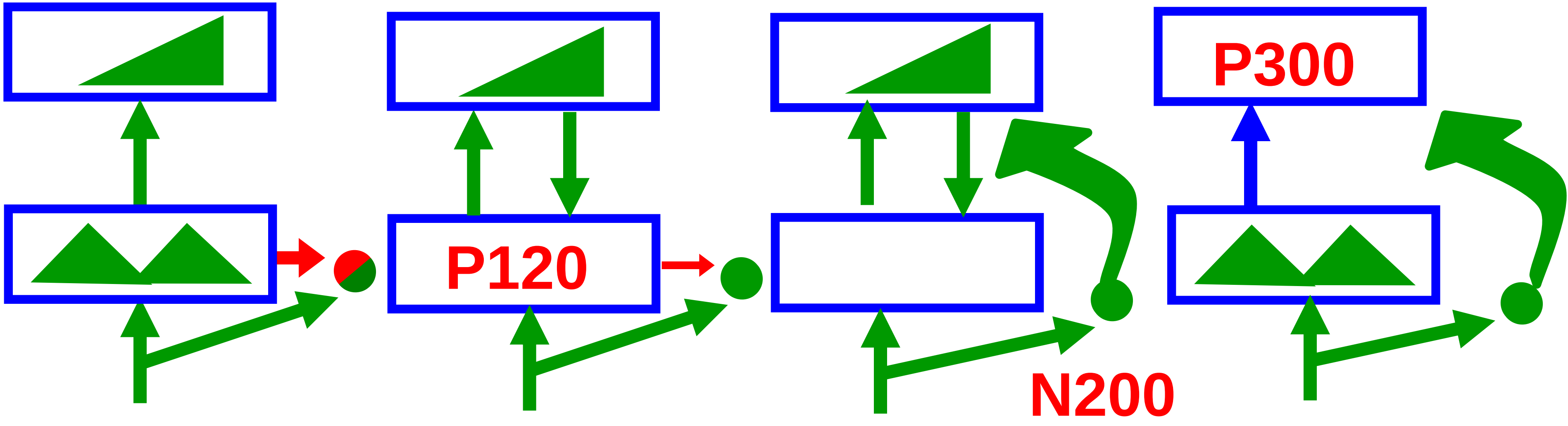
Event-Related Potentials: Human Scalp Potentials

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)



ART LEARNING CYCLE

A dynamic cycle of

RESONANCE

and

RESET

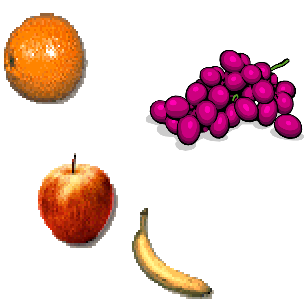
As inputs are learned, search automatically disengages and direct access to globally best-matching category occurs

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

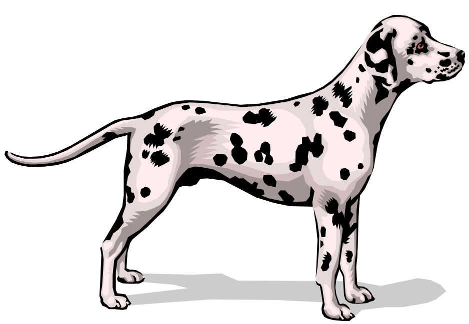
Explains how we can quickly recognize familiar objects and events even if, as we get older, we store enormous numbers of memories

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)

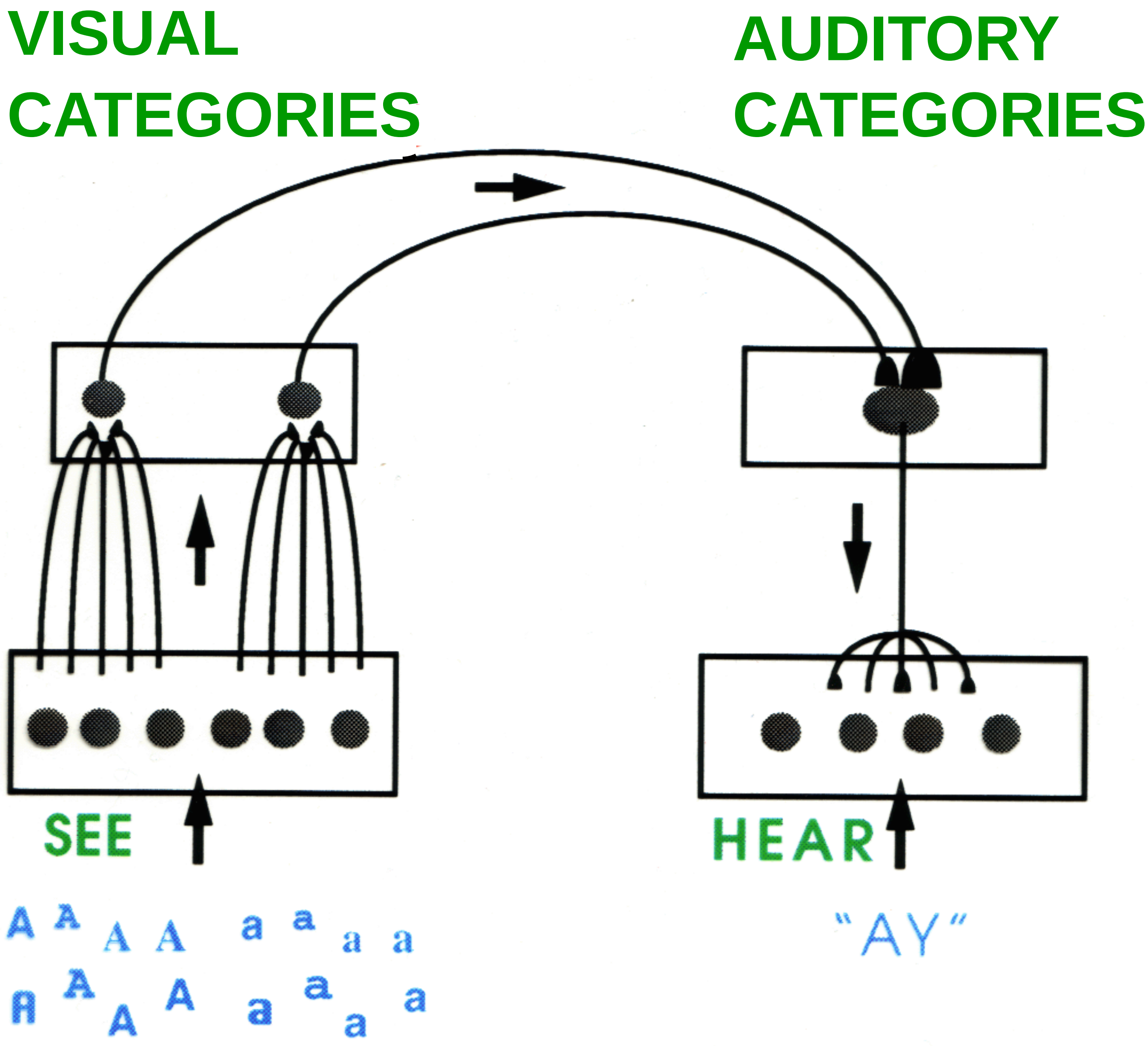


Fruit



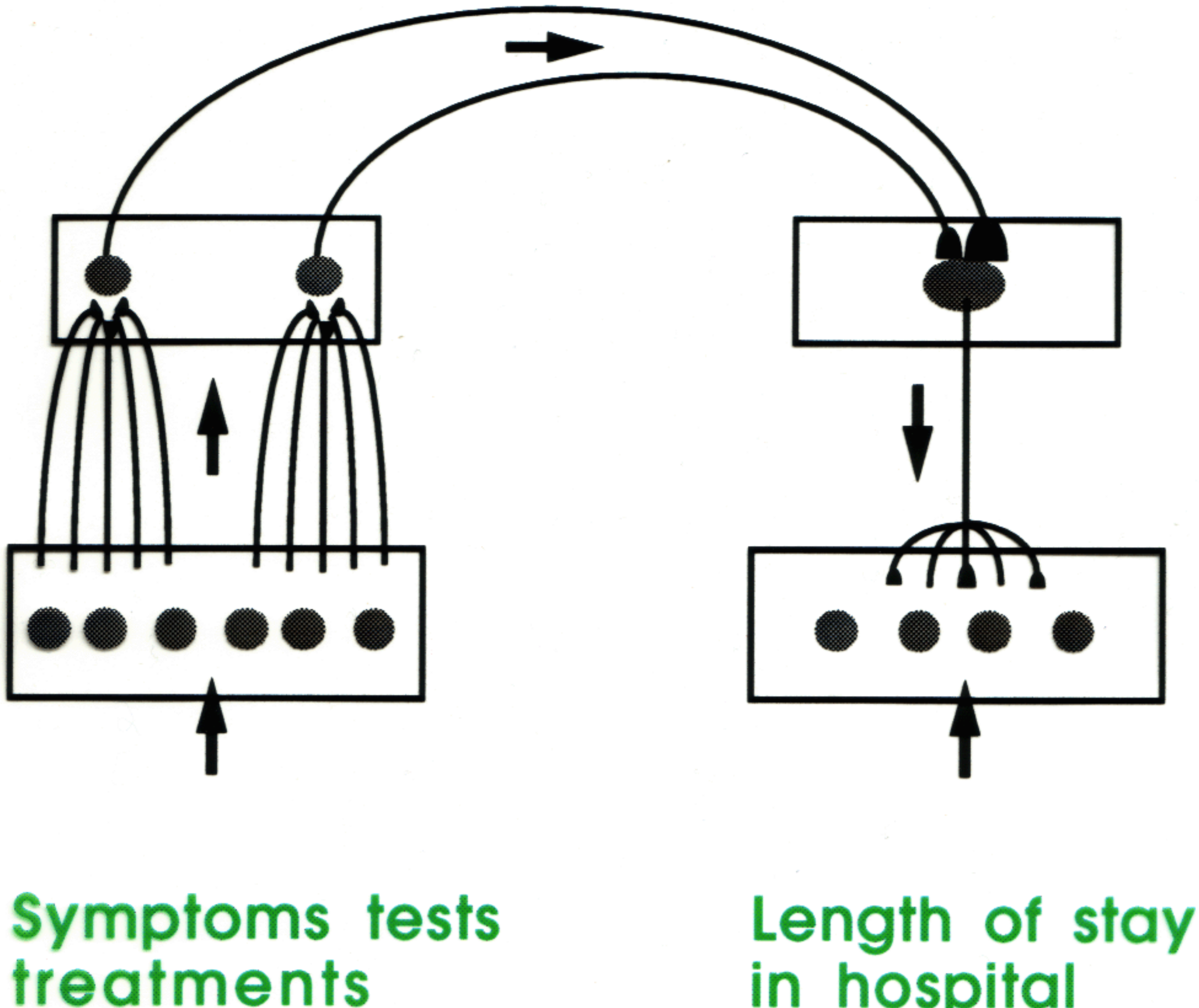
Animal
Mammal
Pet
Dog
Dalmatian
Fireman's Mascot
"Rover"

MANY-TO-ONE MAP
Two Stages of Compression



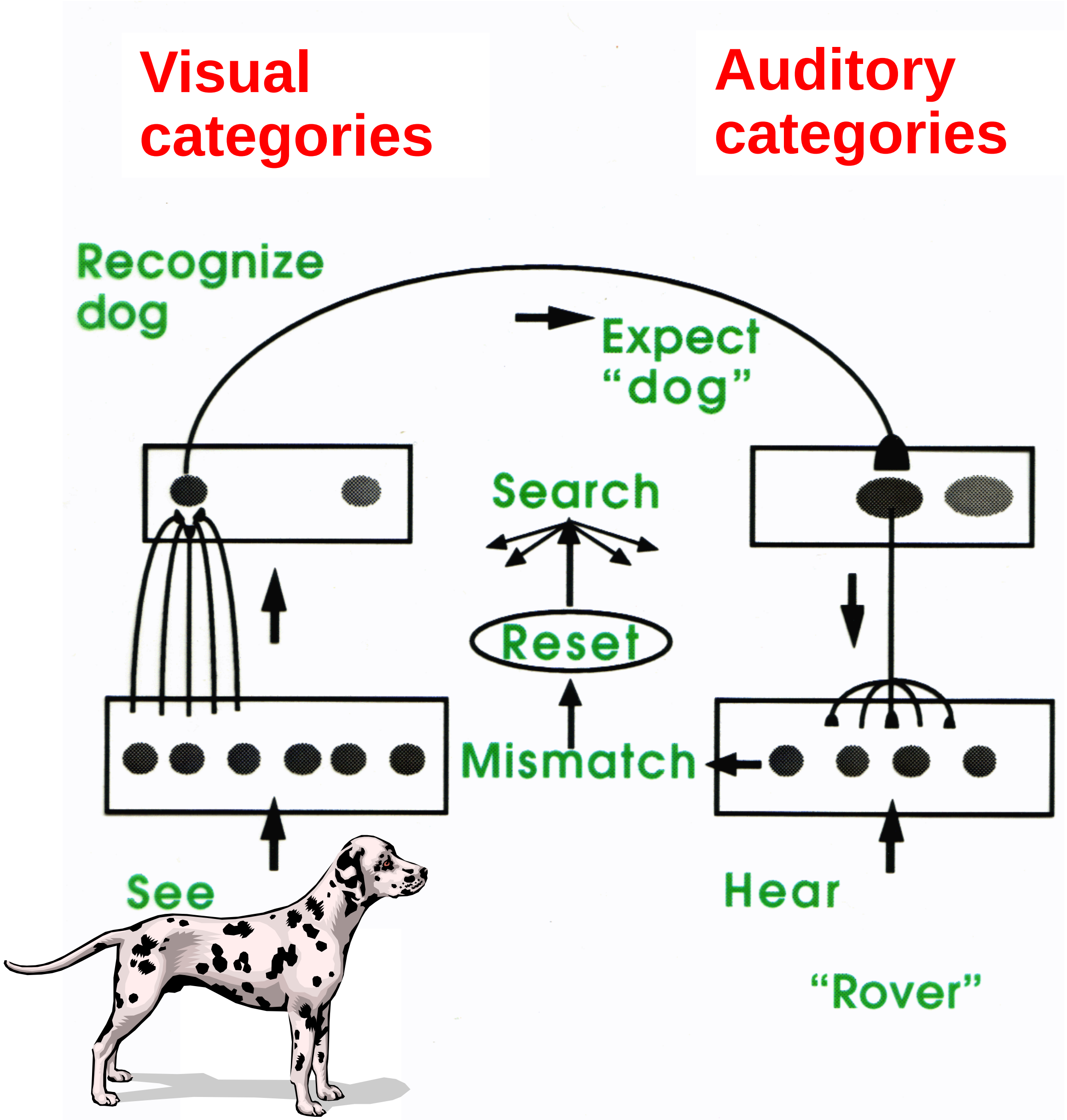
MANY-TO-ONE MAP

IF-THEN RULES



ONE-TO-MANY MAP

Expert Knowledge



VIGILANCE CONTROL

How do visual categories shape themselves

to fit the statistics of the environment?

How is the degree of abstractness or generalization

controlled?

Bridging between DISTRIBUTED PATTERN and SYMBOL

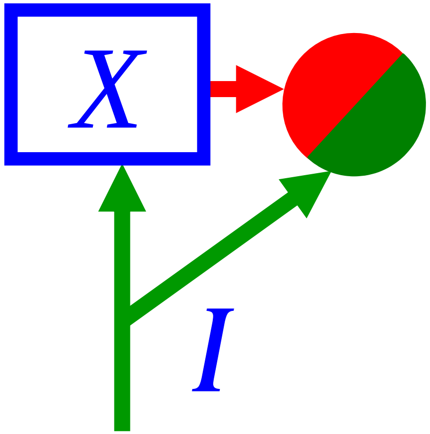
Low Vigilance – Broad Categories

High Vigilance – Narrow Categories

VIGILANCE CONTROL

$\rho|I| - |X| \leq 0$ **resonate and learn**

$\rho|I| - |X| > 0$ **reset and search**



ρ **is a sensitivity or gain parameter**

MINIMAX LEARNING PRINCIPLE

How to conjointly

minimize predictive error

and

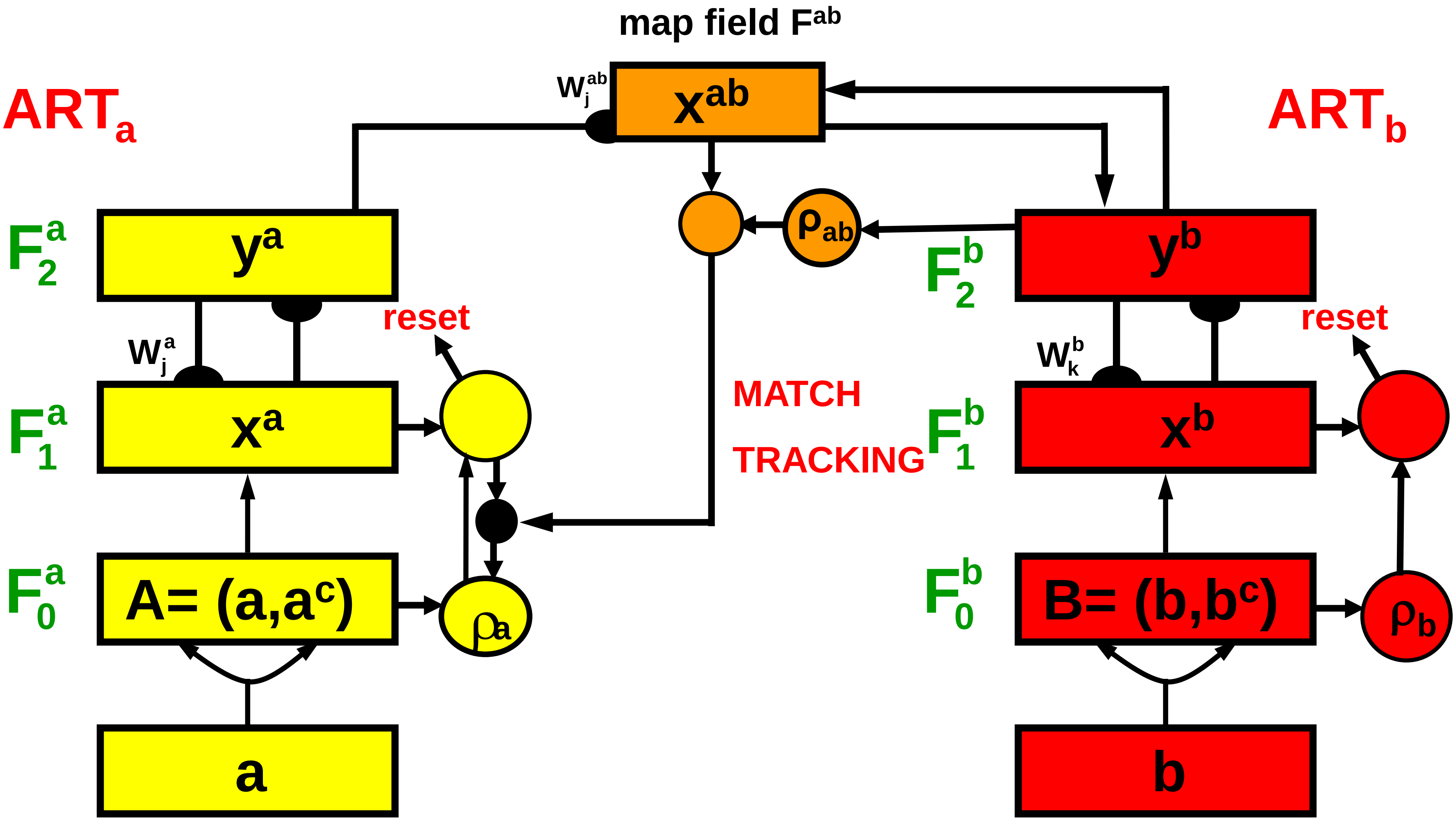
maximize generalization

using error feedback

in an incremental fast learning context

in response to nonstationary data?

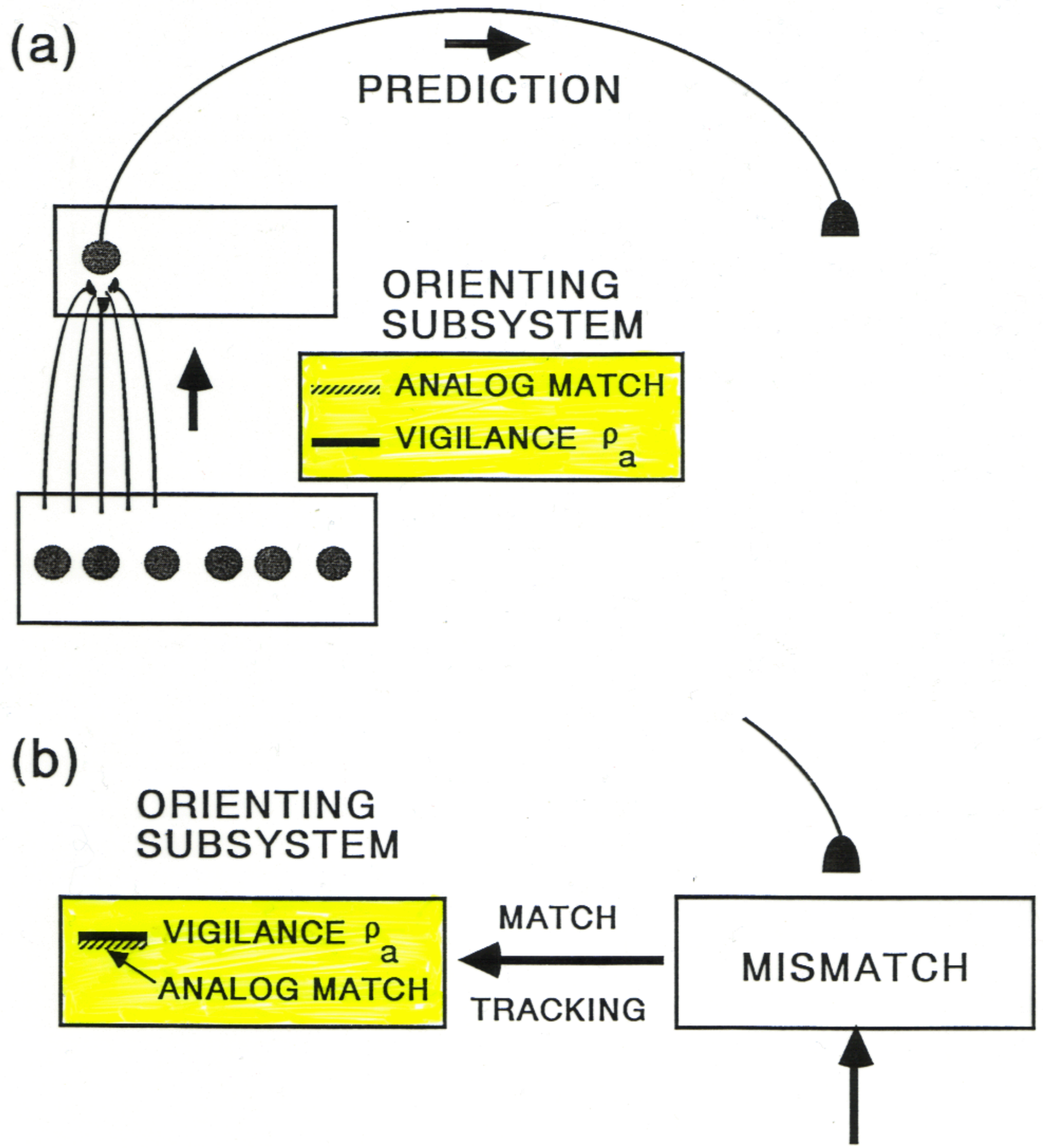
FUZZY ARTMAP



MATCH TRACKING realizes Minimax Learning Principle:

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

MATCH TRACKING



VIGILANCE CONTROL 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)

ACTIVE MATCHING AND RESET IN INFEROTEMPORAL CORTEX

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)

DYNAMIC PHASE OF MEMORY CONSOLIDATION

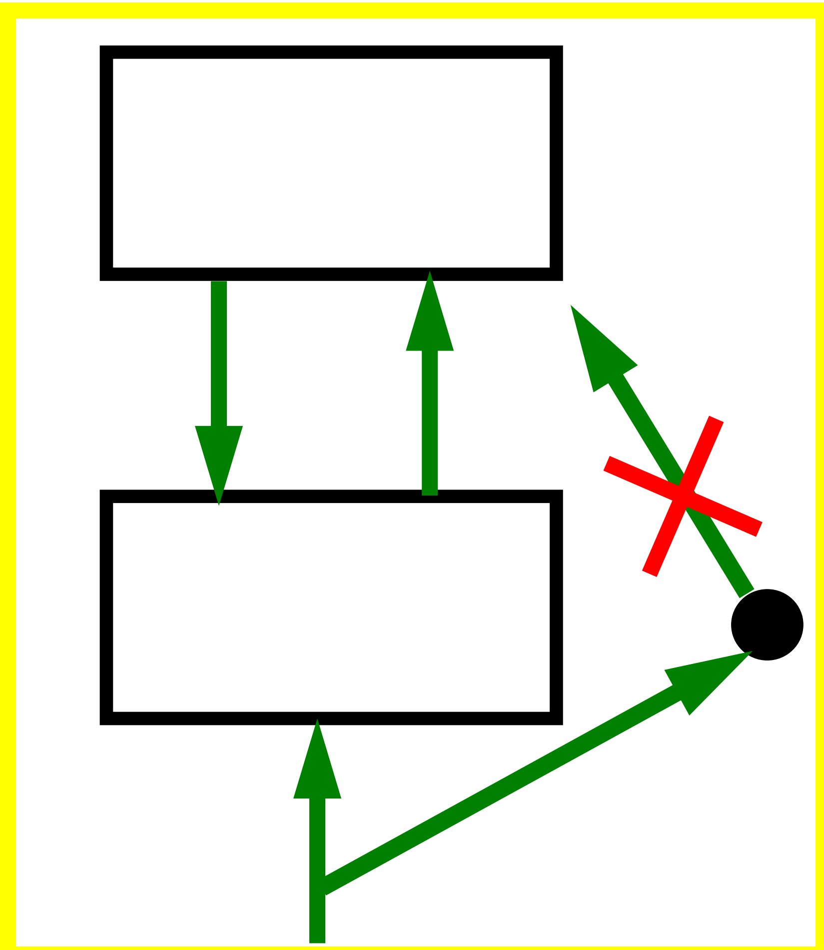
While input exemplar still drives memory search

Before direct access occurs

An emergent property of the entire circuit

A FORMAL AMNESIC SYNDROME:

Damage medical temporal brain structures – HIPPOCAMPUS



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)

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)

PREDICTION

The generators of novelty-related potentials in the

HIPPOCAMPAL FORMATION

Otto and Eichenbaum (1992)

influence the specificity of recognition codes learned by the

INFEROTEMPORAL CORTEX

Spitzer, Desimone, and Moran (1988)

SUPPORT FOR ART PREDICTIONS
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 also implicitly needs BU and TD feedback between exemplars and a category PROTOTYPE

GEDANKEN EXPERIMENT

Use a THOUGHT EXPERIMENT to introduce main ART ideas with a minimum of technical details

MAIN ISSUE:

How can a self-organizing system autonomously correct predictive errors?

A main tool:

PRINCIPLE OF SUFFICIENT REASON

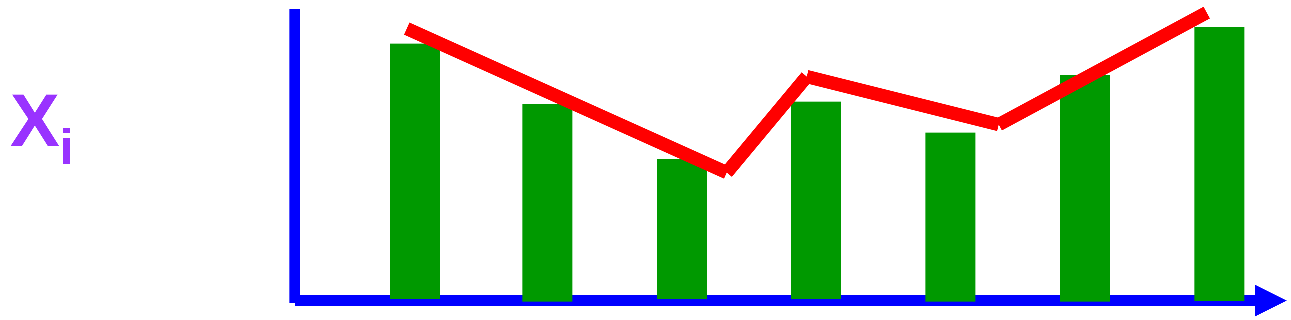
A main theme:

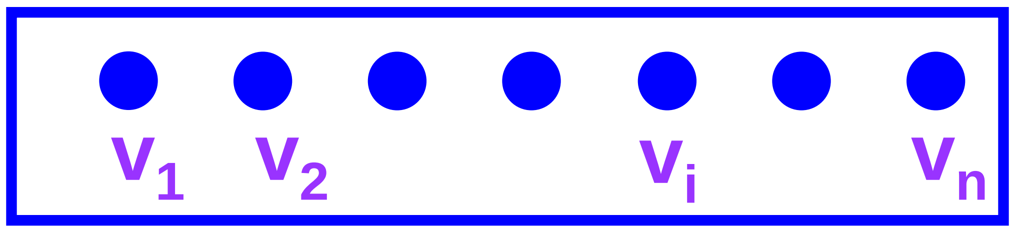
How COMPLEMENTARY types of information interact to correct errors during incremental learning about an ever-changing world

Derive data and predictions along the way

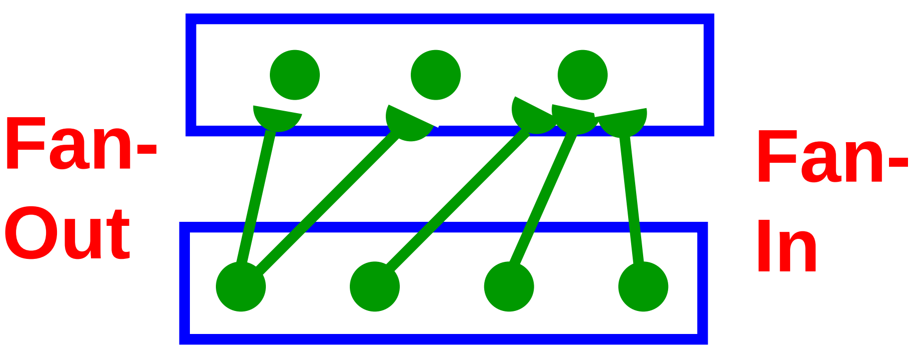
FUNCTIONAL UNIT

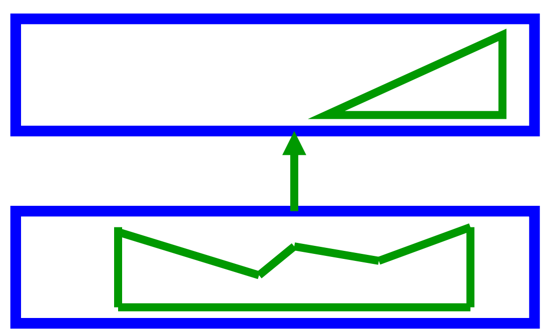
Pattern of Activity (Potential)





Write $X = (x_1, x_2, \ldots, x_i, \ldots, x_n)$





BASIC CODING STRUCTURE

Self-organizing Map

Competitive Learning

Learned Vector Quantization

Introduced by

1970-1978: Introduced by Grossberg & von der Malsburg

1980's:

Amari & Takeuchi

Cohen & Grossberg

Edelman

Grossberg & Kuperstein

Kohonen (his book greatly popularized the model)

Linsker

Rumelhart & Zipser

COMPETITIVE LEARNING/SELF-ORGANIZING MAP

Grossberg ,1976, Biol. Cybernetics, 23, 121

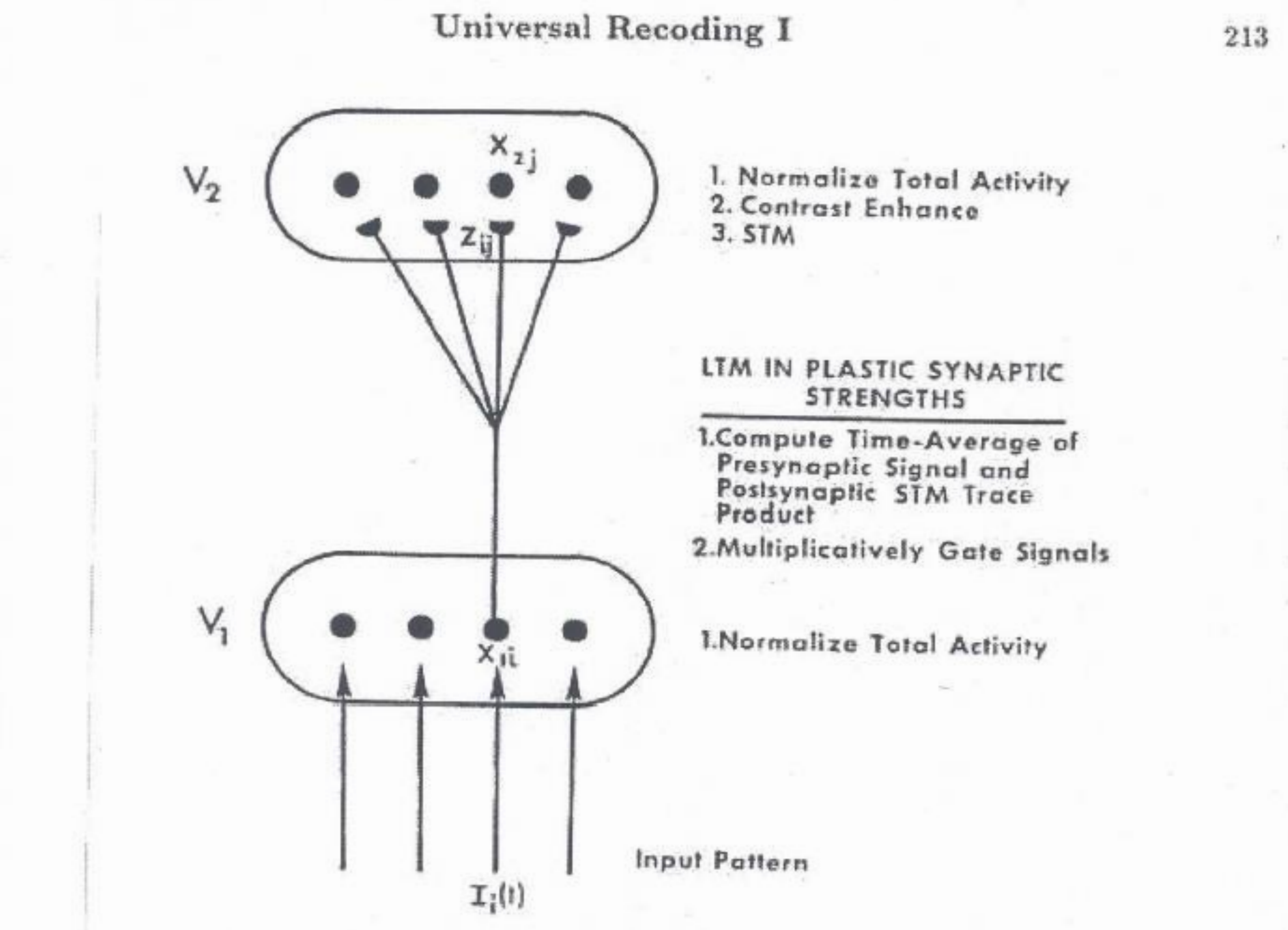
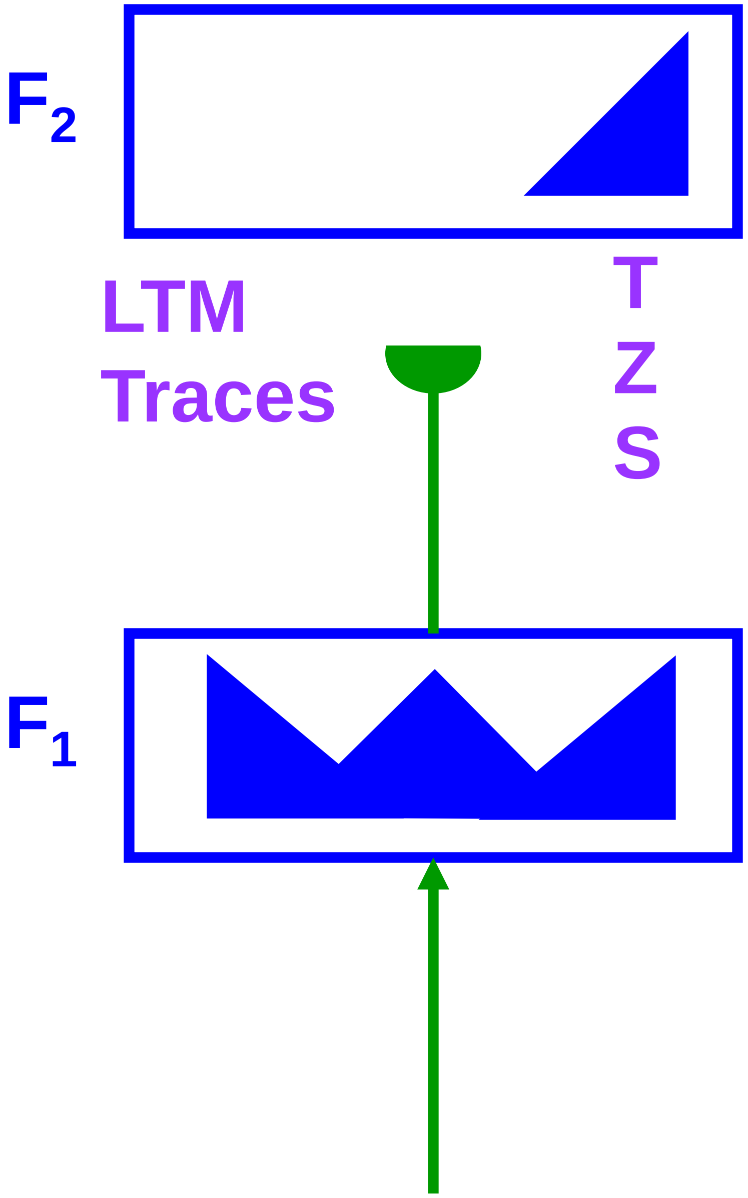


Figure 1. Minimal model of developmental tuning using STM and LTM mechanisms.

COMPETITIVE LEARNING/SELF-ORGANIZING MAP



Categories

Compressed STM representation

competition

Adaptive Filter

T=ZS

Features

Distributed STM representation

Inputs

STABLE SPARSE LEARNING THEOREM

Grossberg (1976)

In response to an input sequence to F_1 that does not form too many clusters relative to the number of coding nodes in F_2, learning is

stable

self-normalizing

tracks input statistics

Bayesian

In general, learning is unstable in response to a dense series of nonstationary inputs

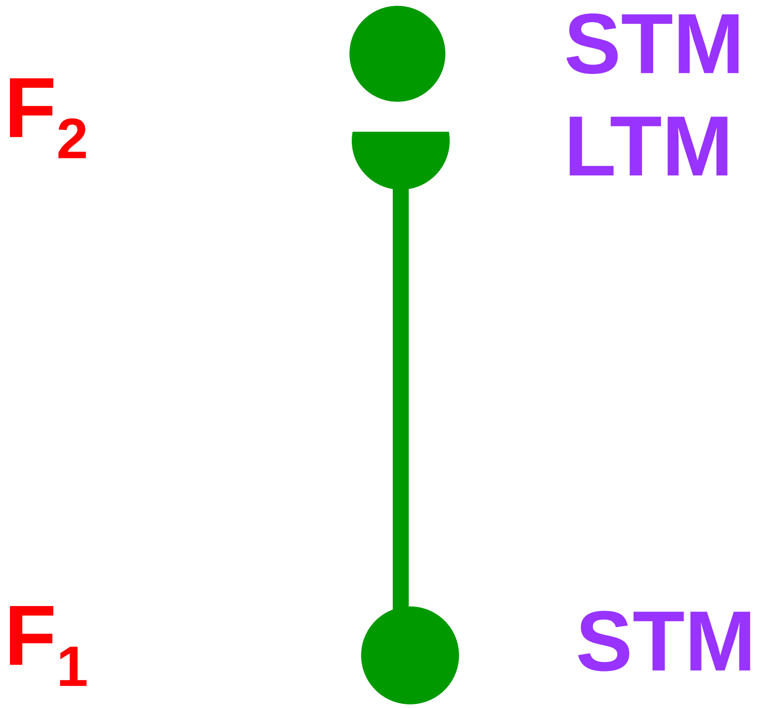
Recent learning can force unselective forgetting or catastrophic forgetting of older learning.

CAUSE OF INSTABILITY

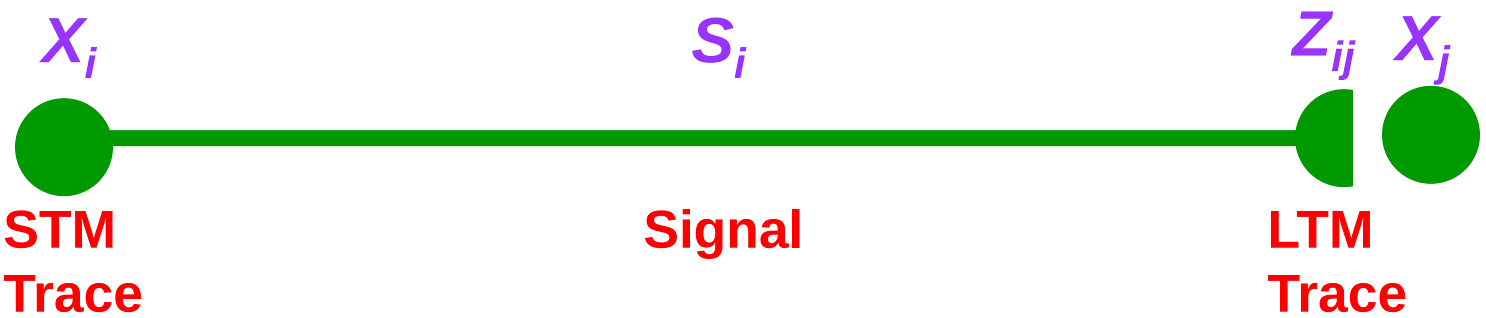
Two Good Properties! Incomplete, not "Wrong"

1. ASSOCIATIVE LEARNING

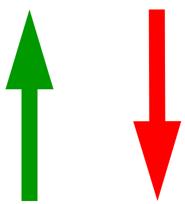
Pavlov, Hebb



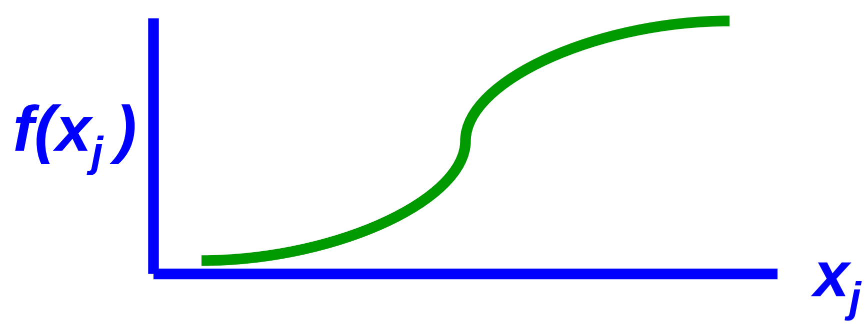
GATED STEEPEST DESCENT LEARNING



Gated Learning and Memory Decay
Steepest Descent



$$\frac{dz_{ij}}{dx} = Ef(x_j)\left[-z_{ij} + S_i\right]$$



Theory: Grossberg (1968+)

Experiments: Rauschecker and Singer, 1979; Levy et al, 1983

CAUSE OF INSTABILITY

2. CONTRAST ENHANCEMENT DUE TO LATERAL INHIBITION

Mach, Kuffler, Von Bekesy, Harline-Ratliff

Why Need It?

- **Compression**
- **Noise Suppression**
- **Stimulus Equivalence**

Shows how many F_1 patterns may be represented by one F_2 category

- **Recognition**
- **Coding**
- **Classification**
- **Abstraction**

A many-to-one transform from exemplar to category

FROM SOM TO ART

How to augment the

ADAPTIVE FILTERING
COMPETITION
ASSOCIATIVE LEARNING

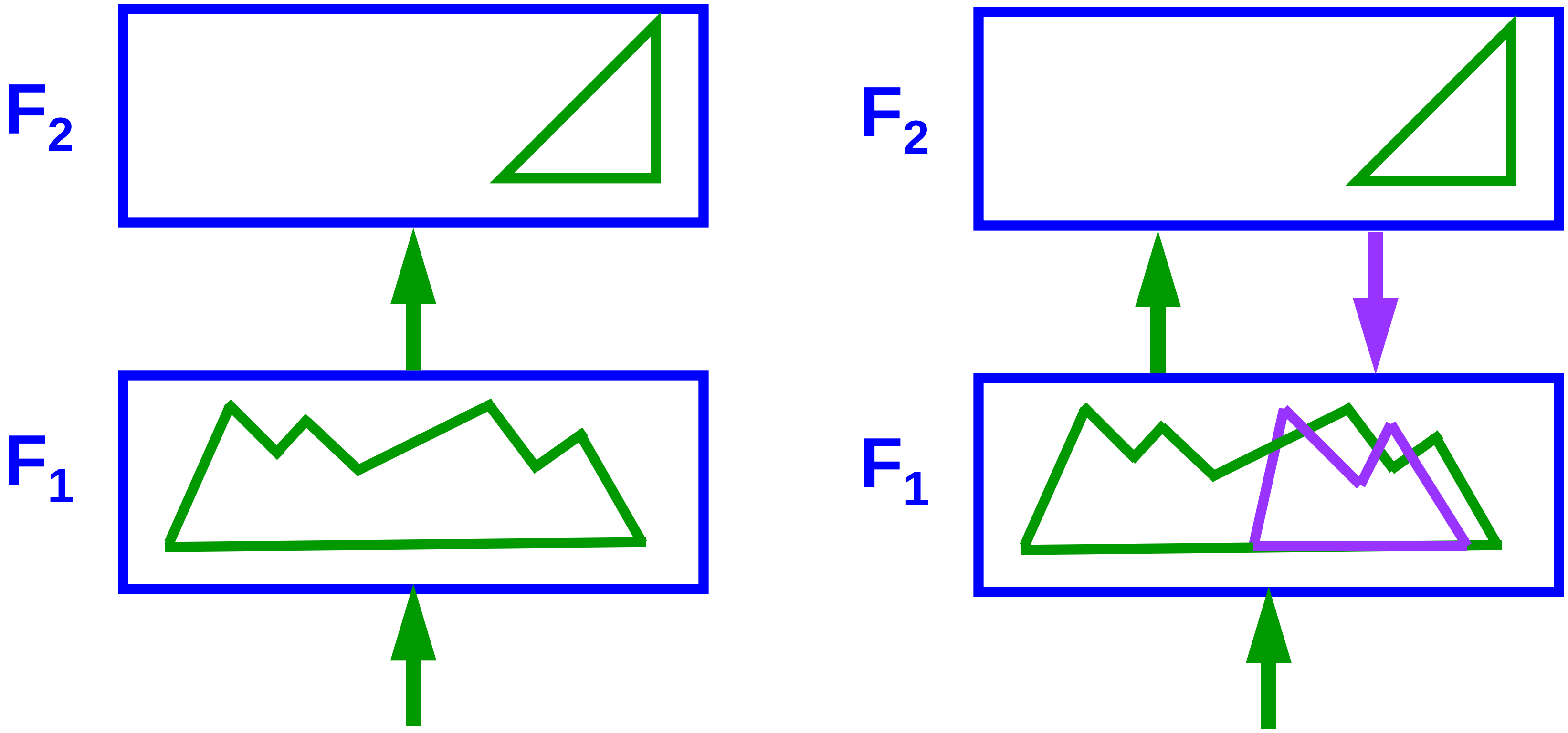
of a self-organizing map to achieve

AUTONOMOUS SELF-STABILIZATION

of learning?

HOW DOES LEARNING SELF-STABILIZE?

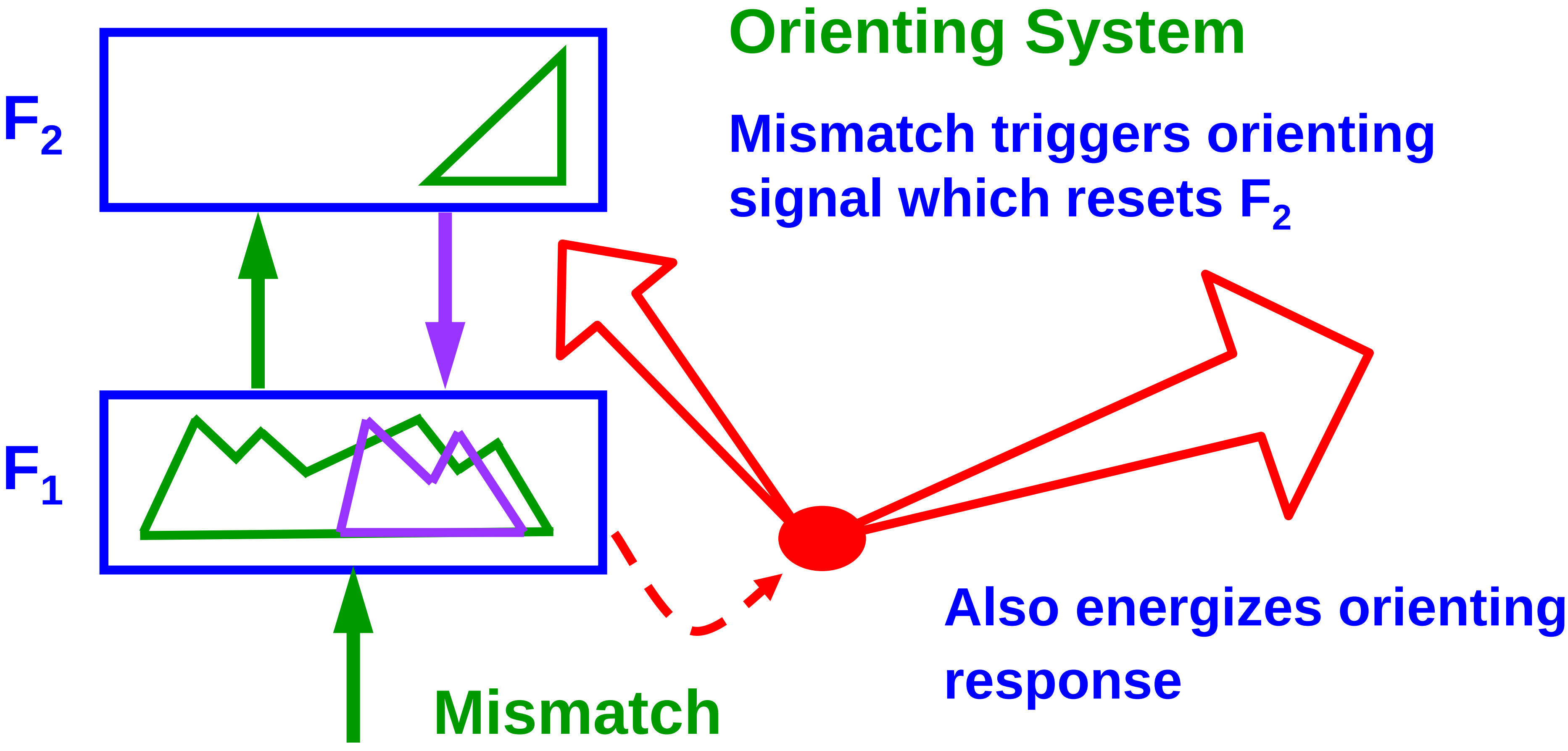
Learned top-down expectancies, or prototypes, can stabilize learning of an arbitrary sequence of input patterns



MATCHING at F1 of BU and TD patterns stabilizes learning

MISMATCH RESET

A "big enough" mismatch at F_1 quickly **resets** the F_2 category before new learning of an erroneous exemplar can occur

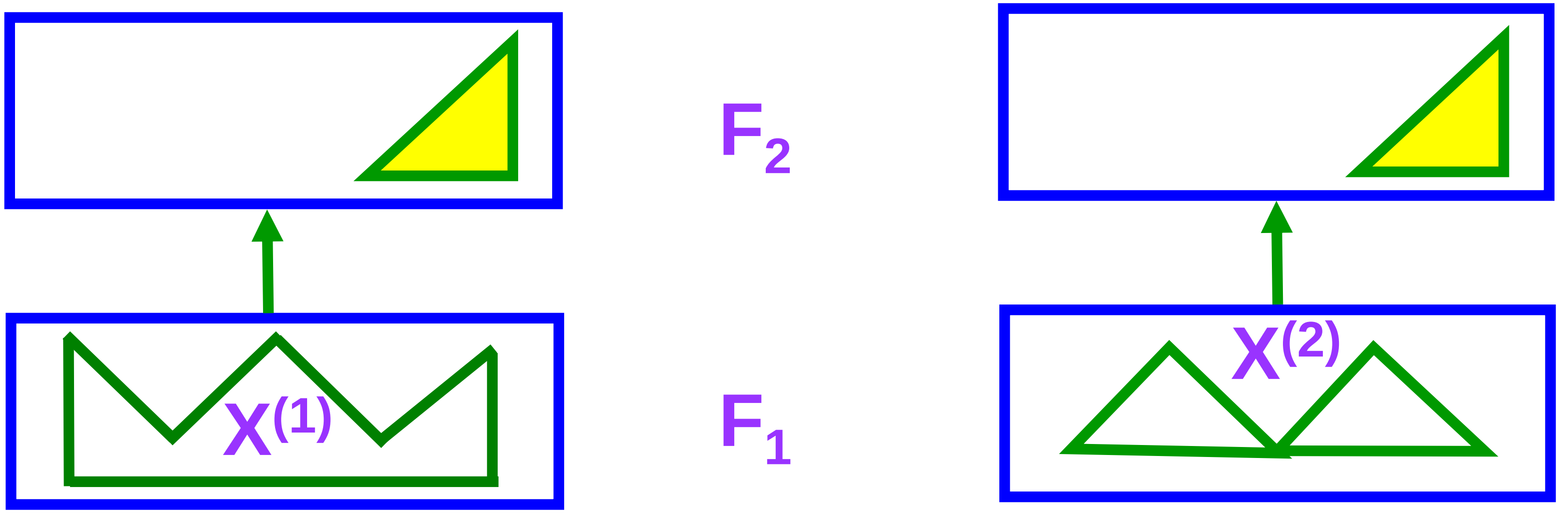


How can we derive this hypothesis from first principles?

MISMATCH INHIBITS ACTIVE CATEGORY

By prior learning, $X^{(1)}$ at F_1 is coded at F_2

Suppose that $X^{(2)}$ incorrectly activates the same F_2 code

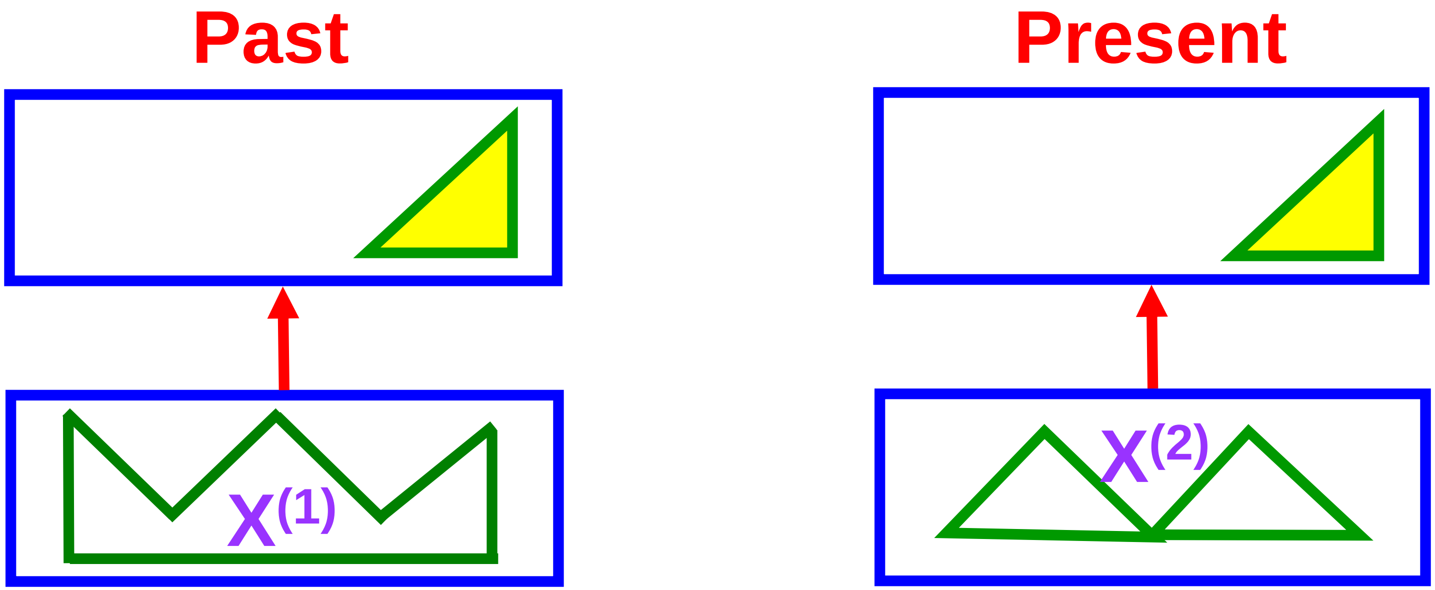


How to correct the error?

Independent of how you define an "error":

Shut off the F_2 code before it can learn the wrong association

COMPRESSION VS. ERROR CORRECTION



Where is the knowledge that error was made?

Not at F_2! The compressed code cannot tell the difference!

$X^{(2)}$ at F_1 when at F_2 defines the error

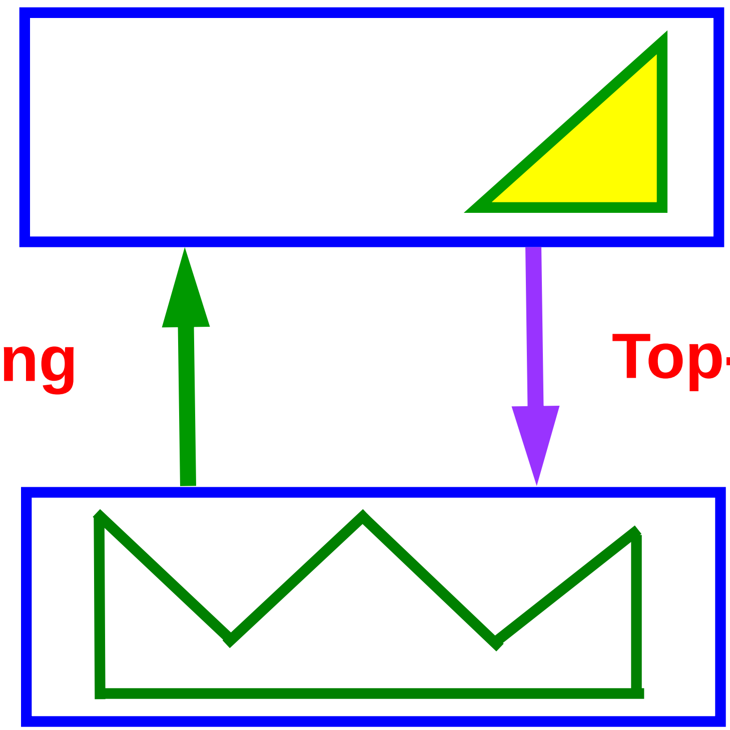
There is a MISMATCH between $X^{(1)}$ and $X^{(2)}$ at F_1

How does the system know this?

LEARNING TOP-DOWN EXPECTATIONS

When the code for $X^{(1)}$ was learned at F_2,
learned to read-out $X^{(1)}$ at F_1

Bottom-Up Learning



Top-Down Learning

$X^{(1)}$

Helmholtz	Unconscious Inference
Tolman	Learn Expectations
Gregory	Cognitive Contours
James	Pragmatism

ART EXPLOITS
COMPLEMENTARY UNCERTAINTIES OF SYMBOLIC AND DISTRIBUTED COMPUTATION

SYMBOLS VS. DISTRIBUTED FEATURES

ART uses the

COMPLEMENTARY properties

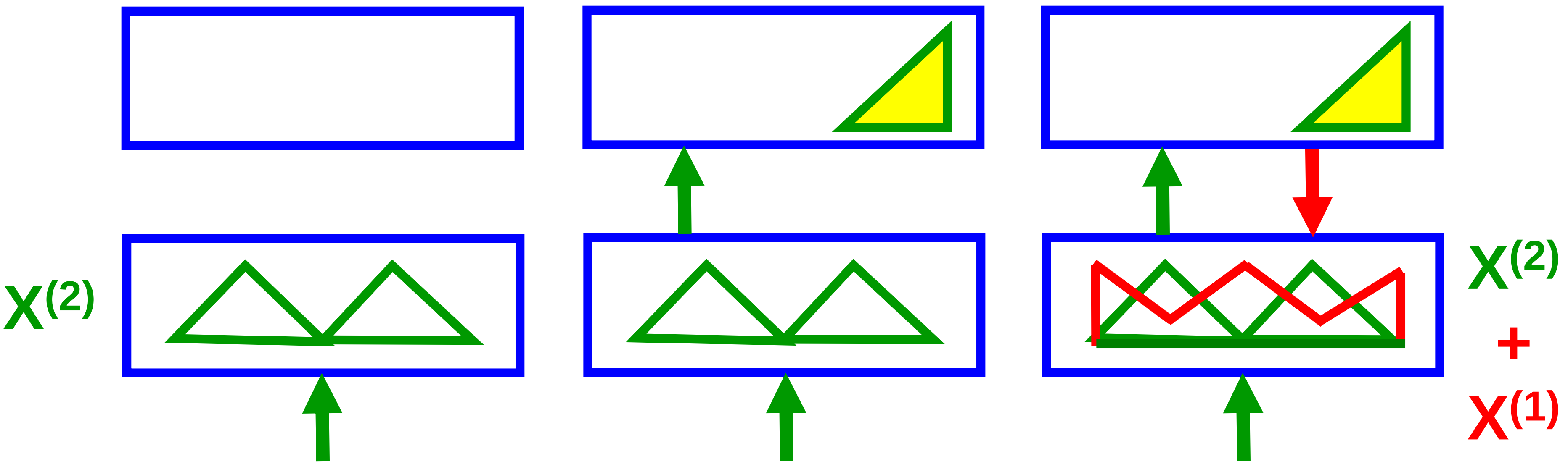
of symbols, or categories,

and of distributed features

in order to CORRECT ERRORS

MATCH DETECTOR

Processing Negativity ERP (Näätänen, 1978)
Olfactory Template (W. Freeman, 1975)



PROCESSING NEGATIVITY ERP:

1. Top-Down
2. Conditionable
3. Specific
4. Match

HOW DOES MISMATCH LEAD TO RESET?

How does mismatch at F_1 shut off incorrect code at F_2?

At F_1, you do not know which cells caused the mismatch

It could have been any or all cells in F_2

F_1 and F_2 experience
complementary types of ignorance:

F_2 cannot tell if there is an error

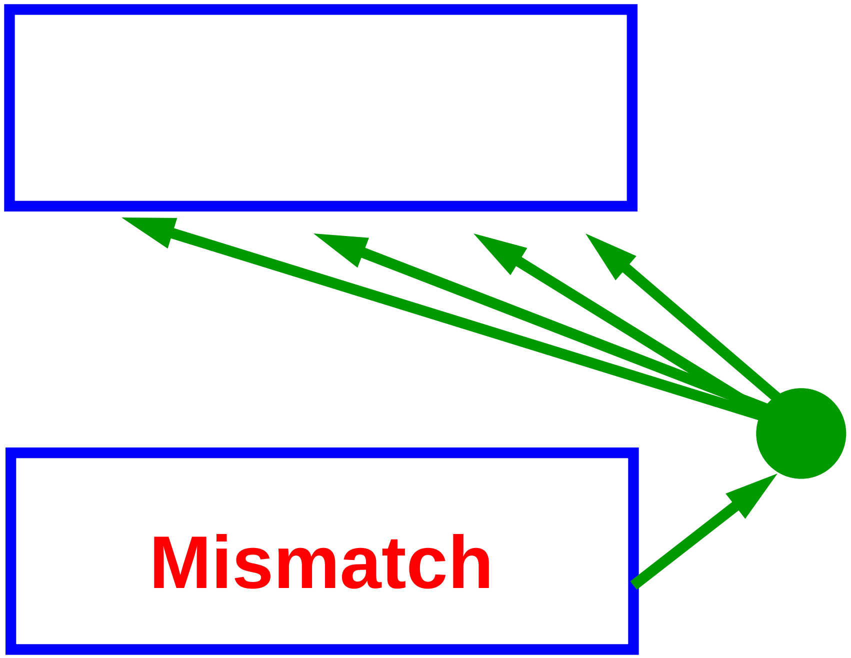
F_1 cannot tell who caused it

Thus by the principle of sufficient reason, all cells in F_2 receive the same mismatch-based signal from F_1

MISMATCH TRIGGERS NONSPECIFIC AROUSAL

Mismatch at F_1 elicits a nonspecific event at F_2

Call this event nonspecific arousal



Nonspecific
Arousal

N200 ERP
Näätänen et al

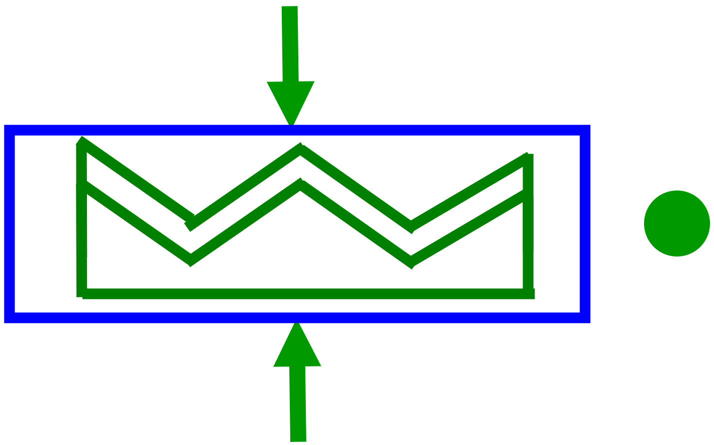
N200 ERP:

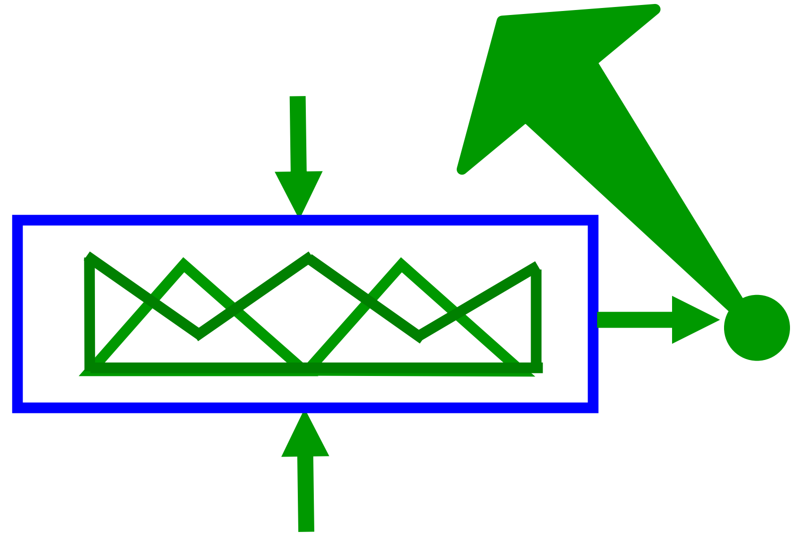
1. Bottom-Up
2. Unconditionable
3. Nonspecific
4. Mismatch

PN AND N200 ARE COMPLEMENTARY WAVES

Match
PN

Mismatch
N200





PN

Top-Down
Conditionable
Specific
Match

N200

Bottom-Up
Unconditionable
Nonspecific
Mismatch

FROM MISMATCH TO AROUSAL

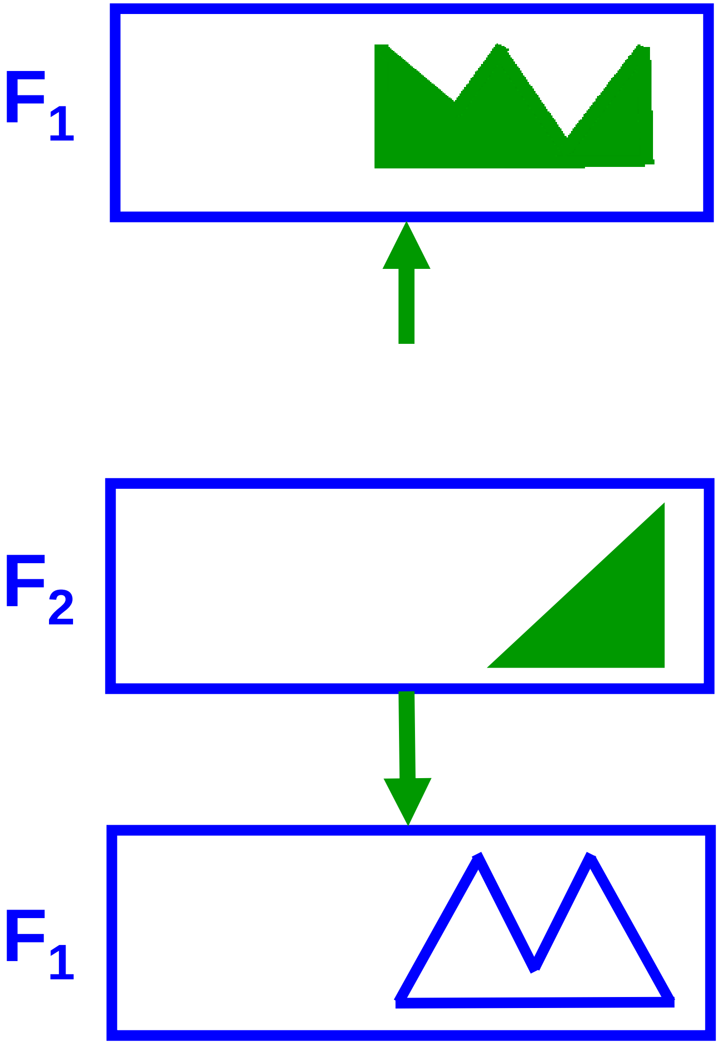
How does mismatch at F_1 release arousal to F_2?

Key design problem

How to Match Patterns?

HOW TO MATCH BU AND TD SIGNALS AT F_1?

Reconcile Two Requirements



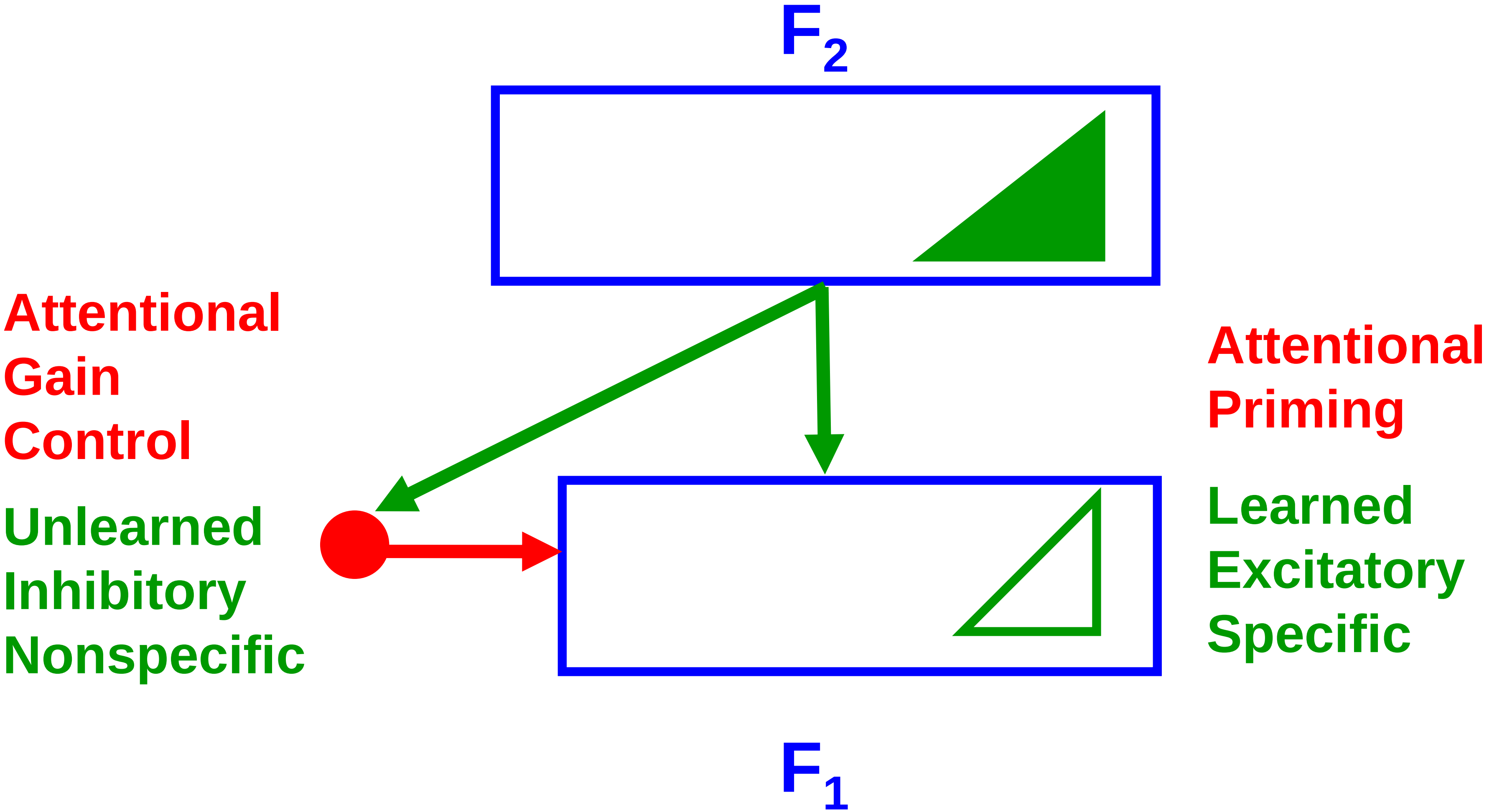
1. SUPRATHRESHOLD activation by BU input patterns

2. SUBTHRESHOLD activation by TD input patterns

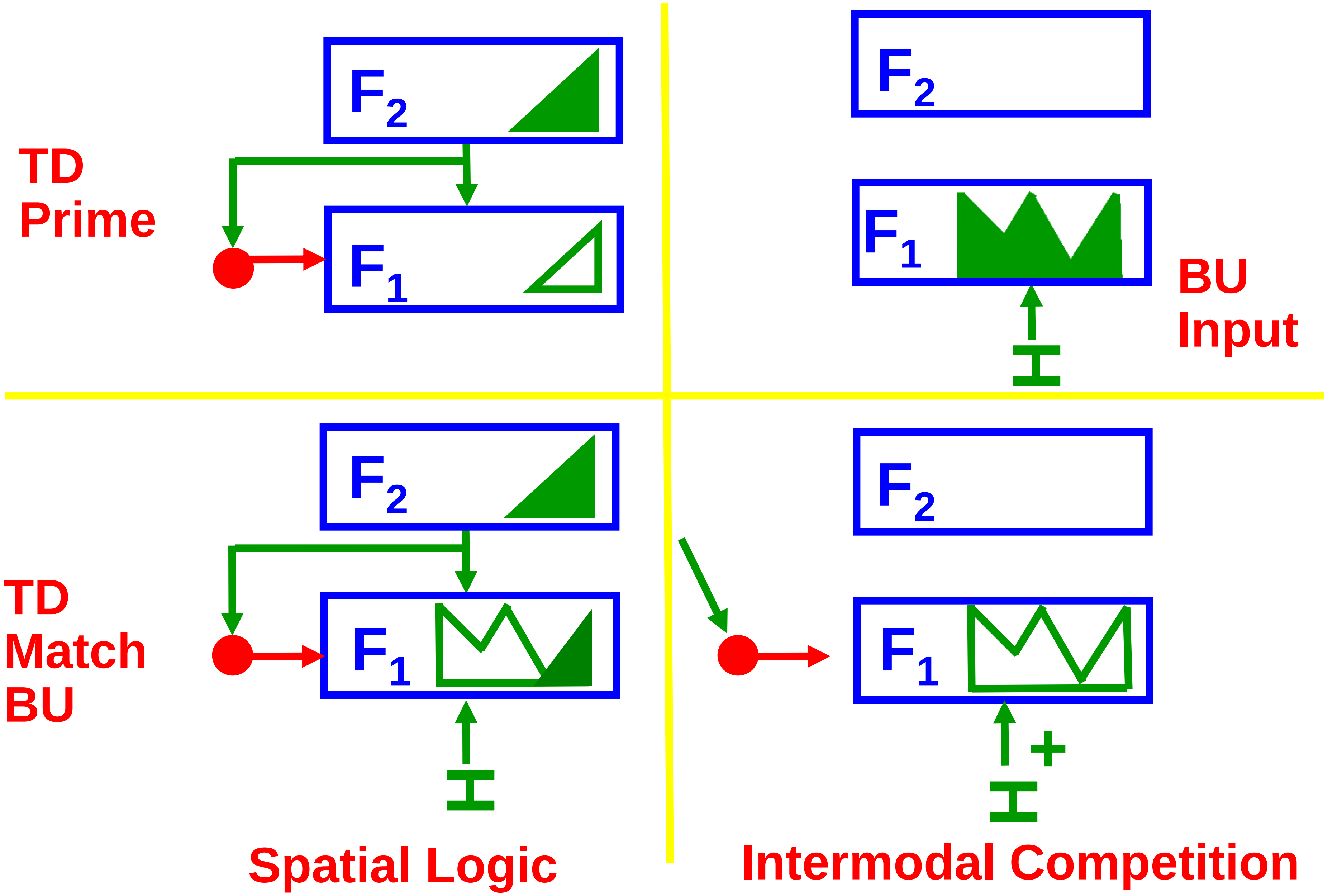
Expectancy
Intentionality
Modulation

HOW DOES F_1 PROCESS BU AND TD DIFFERENTLY?

COMPLEMENTARY parallel processing



ART PRIMING AND MATCHING



ART MATCHING RULE IN SPEECH AND LANGUAGE

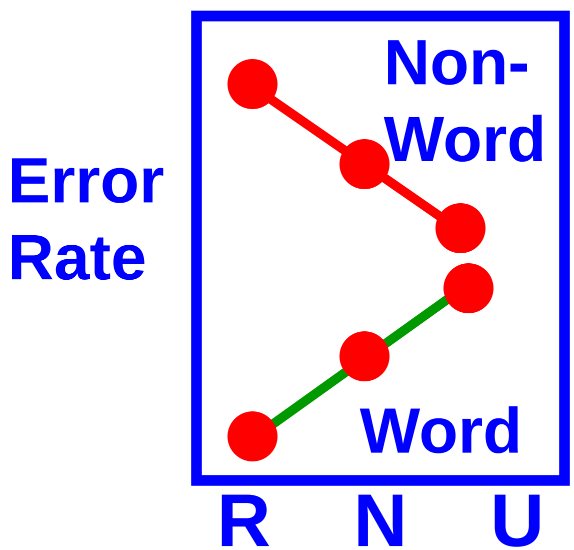
Phonemic Restoration

ST⊗ND ↑ Noise

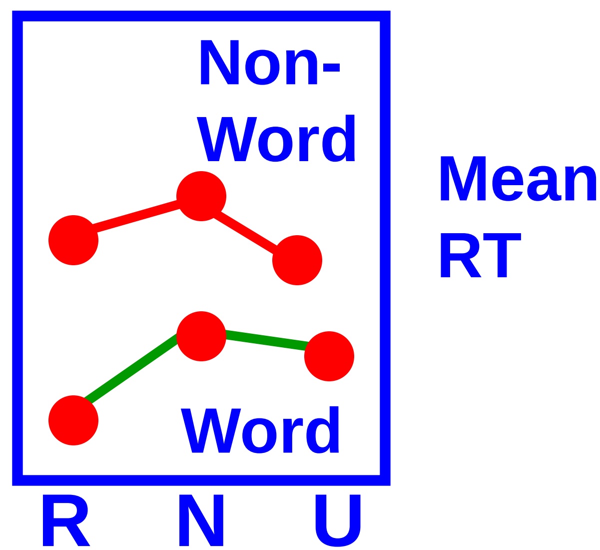
ST ND ↑ Silence

Warren & Warren; Samuel

Lexical Decision



Type of Word Prime



Type of Word Prime

Schvaneveldt & McDonald, 1981; Grossberg & Stone, Psych Rev., 1986

MATCHING STABILIZES LEARNING

The ART Matching Rule
is necessary for
stable learning
given arbitrary inputs

How you match determines
if you can stably learn

Grossberg, 1976
Carpenter and Grossberg, 1987+

HOW DOES FEATURE MISMATCH CAUSE CATEGORY RESET?

Mismatch at F_1

leads to

Inhibition of F_2

MISMATCH TRIGGERS NONSPECIFIC AROUSAL

How does inhibition of F_1 release nonspecific arousal to F_2?

Where does the activity that drives the arousal come from?

Endogenous Arousal (Tonic)?

Then F_2 would be flooded with arousal whenever F_1 was inactive

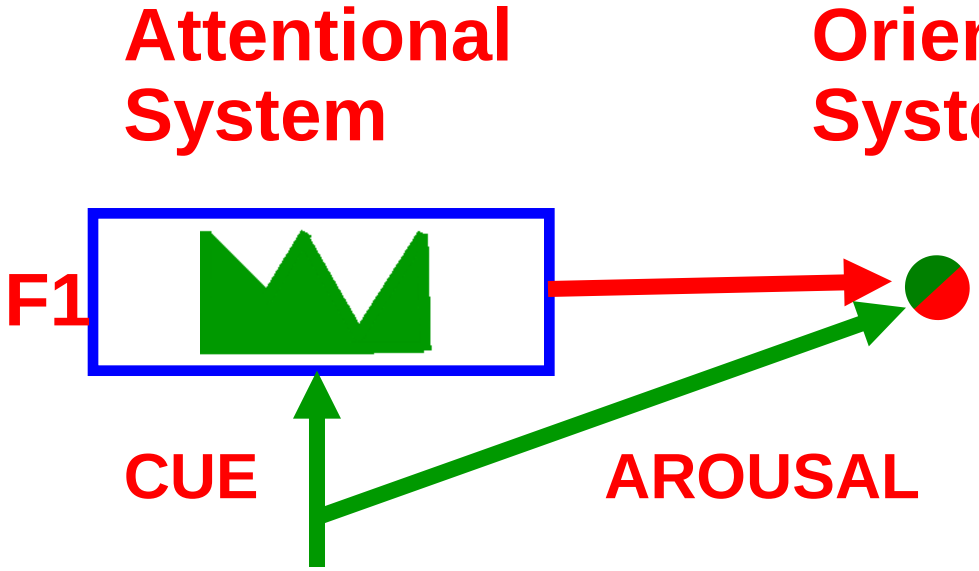
Passive inactivity is arousing

Exogenous Arousal (Phasic)!

The input also activates the arousal pathway

Active mismatch is arousing

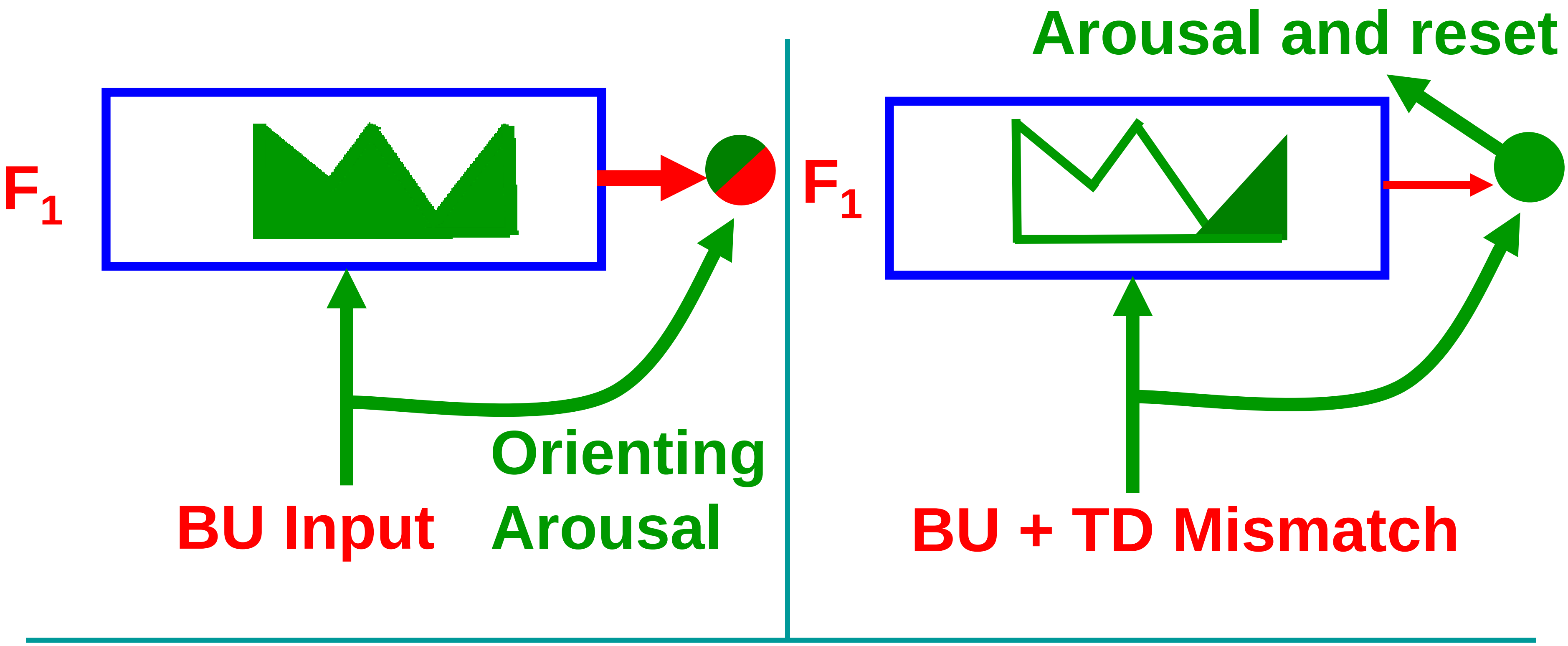
ATTENTIONAL AND ORIENTING SYSTEMS



Every event has a CUE (specific) and an AROUSAL (nonspecific) function

Hebb, CNS, 1975

MISMATCH ⇨ INHIBITION ⇨ AROUSAL ⇨ RESET



ART MATCHING RULE:

TD mismatch can suppress a part of F_1 STM pattern

F2 is reset if

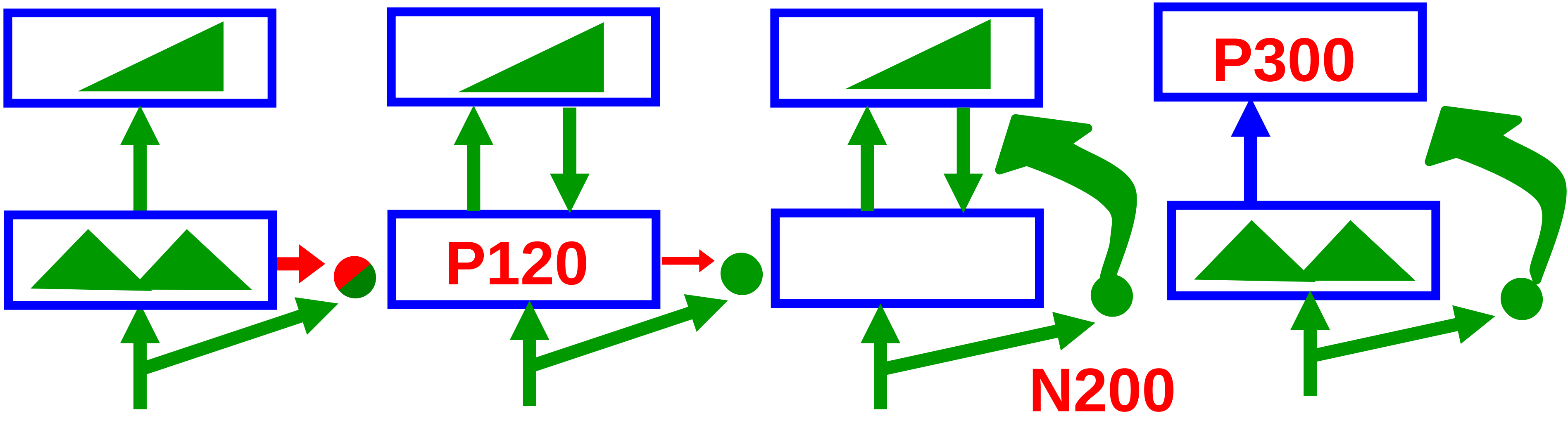
Degree of Match < Vigilance (sensitivity, gain)

EVENT RELATED POTENTIALS

Correlated sequences of P120-N200-P300

Event Related Potentials during oddball learning

Banquet and Grossberg, 1987



ADAPTIVE RESONANCE THEMES

Resonant data are the data to which we pay attention

Gibson

The cognitive code of a network is the set of stable resonances that it can support in response to a prescribed input environment

A dynamic rhythm exists between reset and resonance rather than just "processing and more processing"

Neisser

Adaptive resonance regulates the balance between stability and plasticity In a network capable of behavioral self-organization in a changing world

CONSCIOUSNESS

When can conscious states occur?

ART HYPOTHESIS (Grossberg, 1976):

All conscious states are resonant states

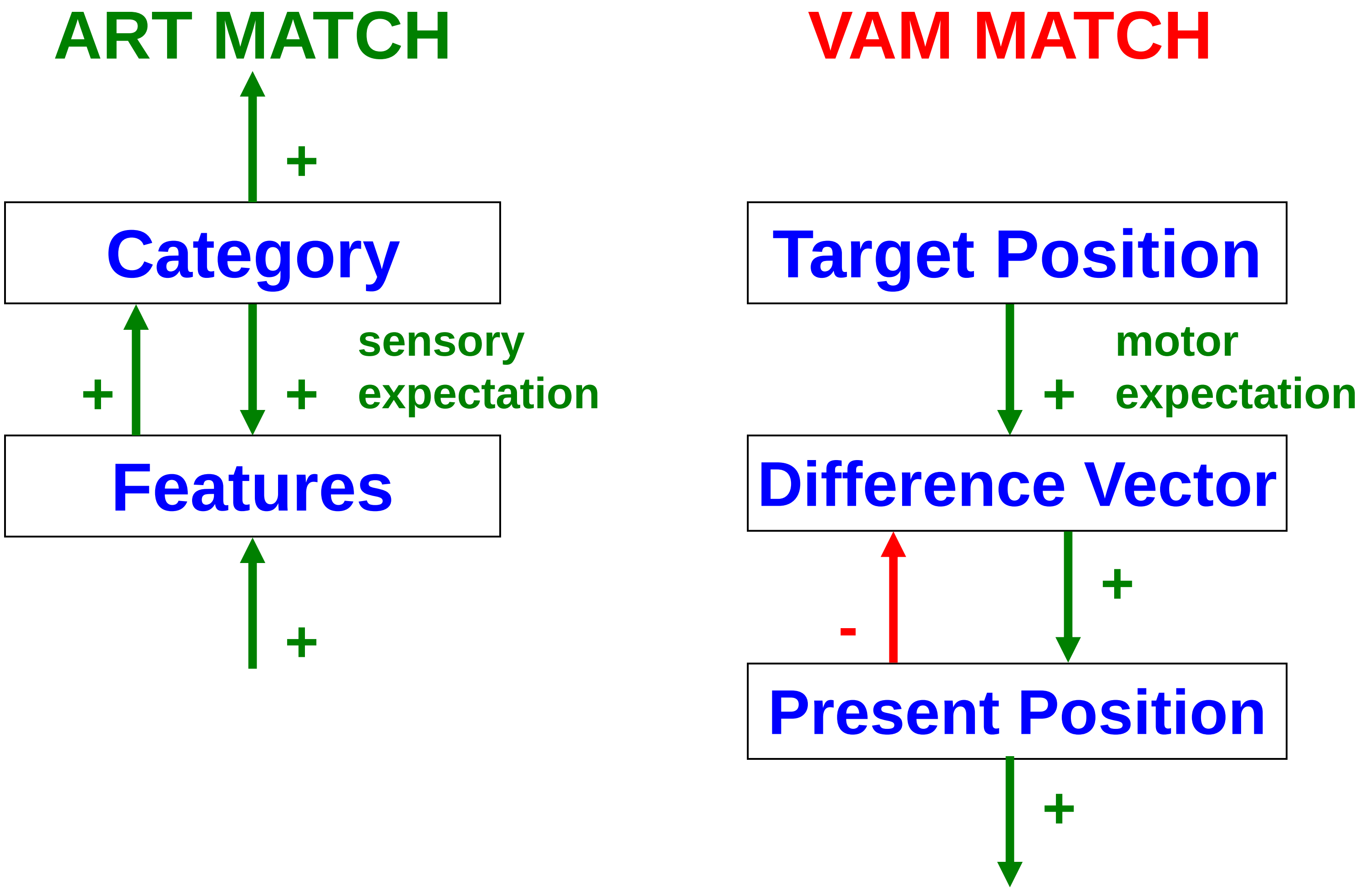
Explains why priming is unconscious.

Need matched bottom-up and top-down for resonance

Why are not procedural memories conscious?

Their matching and learning laws are not resonant!

SENSORY EXPECTATION vs MOTOR EXPECTATION



Match Amplifies
Match Learning

Match Suppresses
Mismatch Learning

SPATIAL AND MOTOR LEARNING

in the WHERE stream is often

MISMATCH LEARNING

VAM

Continual recalibration

SENSORY AND COGNITIVE LEARNING

in the WHAT stream is often

MATCH LEARNING

ART

solves Stability-Plasticity dilemma

WHAT and WHERE LEARNING and MATCHING are COMPLEMENTARY

	WHAT	WHERE
MATCHING	EXCITATORY	INHIBITORY
LEARNING	MATCH	MISMATCH

WHAT	WHERE
STABILITY-PLASTICITY DILEMMA	
Fast learning without catastrophic forgetting	Continually update sensory-motor maps and gains
Spatially invariant recognition	Spatially variant reaching and movement
IT	PPC

THE LINK BETWEEN BRAIN LEARNING, ATTENTION, AND CONSCIOUSNESS

What is the proposed link?

BRAIN RESONANCE

Hypothesis:

ALL CONSCIOUS STATES ARE RESONANT STATES

ADAPTIVE RESONANCE THEMES

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TEMPORAL ART

AUDITORY STREAMING
The Cocktail Party Problem
and
VARIABLE-RATE SPEECH PERCEPTION

A seemingly different sort of anticipatory dynamics

During the question period, if there is interest

TEMPORAL ART:
AUDITORY STREAMING

A seemingly different sort of anticipatory dynamics

How does the brain solve the
COCKTAIL PARTY PROBLEM?

**Pitch-based pop-out of acoustic sources
such as voices or instruments
in a multiple-source environment**

Primitive streaming (Bregman, 1990)

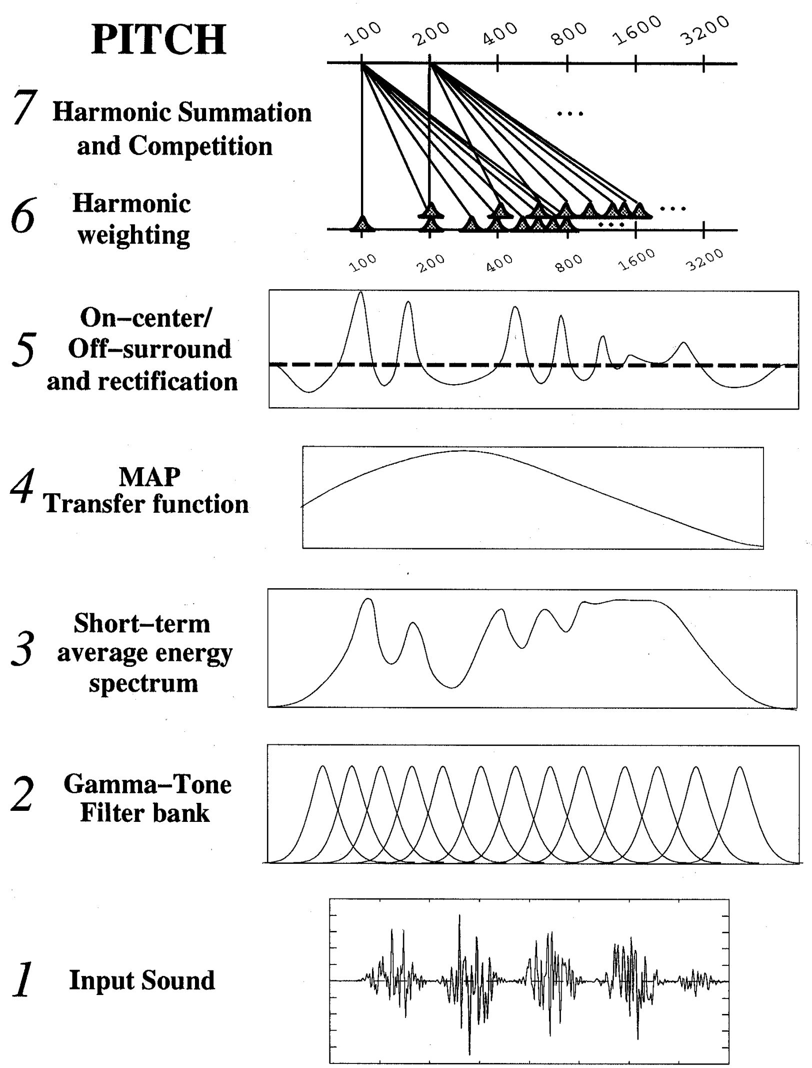
**Grossberg, 1998, in Griffiths and Todd, Musical Networks, MIT Press
Grossberg, Govindarajan, Wyse, and Cohen, 2004, Neural Networks**

SPINET MODEL

Spatial PItch NETwork

Cohen, Grossberg, and Wyse, 1995, JASA

Transforms temporal auditory signals into spatial representations of frequency spectrum and pitch categories



Pitch categories

Harmonic filter

Frequency map

A specialized Self-Organizing Map

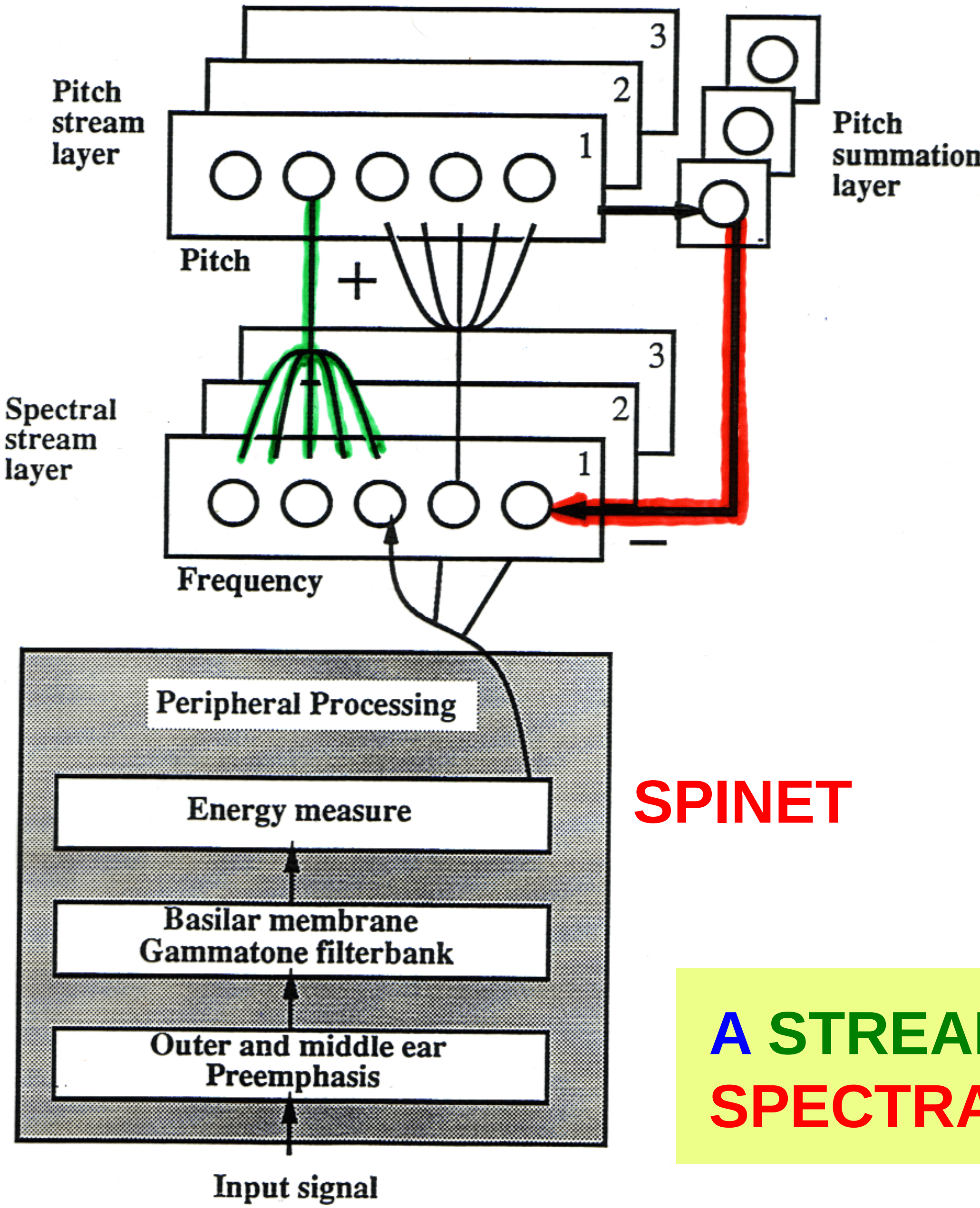
SPINET MODEL

Explains pitch data for

- the phase of mistuned components
- shifted harmonics
- dominance region
- octave shift slopes
- pitch shift slopes
- pitch of narrow bands of noise
- rippled noise spectra
- tritone paradox
- edge pitch
- distant modes

ARTSTREAM MODEL: FROM TEMPORAL SOM TO ART

Grossberg, 1999; Grossberg, Govindarajan, Wyse, and Cohen, 2004



SPINET

Frequency and pitch STRIPS

BU harmonic sieve

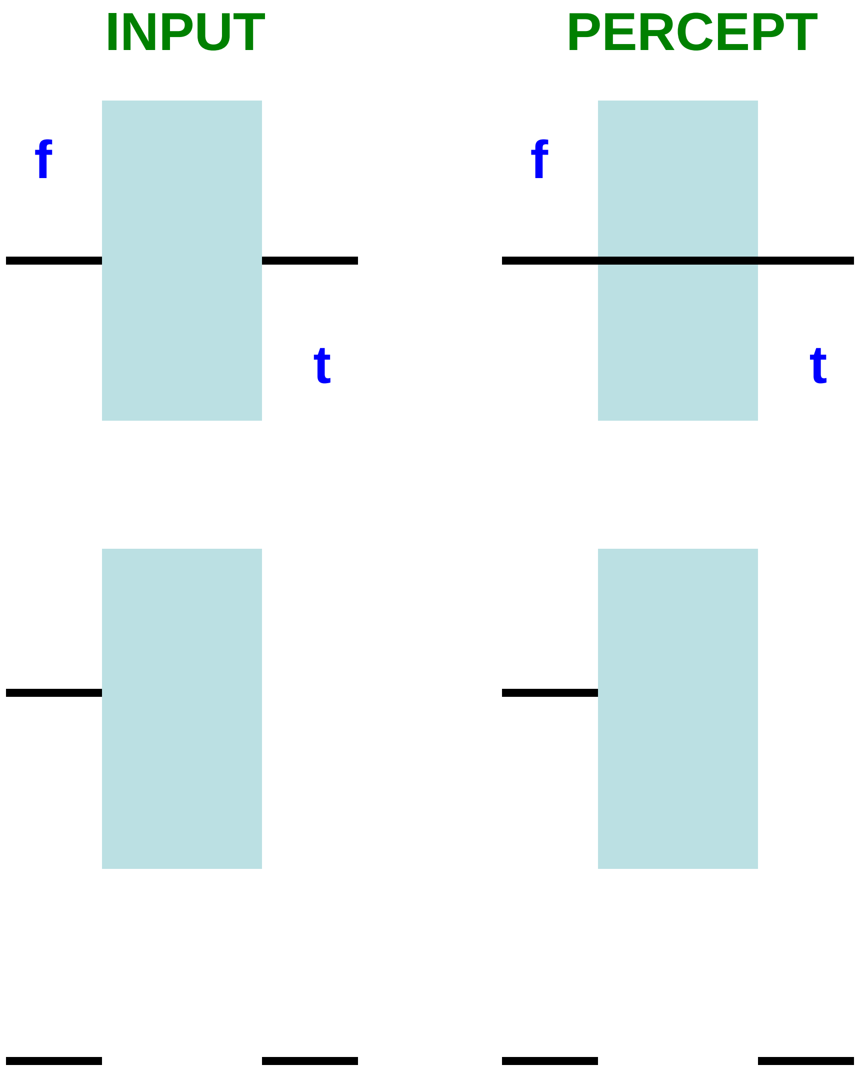
TD harmonic ART matching

Exclusive allocation

LEARN pitch categories based on early harmonic processing

A STREAM is a SPECTRAL-PITCH RESONANCE!

AUDITORY CONTINUITY ILLUSION



BACKWARDS IN TIME

How does future sound let past sound continue through noise?

RESONANCE!

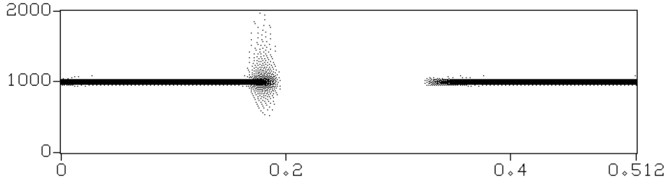
It takes awhile to kick in. After it starts, a future tone can maintain it much more quickly

WHY DOES THIS NOT HAPPEN IF THERE IS NO NOISE?

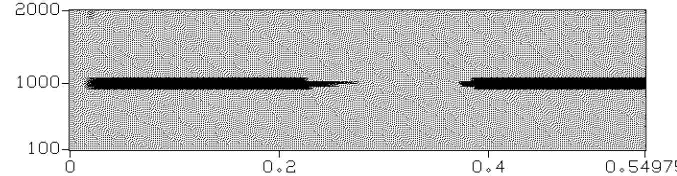
ART MATCHING RULE!

TD harmonic filter is modulatory without BU input. It cannot create something out of nothing

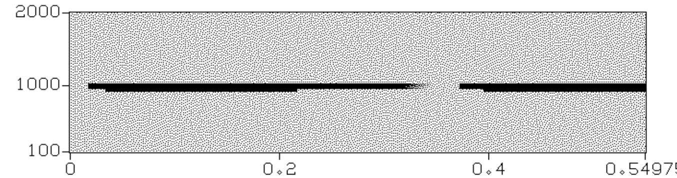
AUDITORY CONTINUITY ILLUSION



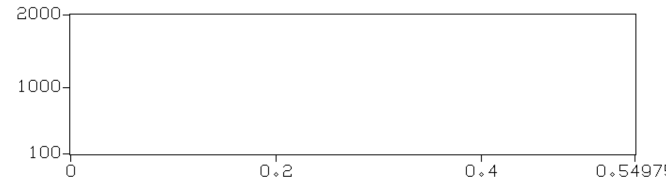
Input



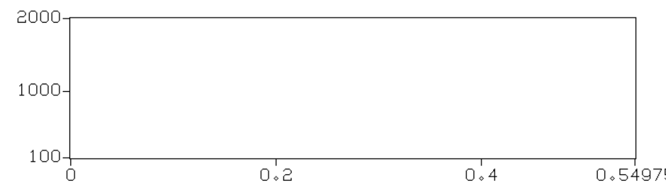
Pitch$_1$



Spectral$_1$



Pitch$_2$



Spectral$_2$

WHERE ELSE IN THE AUDITORY SYSTEM ARE ART DYNAMICS USED?

Compare and contrast with:

Variable-rate speech perception

Schema-based streaming (Bregman, 1990)

Grossberg, Boardman, and Cohen, 1997, JEP:HPP

Boardman, Grossberg, Myers, and Cohen, 1999, P&P

Grossberg and Myers, 2000, Psychological Review

Grossberg, 2004, J. Phonetics

Differences: e.g., different processing of harmonics

Remez et al., 1994, 2001, 2003

Similarities?

ART IN PHONEMIC RESTORATION

⊗ eel was on the _ _ _ _ _ .

noise

wh	axle
h	shoe
p	orange
m	table

ART
MATCHING
RULE!

Warren, Warren, and Sherman (1970)

1. FUTURE ⟶ PAST
2. MEANING ⟶ PHONETICS

Vs. SILENCE

Samuel (1980's)

eel

WE DO NOT HEAR THE NOISE ⊗ IN

⊗EEL WAS ON THE __________.

BOTTOM-UP ACTIVATION	≠	BOTTOM-UP ACTIVATION

BOTTOM-UP AND TOP-DOWN ACTIVATIONS
COMBINE ON A
SLOWER TIME SCALE (RESONANCE!)
TO GENERATE A CONSCIOUS SPEECH CODE

ITEM-LIST RESONANCE!

CONSCIOUS SPEECH IS A RESONANT WAVE

SILENCE IS A DISCONTINUITY IN THE RATE WITH WHICH THE WAVE ENVOLVES

ARTMAP BENCHMARK STUDIES

Database benchmark:

- MACHINE LEARNING (90-95% correct)
- ARTMAP (100% correct on a training set an order of magnitude smaller)

Medical database:

- STATISTICAL METHOD (60% correct)
- ARTMAP (96% correct)

Letter recognition database:

- GENETIC ALGORITHM (82% correct)
- ARTMAP (96% correct)

Database benchmarks:

- BACKPROPAGATION (10,000 – 20,000 training epochs)
- ARTMAP (1-5 epochs)

Used in applications where other algorithms fail

e.g. Boeing CAD Group Technology

- Part design reuse and inventory compression
- Need fast stable learning and search of a huge (16 million 1 million dimensional vectors) and continually growing nonstationary parts inventory

TRENDS IN SCIENCE AND TECHNOLOGY THAT LOOK TO NEURAL NETWORK RESEARCH

WORLD

CONTROL

EXTERNAL (SUPERVISED)

AUTONOMOUS (UNSUPERVISED)

STATIONARY

NON-STATIONARY