# NEUROCOMPUTATIONAL MODELS OF PERCEPTUAL CATEGORIZATION: FROM LEARNING TO AUTOMATICITY

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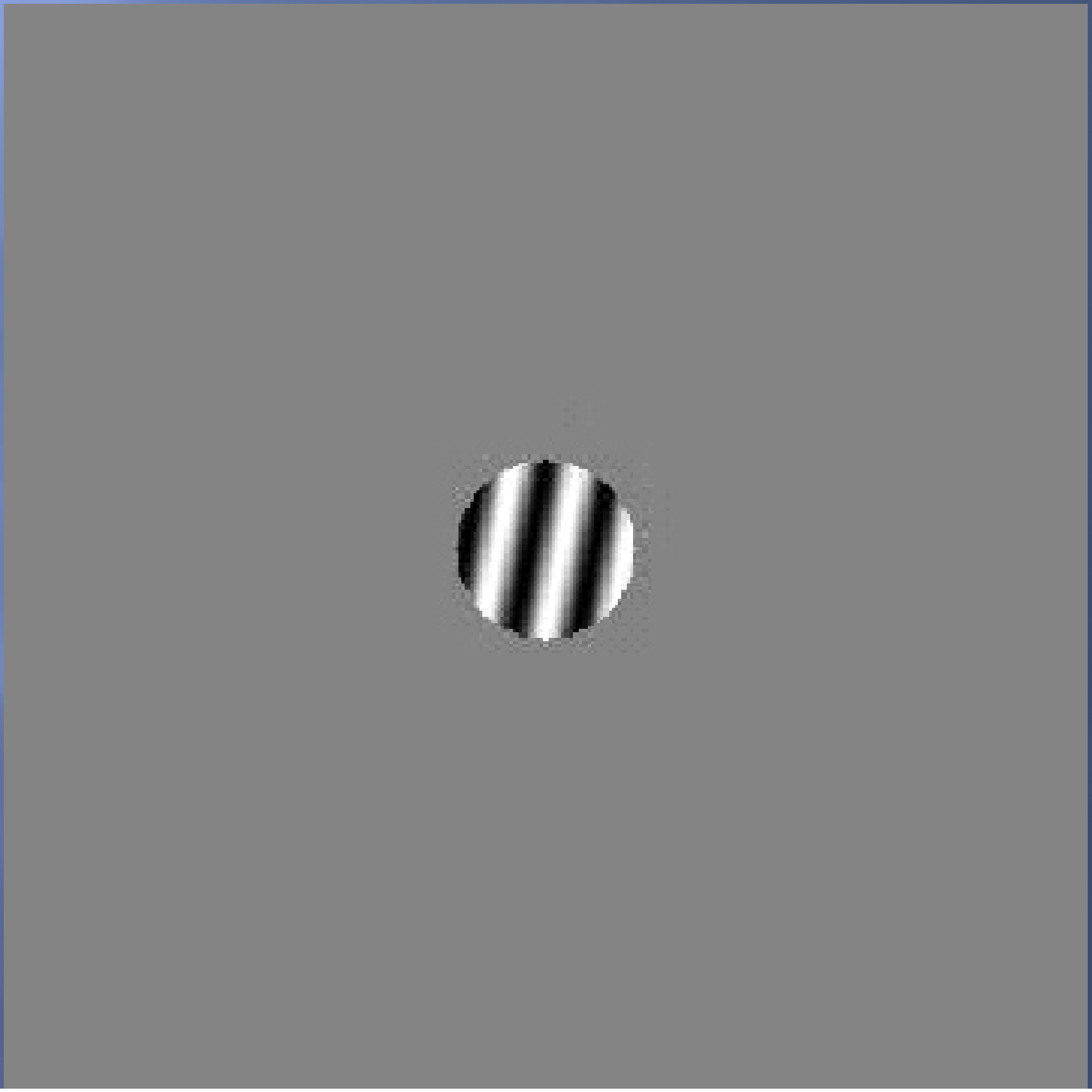
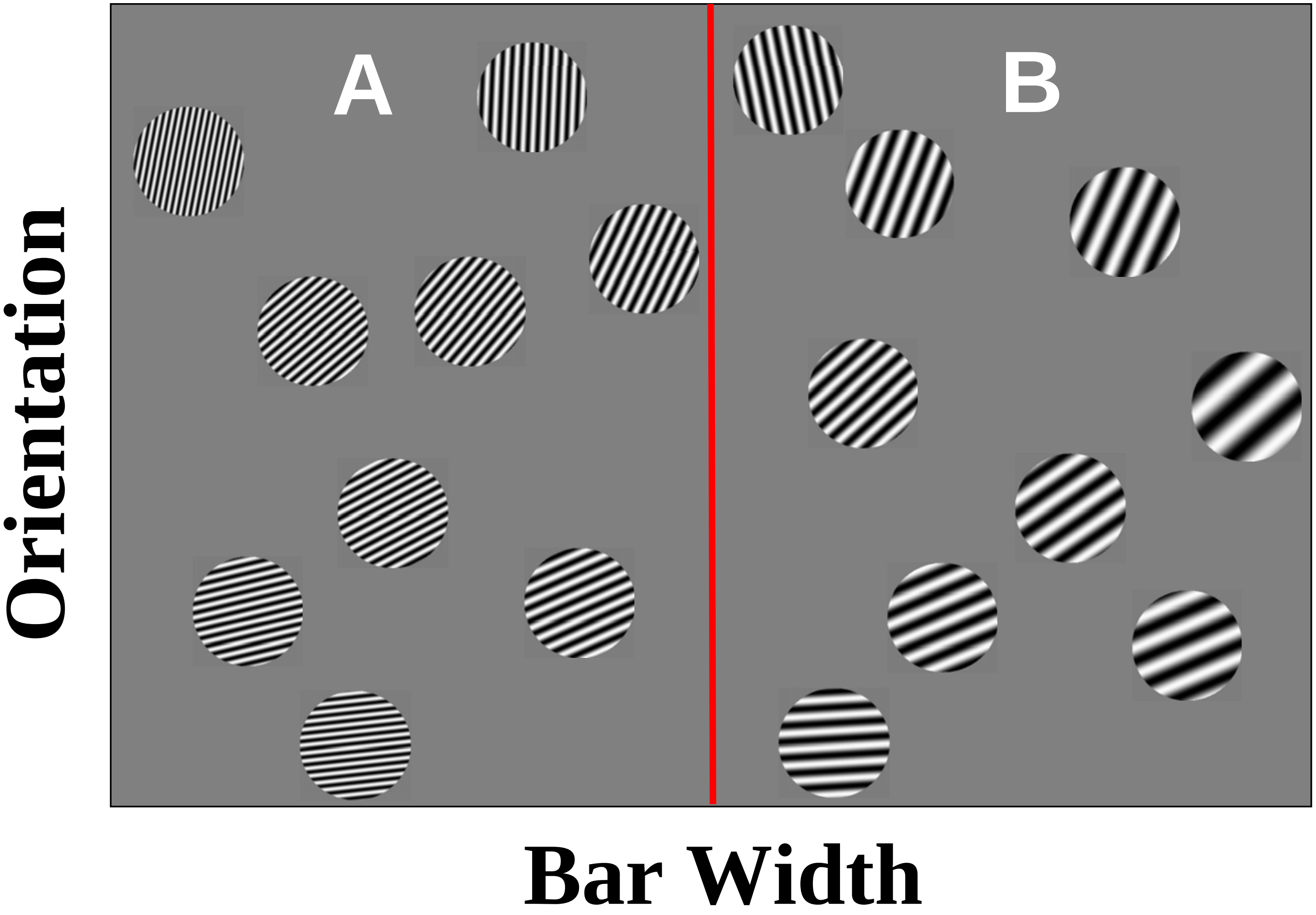
# OUTLINE

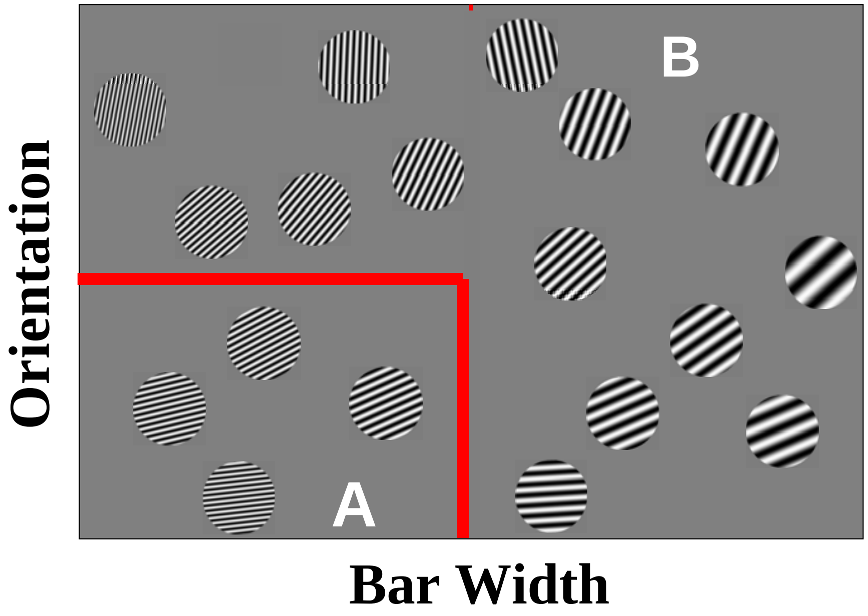
1) category learning
    A) Experiments
    B) Theory
2) categorization automaticity
    A) Computational neuroscience model
    B) Tests of the model

# STIMULUS ON A SINGLE CATEGORY-LEARNING TRIAL



# RULE-BASED CATEGORY LEARNING





# Rule-Based Category Learning

Categorization rule is easy to describe

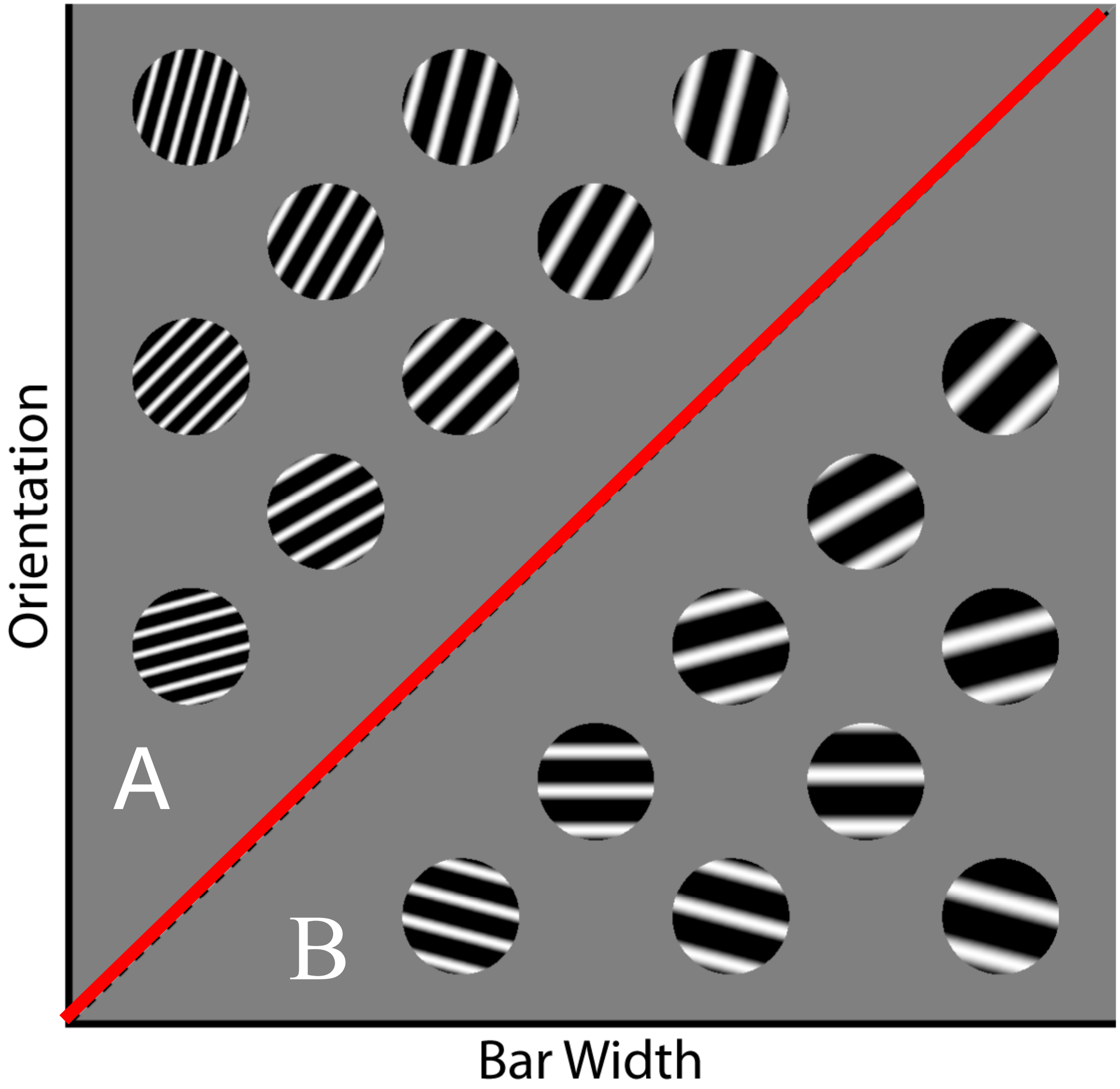
Effective learning requires:

- no distractions
- active and effortful processing of feedback

But the nature and timing of feedback is not critical

(cluster learning is possible)

# Information-Integration Category Learning



# A REAL-LIFE II TASK?

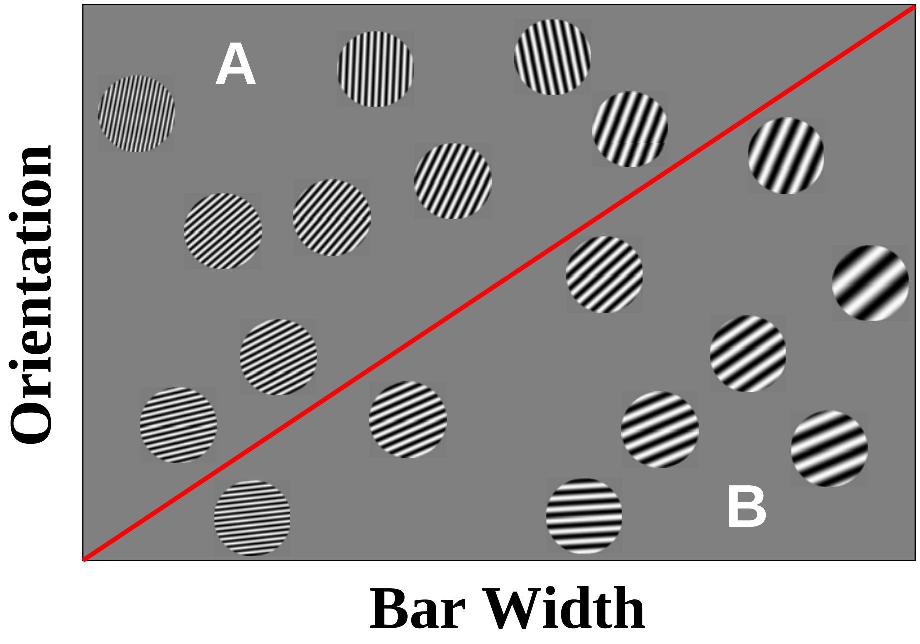
Does this mammogram show a tumor?

i.e., is it in the category "tumor" or the category "nontumor"?

# A REAL-LIFE II TASK?

Tumor!

# Information-Integration Category Learning



Categorization rule is difficult to describe

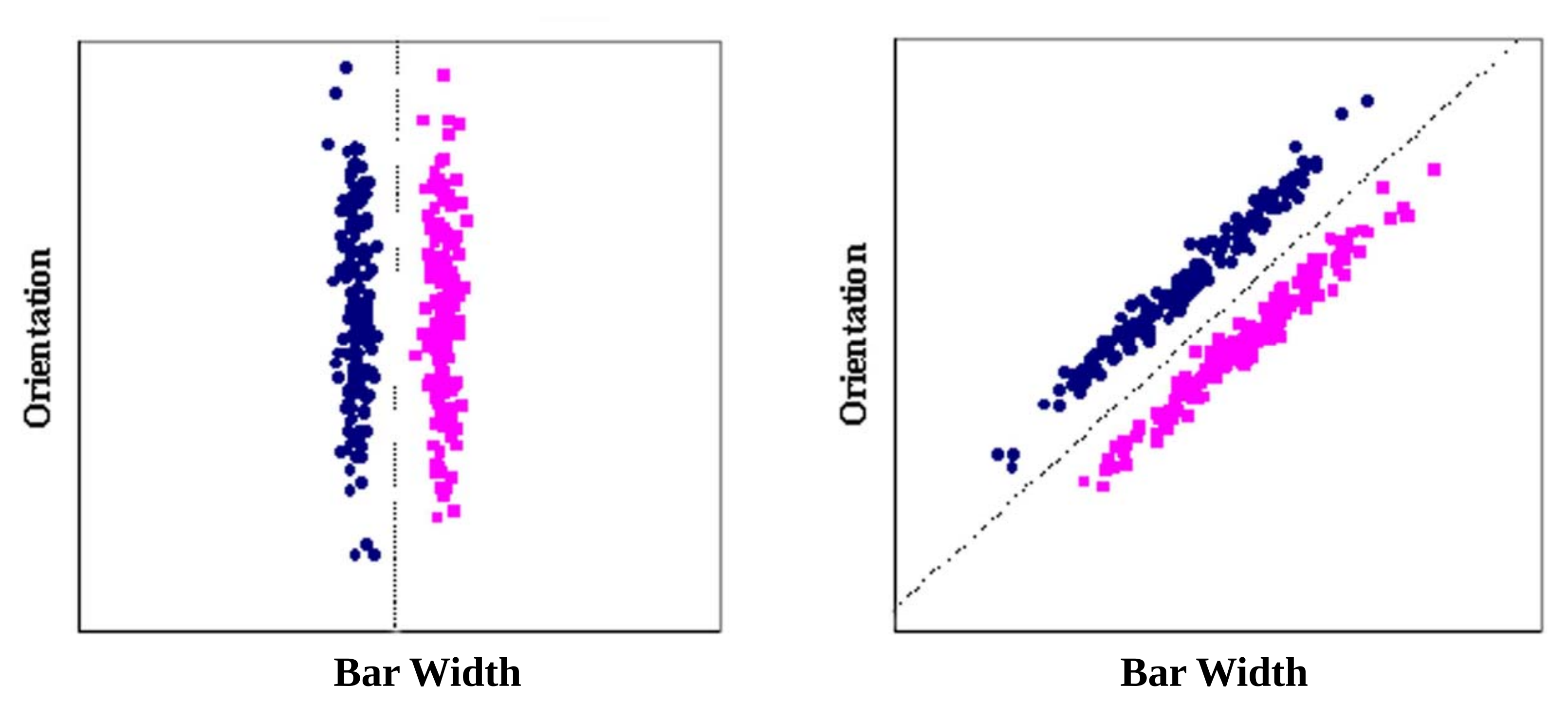
Effective learning requires:

- consistent feedback immediately after response
- consistent mapping from category to response location
- no active feedback processing

(no evidence that cluster learning is possible)

# Categories

Rule Based	Information Integration



Is the information-integration task inherently more difficult?

# THE TWO COGNITIVE DYNAMIC SYSTEMS OF COVIS

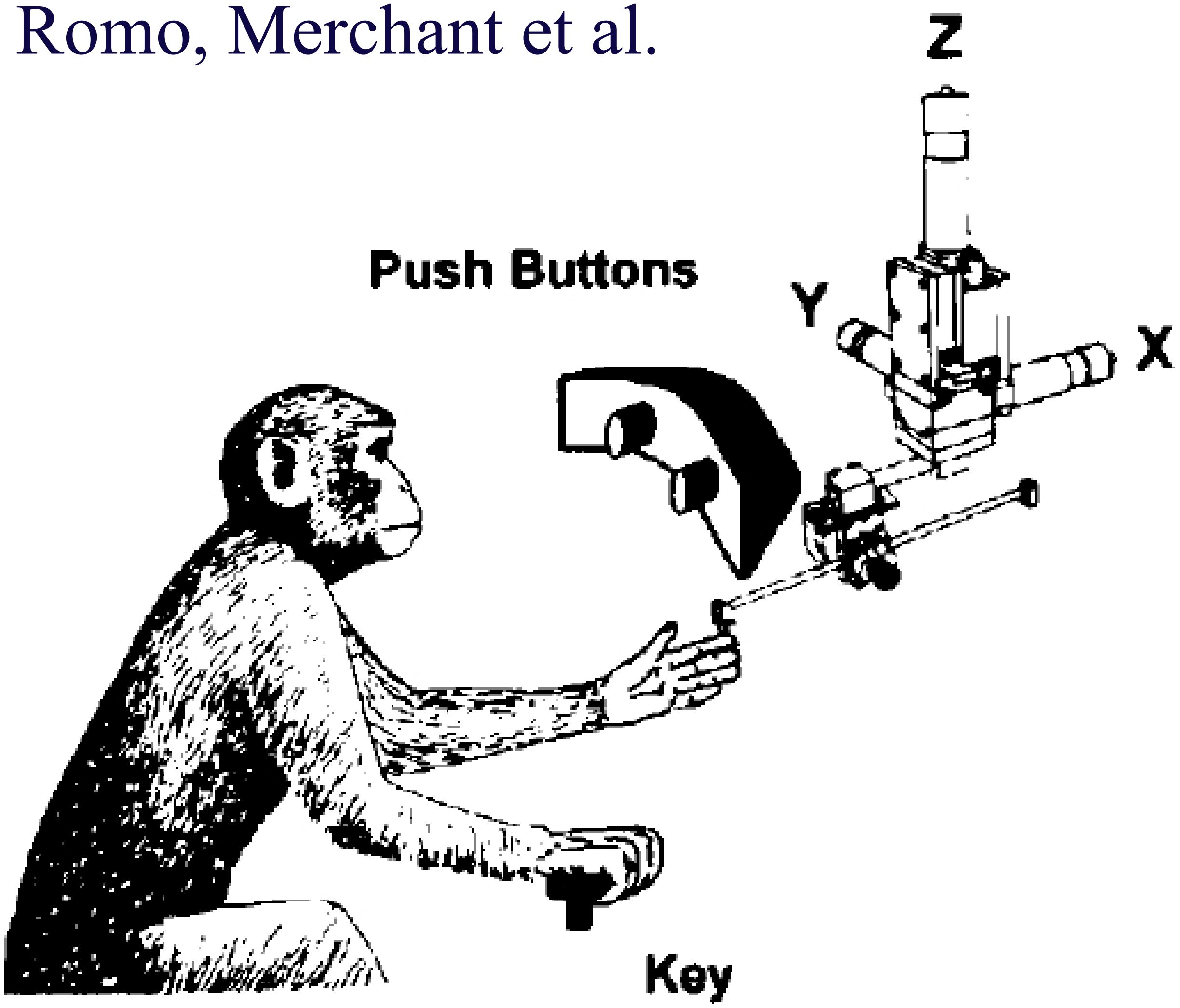
(Ashby, Alfonso-Reese, Turken, & Waldron, *Psychological Review*, 1998)

- explicit, logical-reasoning system
  - -- quickly learns explicit rules
- procedural- or habit-learning system
  - -- slowly learns similarity-based rules
- simultaneously active in all tasks (at least initially)

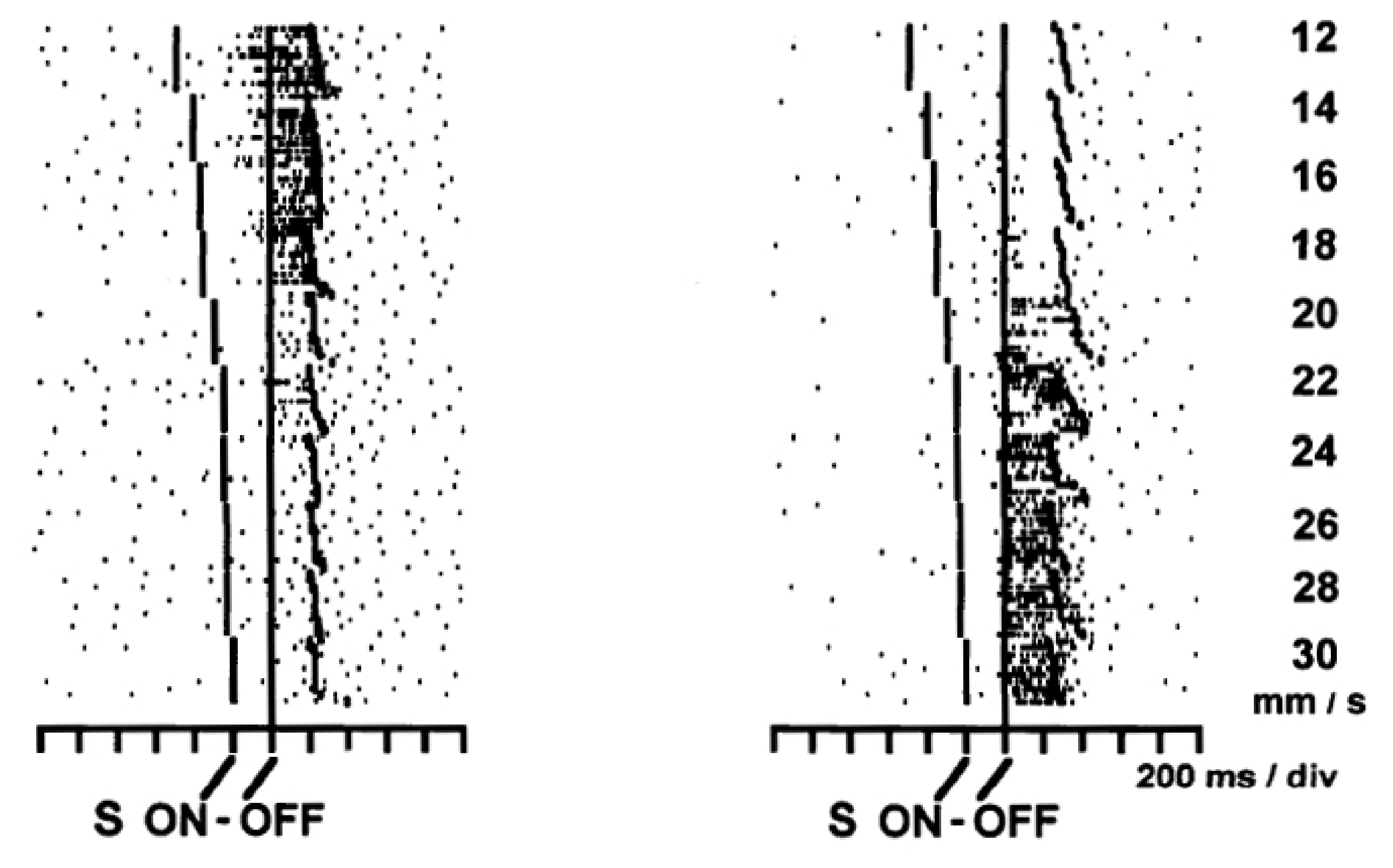
# The Caudate Nucleus

# Tactile Category Learning

Romo, Merchant et al.



# Single Cell Responses – Putamen



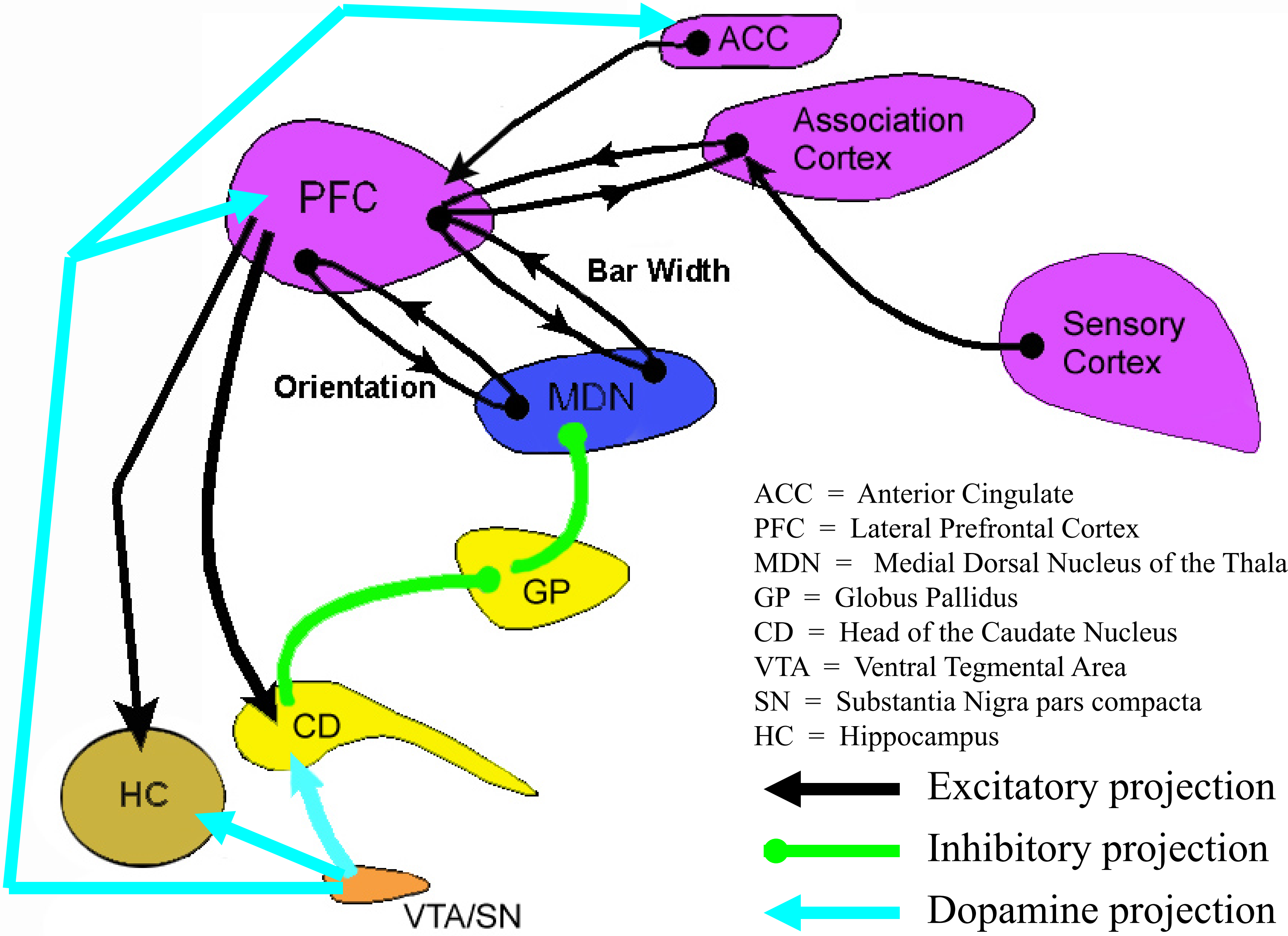
Merchant et al. (1997, J. of Neurophysiology)

# THE COVIS EXPLICIT SYSTEM

- logical reasoning system
- uses working memory and executive attention
- prefrontal cortex, anterior cingulate, head of the caudate nucleus, thalamo-cortical loops, medial temporal lobe structures

- Working memory & attentional switching component – FROST (Ashby, Ell, Valentin, & Casale, 2005, *J. of Cognitive Neuroscience*)

# The COVIS Explicit System

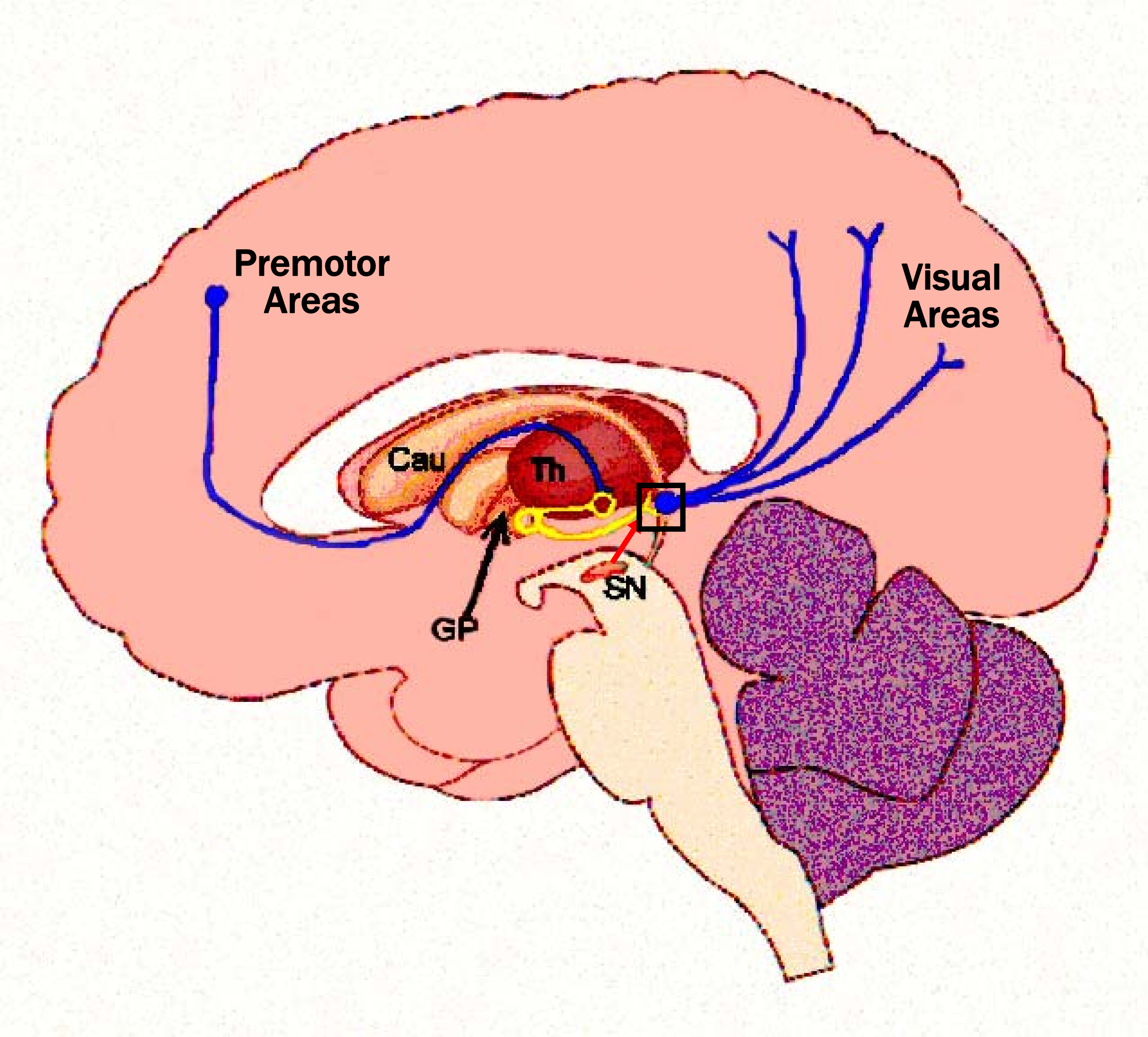


ACC = Anterior Cingulate
PFC = Lateral Prefrontal Cortex
MDN = Medial Dorsal Nucleus of the Thalamus
GP = Globus Pallidus
CD = Head of the Caudate Nucleus
VTA = Ventral Tegmental Area
SN = Substantia Nigra pars compacta
HC = Hippocampus

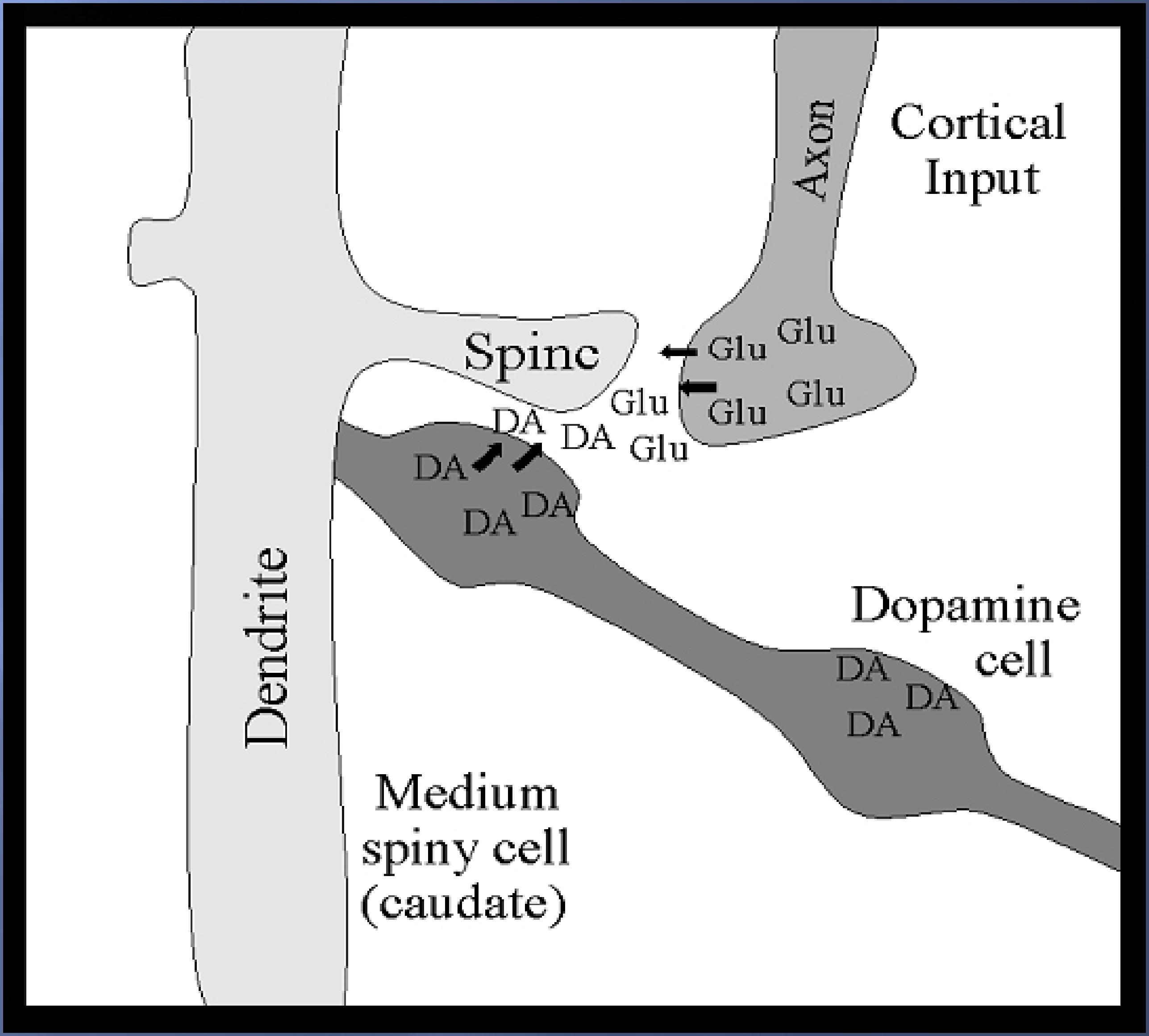
⟵ Excitatory projection
●— Inhibitory projection
⟵ Dopamine projection

# The COVIS Procedural-Learning System

The Striatal Pattern Classifier (Ashby & Waldron, 1999)



# A Cortical-Striatal Synapse

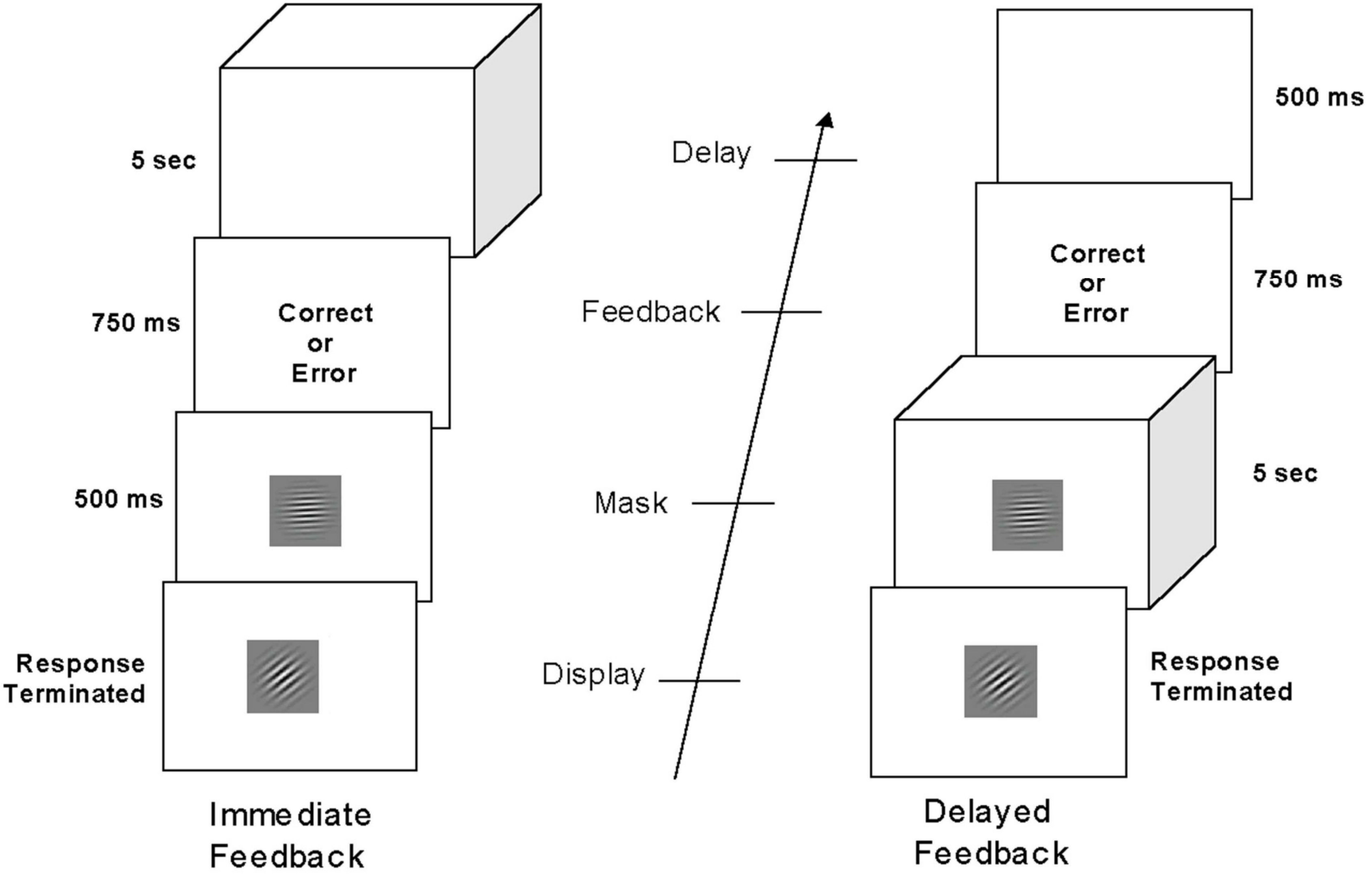


# FEEDBACK PREDICTION

- Information-integration category learning should be sensitive to feedback delay

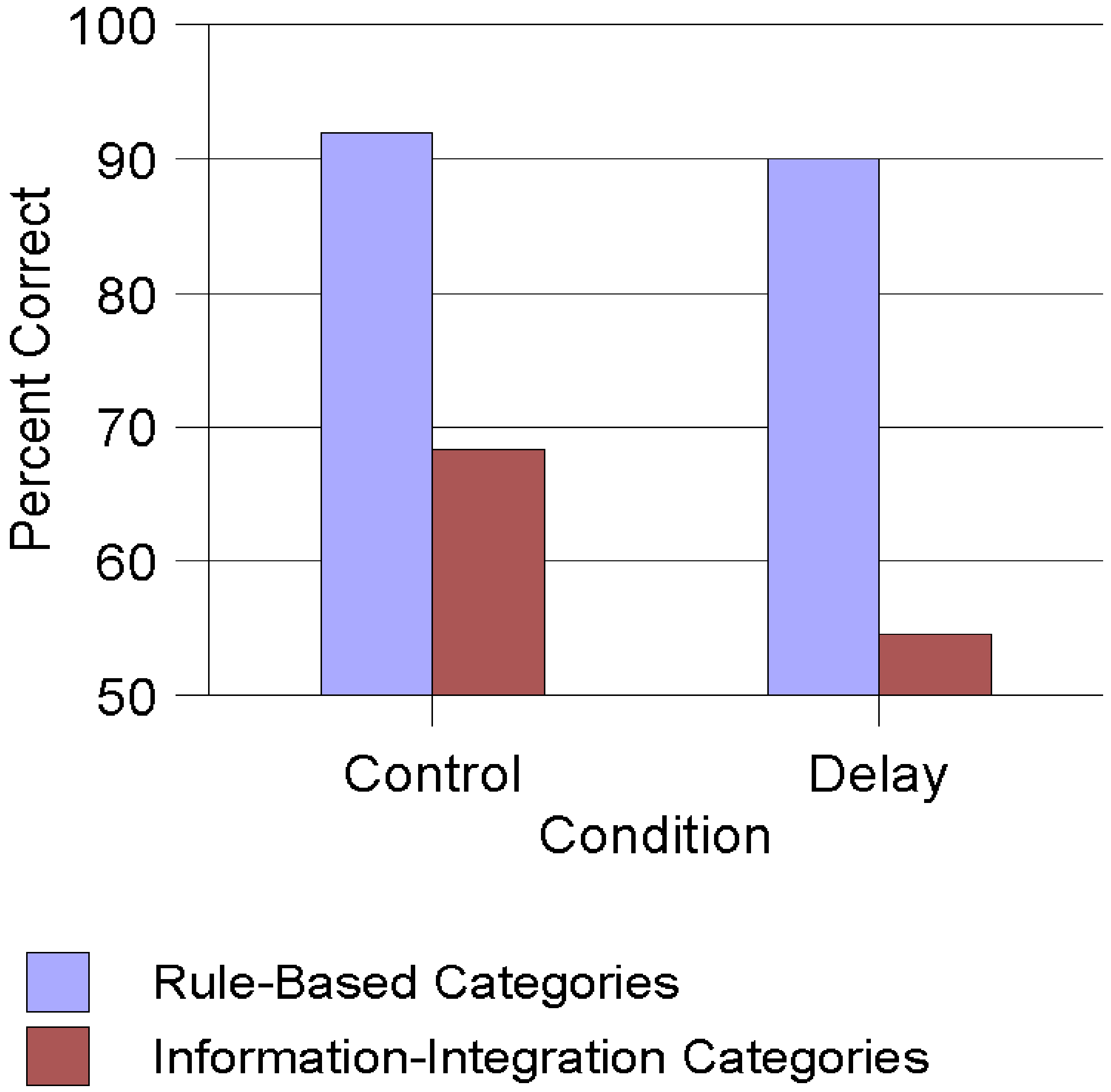
- Rule-based category learning should not be sensitive to feedback delay

# Design of Feedback-Delay Experiment



Maddox, Ashby, & Bohil (2003, *JEP:LM&C*)

# Effects of Feedback Delay



Maddox, Ashby, & Bohil (2003, *JEP:LM&C*)

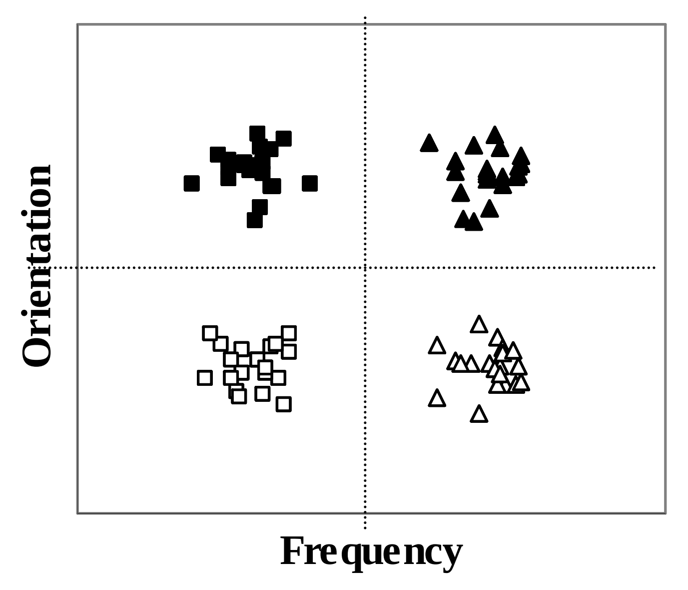
# FOLLOW-UP EXPERIMENTS

- Results identical with 2.5 and 10 sec delays
- RB results replicated at 4 increased levels of difficulty
- Replication with a rule-based task that uses a conjunction rule?

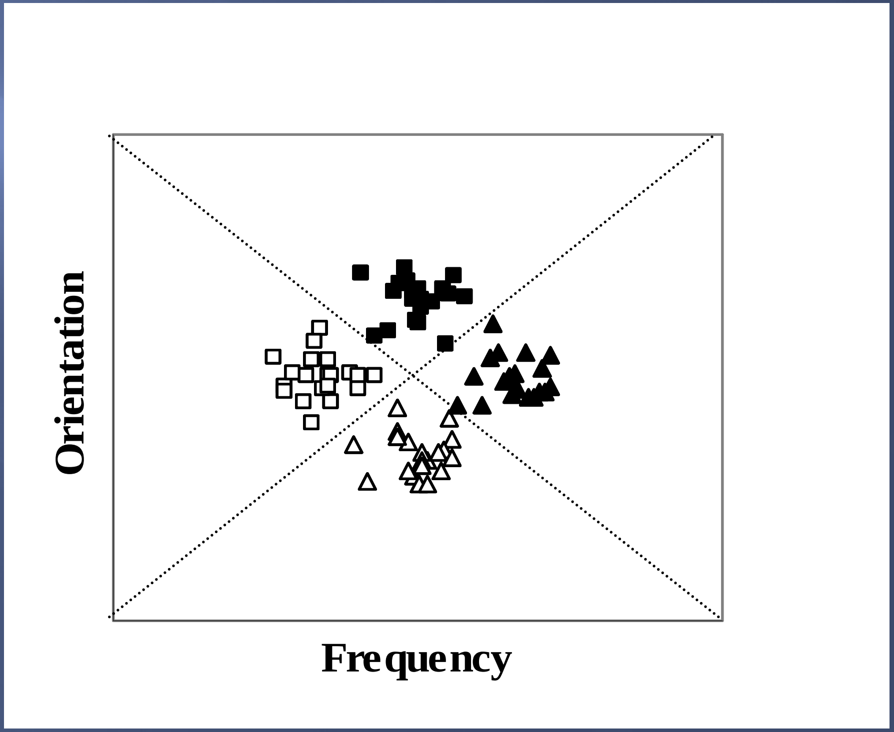
# Category Structures

(Note: Rule-based discriminability higher)

Rule-Based

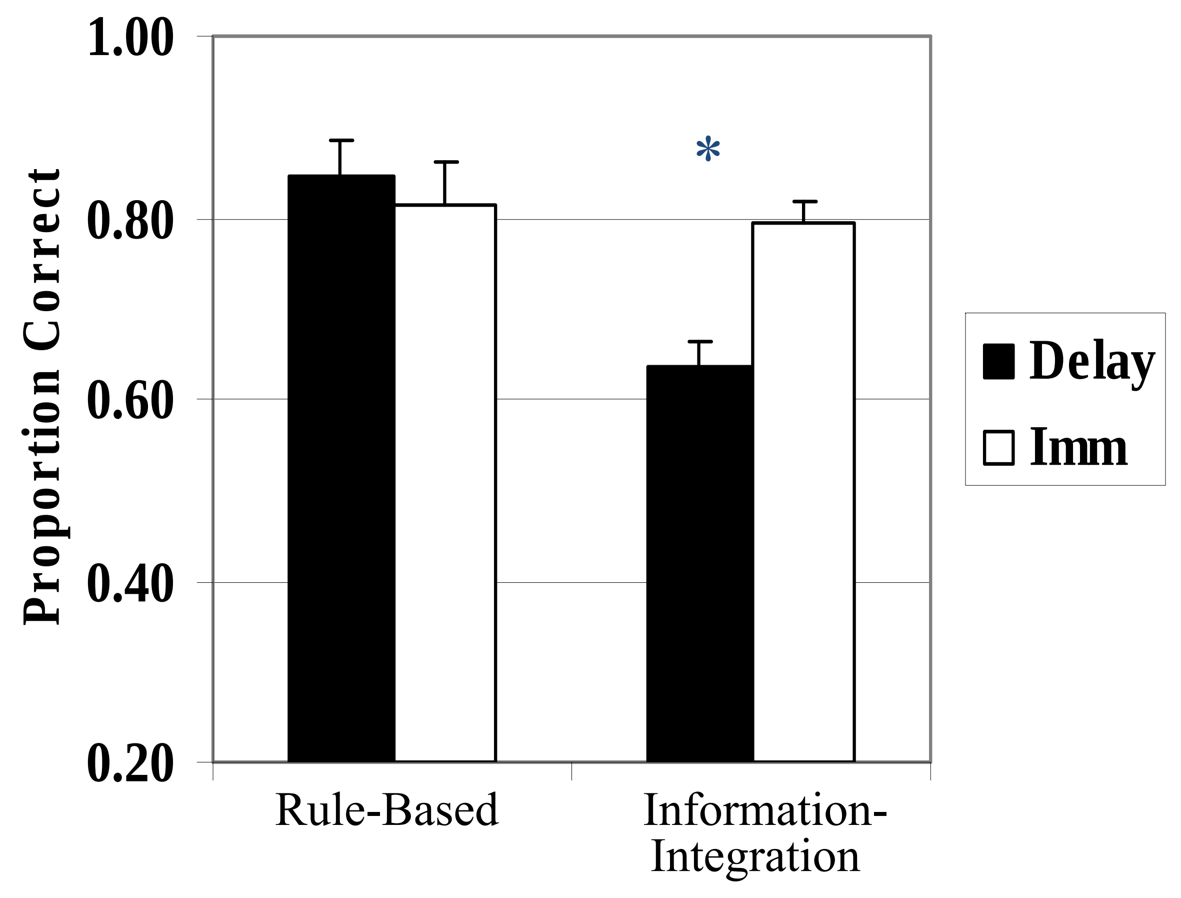


Information-Integration



Maddox & Ing (2005, JEP:LM&C)

# Final Block Accuracy



Maddox & Ing (2005, JEP:LM&C)

# CONCLUSIONS

Feedback delay interferes with information-integration category learning, but not with rule-based category learning.

# EVIDENCE SUPPORTING COVIS

## Single-cell recording studies

Asaad, Rainer, & Miller, 2000; Hoshi, Shima, & Tanji, 1998; Merchant, Zainos, Hernadez, Salinas, & Romo, 1997; Romo, Merchant, Ruiz, Crespo, & Zainos, 1995; White & Wise, 1999

## Animal lesion experiments

Eacott & Gaffan, 1991; Gaffan & Eacott, 1995; Gaffan & Harrison, 1987; McDonald & White, 1993, 1994; Packard, Hirsch, & White, 1989; Packard & McGaugh, 1992; Roberts & Wallis, 2000

## Neuropsychological patient studies

Ashby, Noble, Filoteo, Waldron, & Ell, 2003; Brown & Marsden, 1988; Cools et al., 1984; Downes et al., 1989; Filoteo, Maddox, & Davis, 2001a, 2001b; Filoteo, Maddox, Ing, Zizak, & Song, in press; Filoteo, Maddox, Salmon, & Song, 2005; Janowsky, Shimamura, Kritchevsky, & Squire, 1989; Knowlton, Mangels, & Squire, 1996; Leng & Parkin, 1988; Snowden et al., 2001

# EVIDENCE SUPPORTING COVIS

## Neuroimaging experiments

Konishi et al., 1999; Lombardi et al., 1999; Nomura et al., in press; Poldrack, et al., 2001; Rao et al., 1997; Rogers, Andrews, Grasby, Brooks, & Robbins, 2000; Seger & Cincotta, 2002; Volz et al., 1997

## Traditional cognitive behavioral experiments

Ashby & Ell, 2002; Ashby, Ell, & Waldron, 2003; Ashby, Maddox, & Bohil, 2002; Ashby, Queller, & Berretty, 1999; Ashby, Waldron, Lee, & Berkman, 2001; Maddox, Ashby, & Bohil, 2003; Maddox, Ashby, Ing, & Pickering, 2004; Maddox, Bohil, & Ing, in press; Waldron & Ashby, 2001; Zeithamova & Maddox, in press

# AUTOMATICITY IN II-TYPE TASKS

# BEAR OR DOG?

# EARLY NOTIONS OF AUTOMATICITY

"As I write, my mind is not preoccupied with how my fingers form the letters; my attention is fixed simply on the thought the words express. But there was a time when the formation of the letters, as each one was written, would have occupied my whole attention.”

Sir Charles Sherrington (1906)

# EARLY NOTIONS OF AUTOMATICITY

"It has been widely held that although memory traces are at first formed in the cerebral cortex, they are finally reduced or transferred by long practice to subcortical levels" (p. 466)

Karl Lashley (1950) In search of the engram.

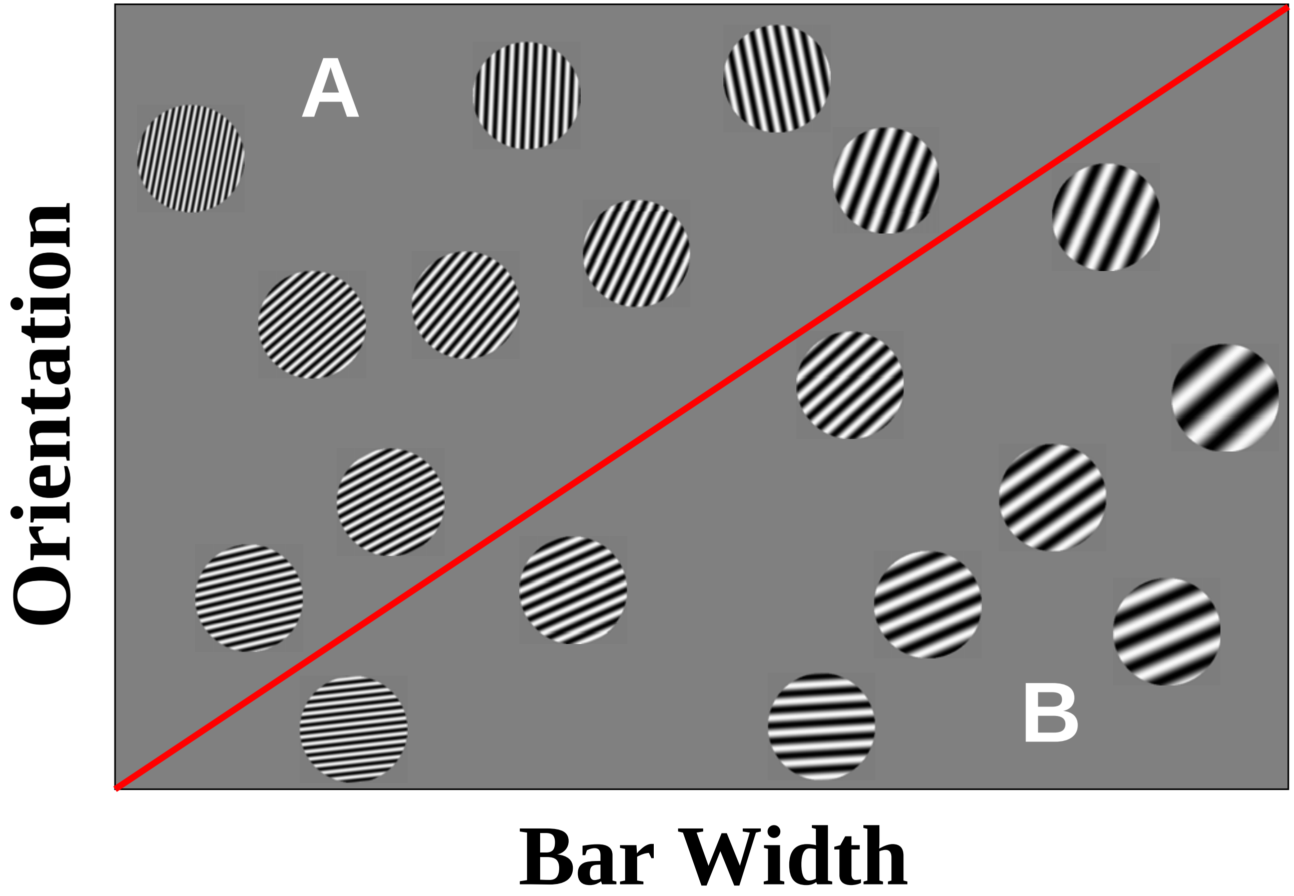
"Routine, automatic, or overlearned behavioral sequences, however complex, do not engage the PFC and may be entirely organized in subcortical structures" (p. 323)

Joaquin Fuster (2001). The prefrontal cortex – an update.

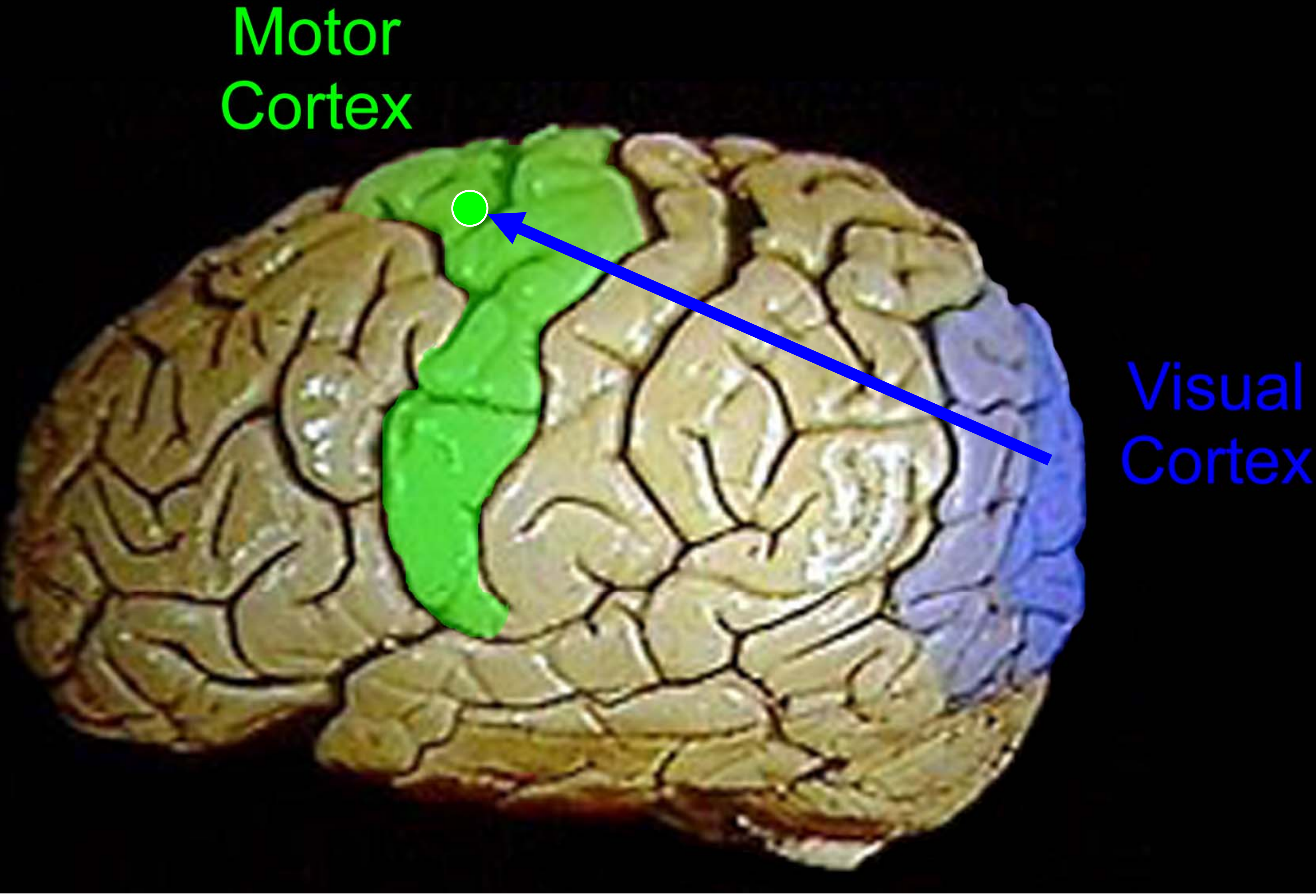
# A DOUBLE DISSOCIATION?

| | Category Learning | Categorization Expertise |
|---|---|---|
| Patients with Basal Ganglia Dysfunction (Parkinson’s disease, Huntington’s disease) | Impaired | Unimpaired |
| Patients with certain visual cortex lesions (category-specific agnosia) | Unimpaired if stimuli are perceived normally? | Impaired |

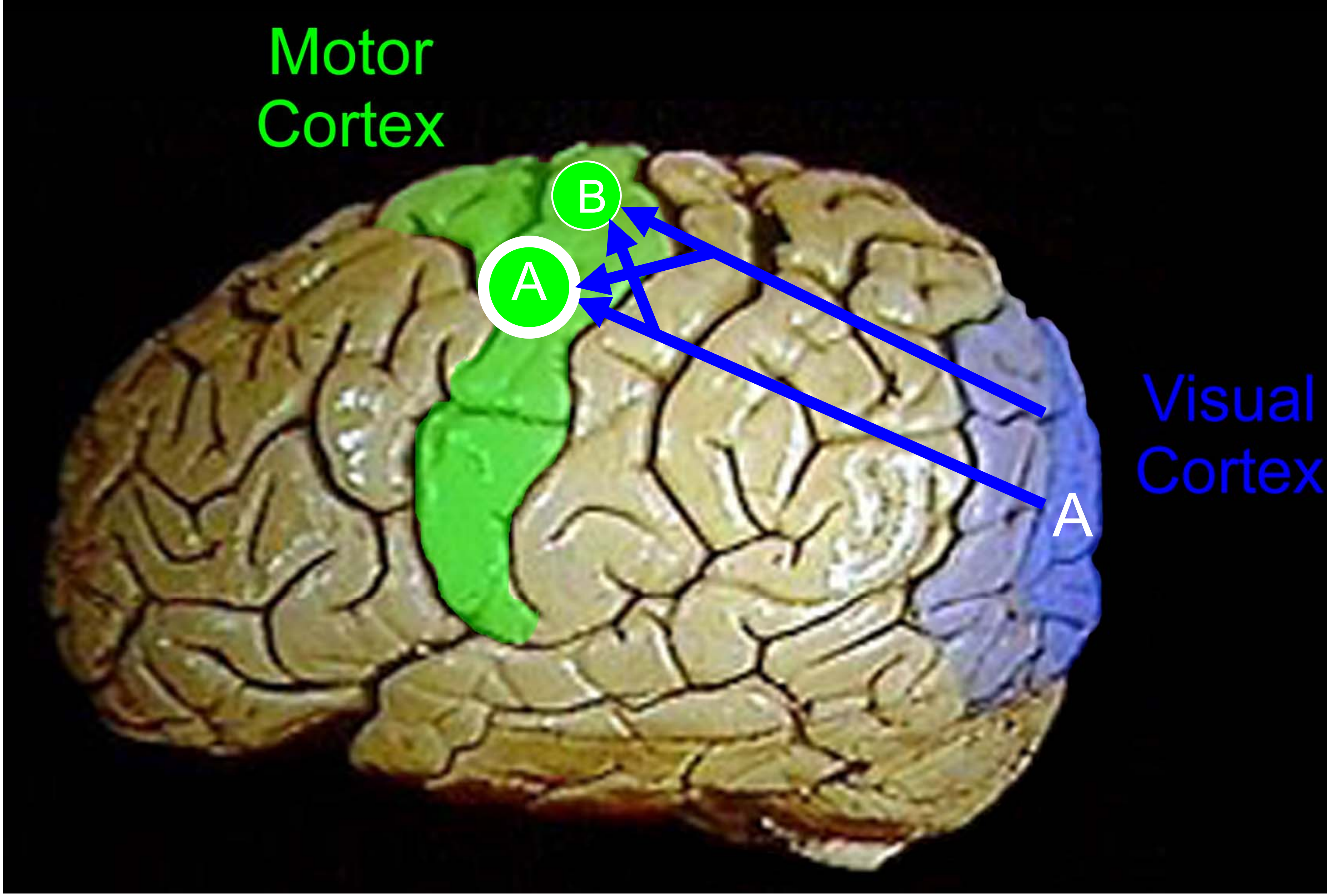
# Information-Integration Category Learning



# BUILDING A MODEL OF AUTOMATICITY

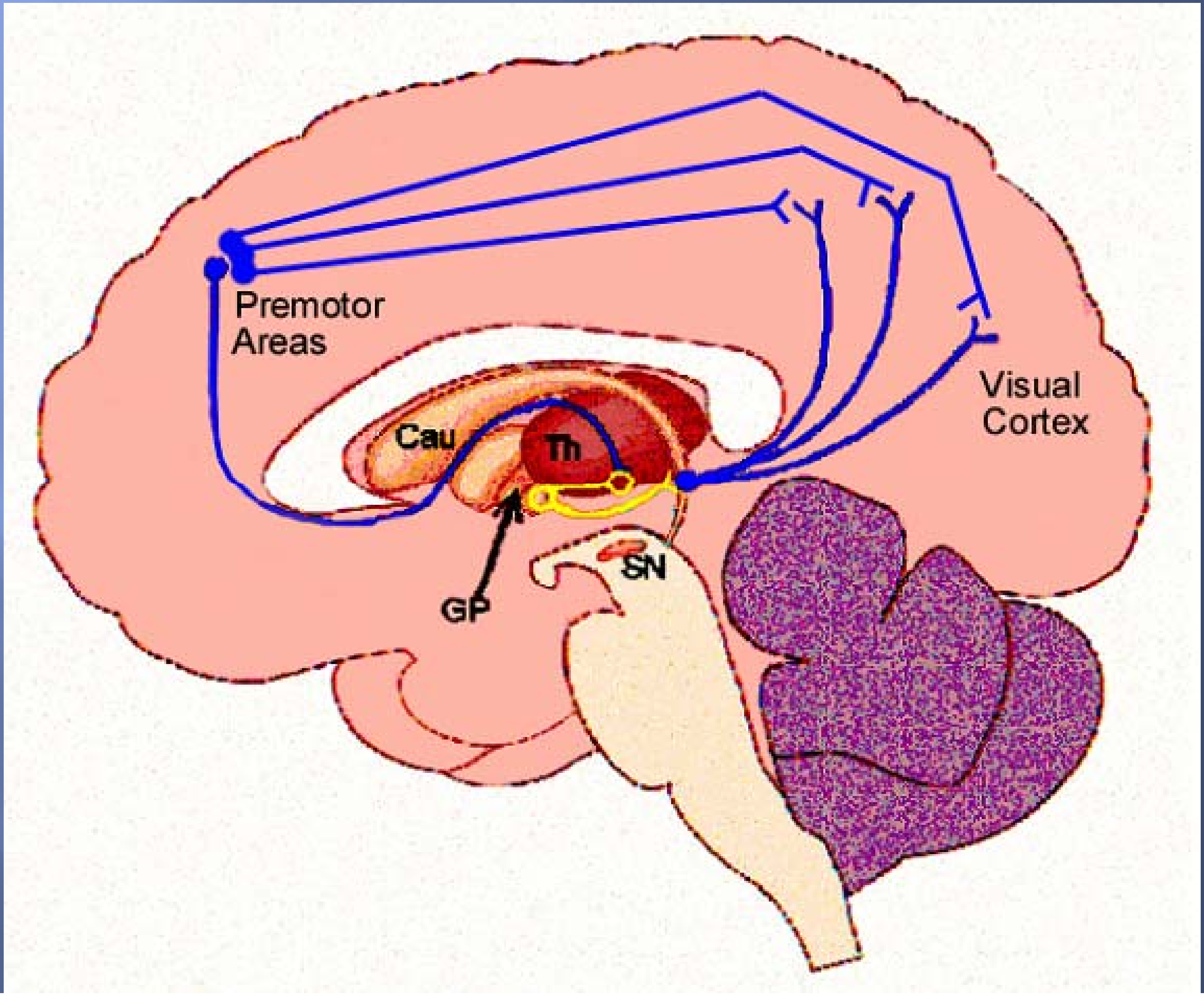


# BUILDING A MODEL OF AUTOMATICITY



# SPEED

Ashby, Ennis, & Spiering (2007, *Psych Review*)

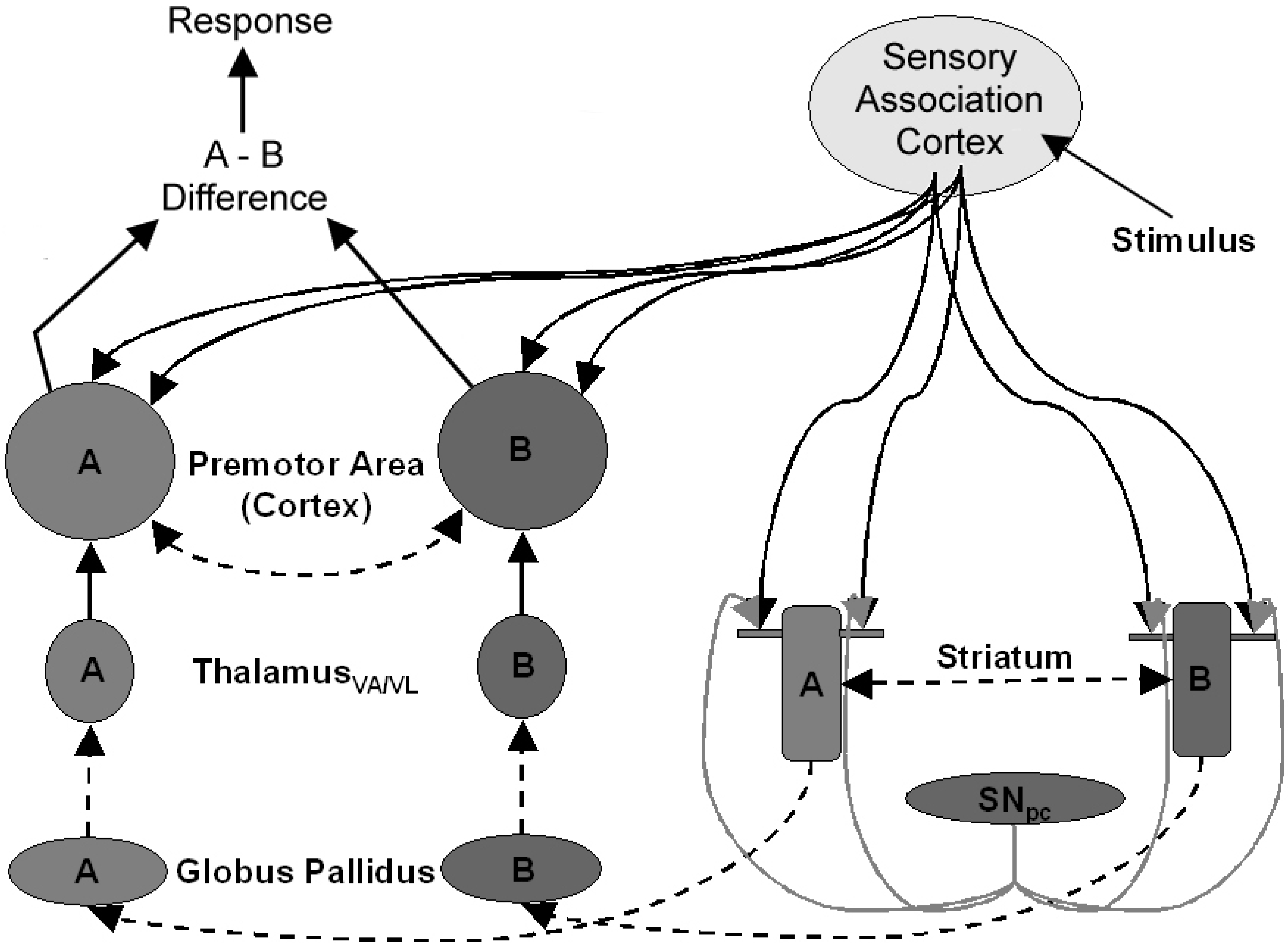


# SPEED

— Excitatory projection (glutamate)

- - - Inhibitory projection (GABA)

— Dopamine projection



Ashby, Ennis, & Spiering (2007, *Psych Review*)

# Activation in Striatum (Medium Spiny Cells)

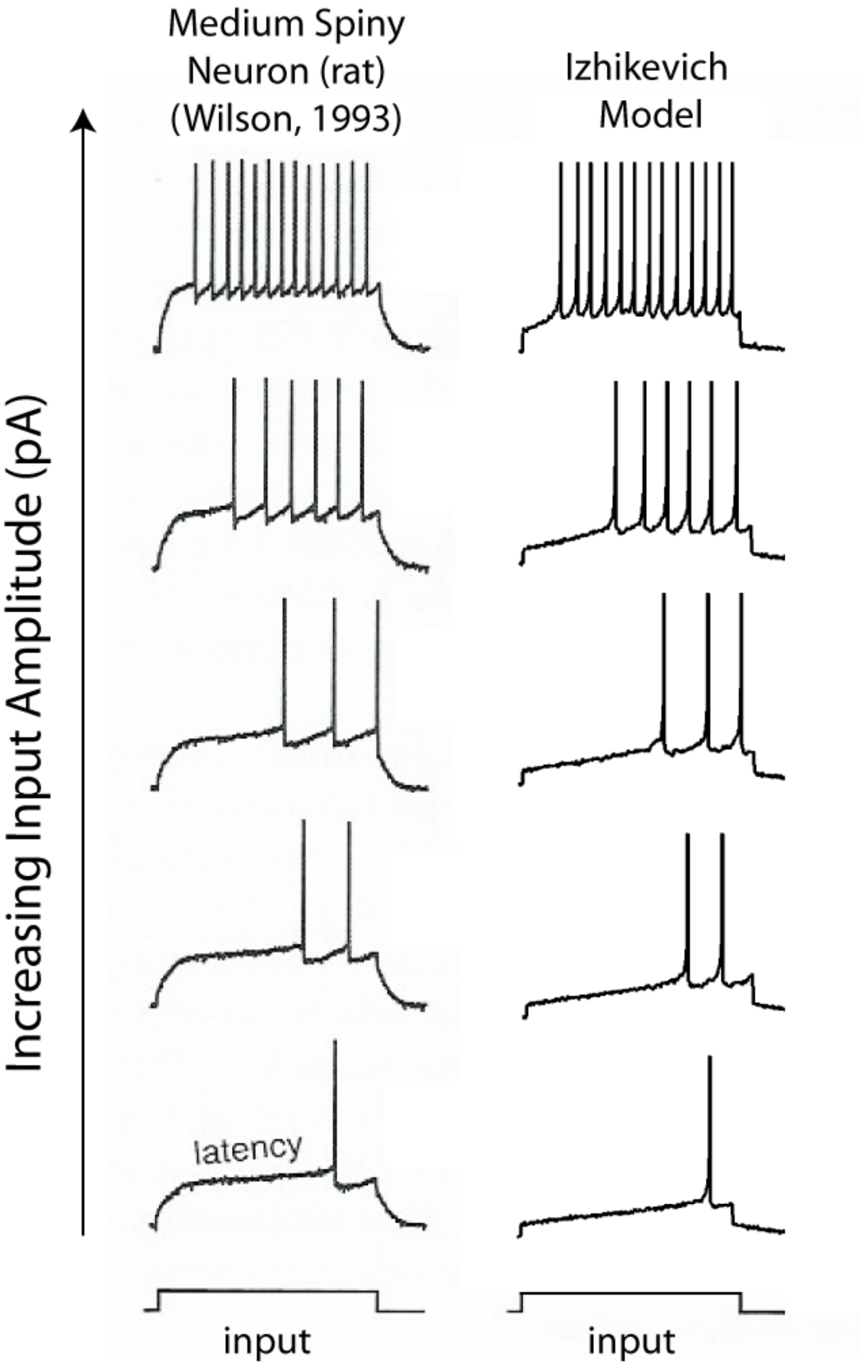
Izhikevich (2003, *IEEE Trans. on Neural Networks*)

$$C\dot{v} = k(v - v_{rest})(v - v_t) - u + I$$

$$\dot{u} = a\left[b\left(v - v_{rest}\right) - u\right]$$

If $v \geq v_{peak}$ then reset v to v = c
and reset u to u + d

$C = 50$, $v_{rest} = -80$, $v_t = -25$, $a = .01$,
$b = -20$, $v_{peak} = 40$, $c = -55$, $d = 150$



# Activation in Striatum (Medium Spiny Cells)

Activation in striatal unit $J$ at time $t$, denoted $S_J(t)$ equals

$$\frac{dS_J(t)}{dt} = \left[\sum_K w_{K,J}(n) I_K(t)\right][1 - S_J(t)] - \beta_S S_M(t) - \gamma_S\left[S_J(t) - S_{base}\right] + \sigma_S \varepsilon(t) S_J(t)[1 - S_J(t)],$$

where $I_K(t)$ is the input from visual cortical unit $K$ at time $t$, and $w_{K,iJ}(n)$ is the strength of the synapse between cortical unit $K$ and spine $i$ on medium spiny cell $J$, and $\varepsilon(\mathrm{t})$ is white noise.

# Modeling Activation in Other Units

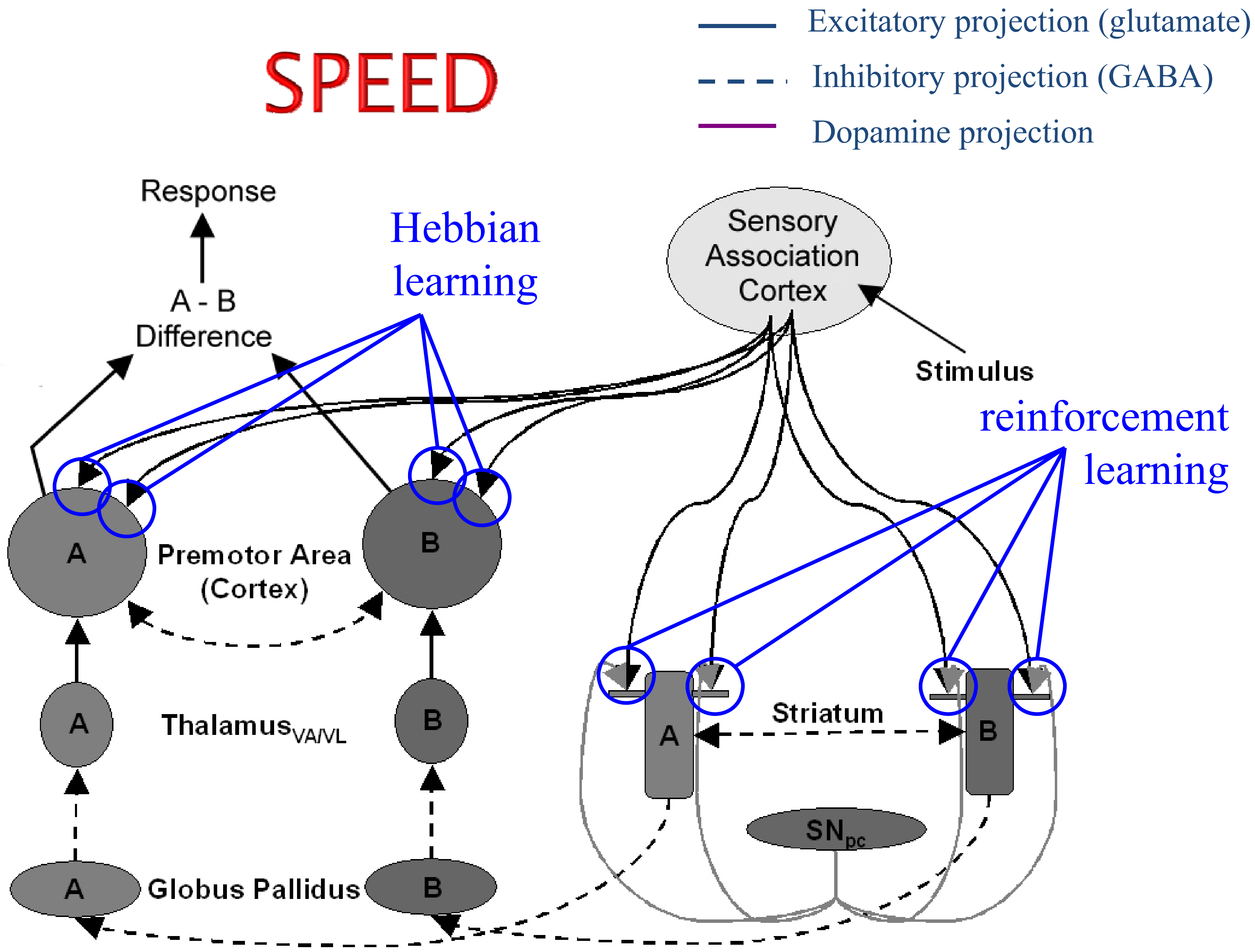
Globus Pallidus $$\frac{dG_J(t)}{dt} = -\alpha_G S_J(t) G_J(t) - \beta_G \left[ G_J(t) - G_{base} \right]$$

Thalamus: $$\frac{dT_J(t)}{dt} = -\alpha_T G_J(t) T_J(t) - \beta_T T_J(t),$$

Premotor Area

$$\frac{dE_J(t)}{dt} = \left[ \alpha_E T_J(t) + \sum_K v_{K,J}(n) I_K(t) \right] \left[ 1 - E_J(t) \right] - \beta_E E_K(t) - \gamma_E \left[ E_J(t) - E_{base} \right] + \sigma_E \varepsilon(t) E_J(t) \left[ 1 - E_J(t) \right],$$

# SPEED



Excitatory projection (glutamate)
Inhibitory projection (GABA)
Dopamine projection
Response
A - B
Difference
Hebbian learning
Sensory Association Cortex
Stimulus
reinforcement learning
A
Premotor Area (Cortex)
B
A
Thalamus$_{VA/VL}$
B
A
Globus Pallidus
B
A
Striatum
B
SN$_{pc}$

# Cortical-Cortical Learning (Hebbian)

## Global Feedback Algorithm

LTP

presynaptic
activation

postsynaptic activation
(above NMDA threshold)

$$v_{K,J}(n+1) = v_{K,J}(n)\boxed{+}\alpha_v \boxed{I_k(t)}\boxed{\left[E_J(t)-\theta_{NMDA}\right]}^+\left[1-v_{K,J}(n)\right]$$

$$\boxed{-}\beta_v I_k(t)\boxed{\left[\theta_{NMDA}-E_J(t)\right]^+}v_{K,J}(t)$$

LTD

postsynaptic activation
(below NMDA threshold)

# Cortical-Striatal Learning

(reinforcement learning – also a global learning algorithm)

LTP

activation above
NMDA threshold

dopamine above baseline
(Correct Response)

$$\begin{aligned} w_{K,iJ}(n+1) = w_{K,iJ}(n) & \\ & \boxed{+}\,\alpha_w S_J(t)\boxed{\left[r_{K,iJ}(t)-\theta_{NMDA}\right]^{+}}\boxed{\left[D(n)-D_{base}\right]^{+}}\left[1-w_{K,iJ}(n)\right] \\ & \boxed{-}\,\beta_w S_J(t)\boxed{\left[r_{K,iJ}(t)-\theta_{NMDA}\right]^{+}}\boxed{\left[D_{base}-D(n)\right]^{+}}w_{K,iJ}(n) \\ & \boxed{-}\,\gamma_w\boxed{\left[\theta_{NMDA}-r_{K,iJ}(t)\right]^{+}}w_{K,iJ}(n), \end{aligned}$$

dopamine below
baseline (error)

activation below
NMDA threshold

activation above
NMDA threshold

LTD

# Dopamine Release

Increases with:

Obtained Reward – Predicted Reward

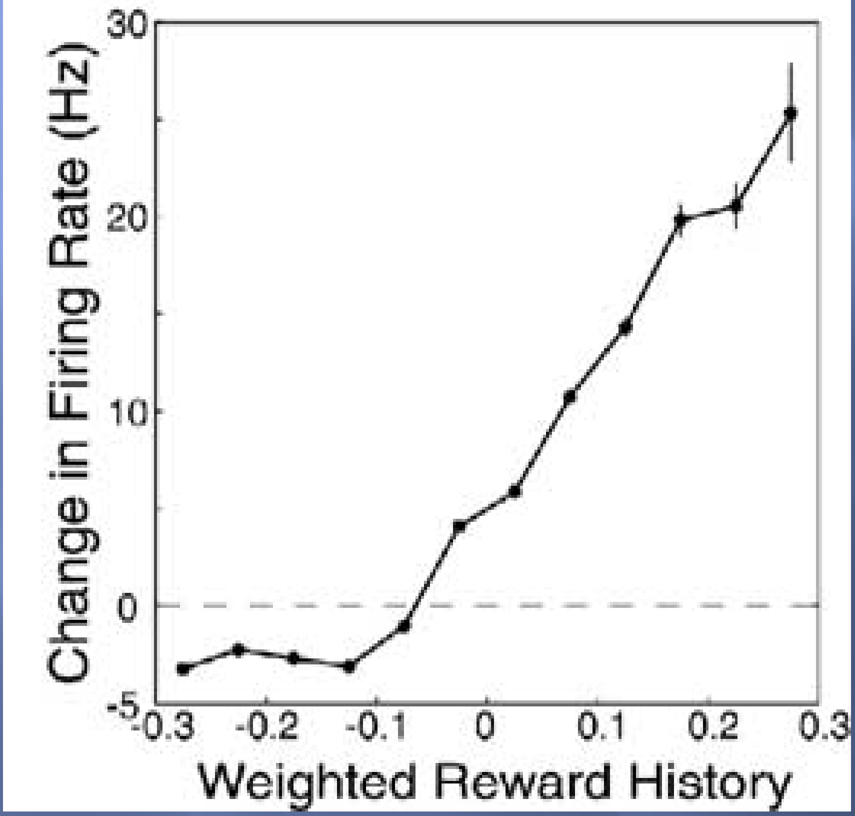
where obtained reward on trial *n* equals

$$R_n = \begin{cases} +1 & \text{if correct feedback is received} \\ 0 & \text{if no feedback is received} \\ -1 & \text{if error feedback is received} \end{cases}$$

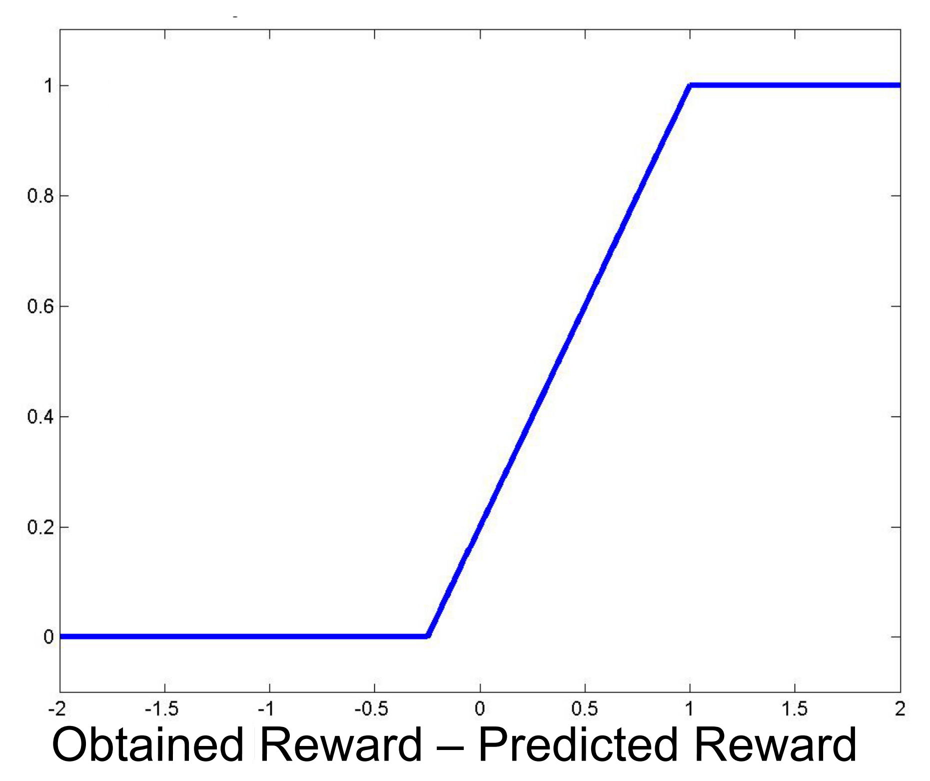
$$\text{and Predicted Reward on trial n} = C\sum_{i=1}^{n-1} e^{\theta(n-i)} R_i$$

# Dopamine Release

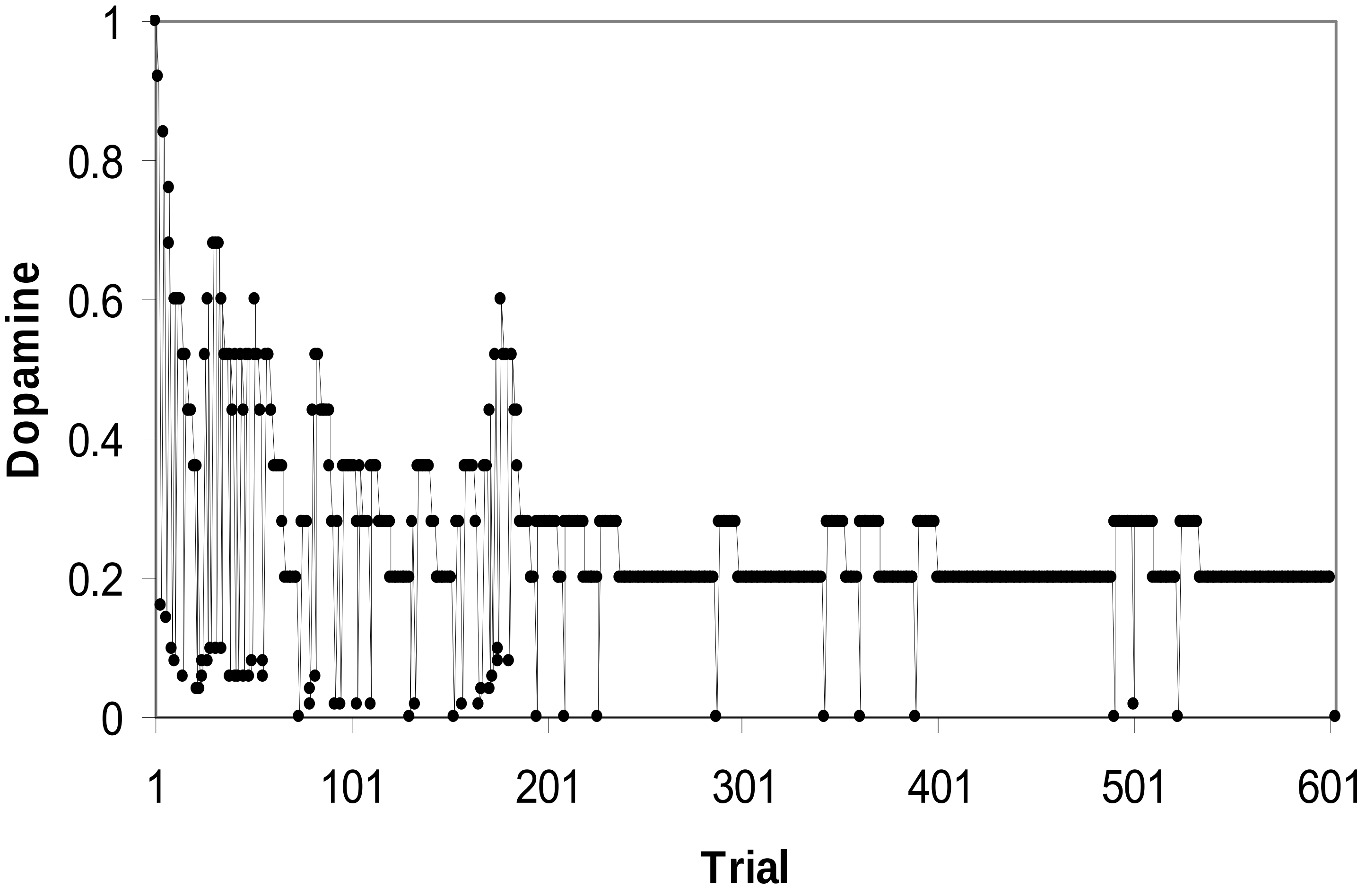
Bayer & Glimcher (2005, *Neuron*)



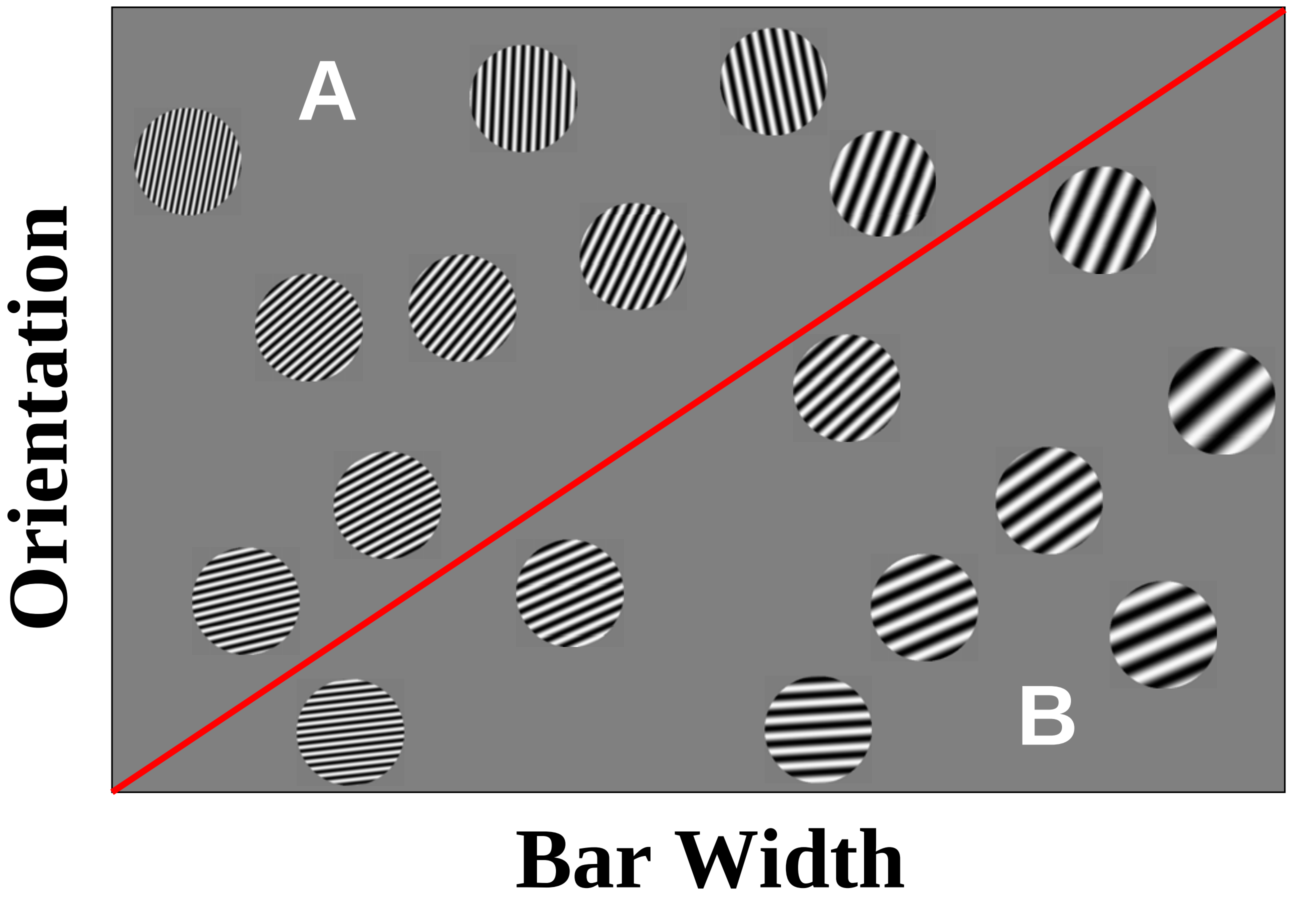
Dopamine Release in SPEED



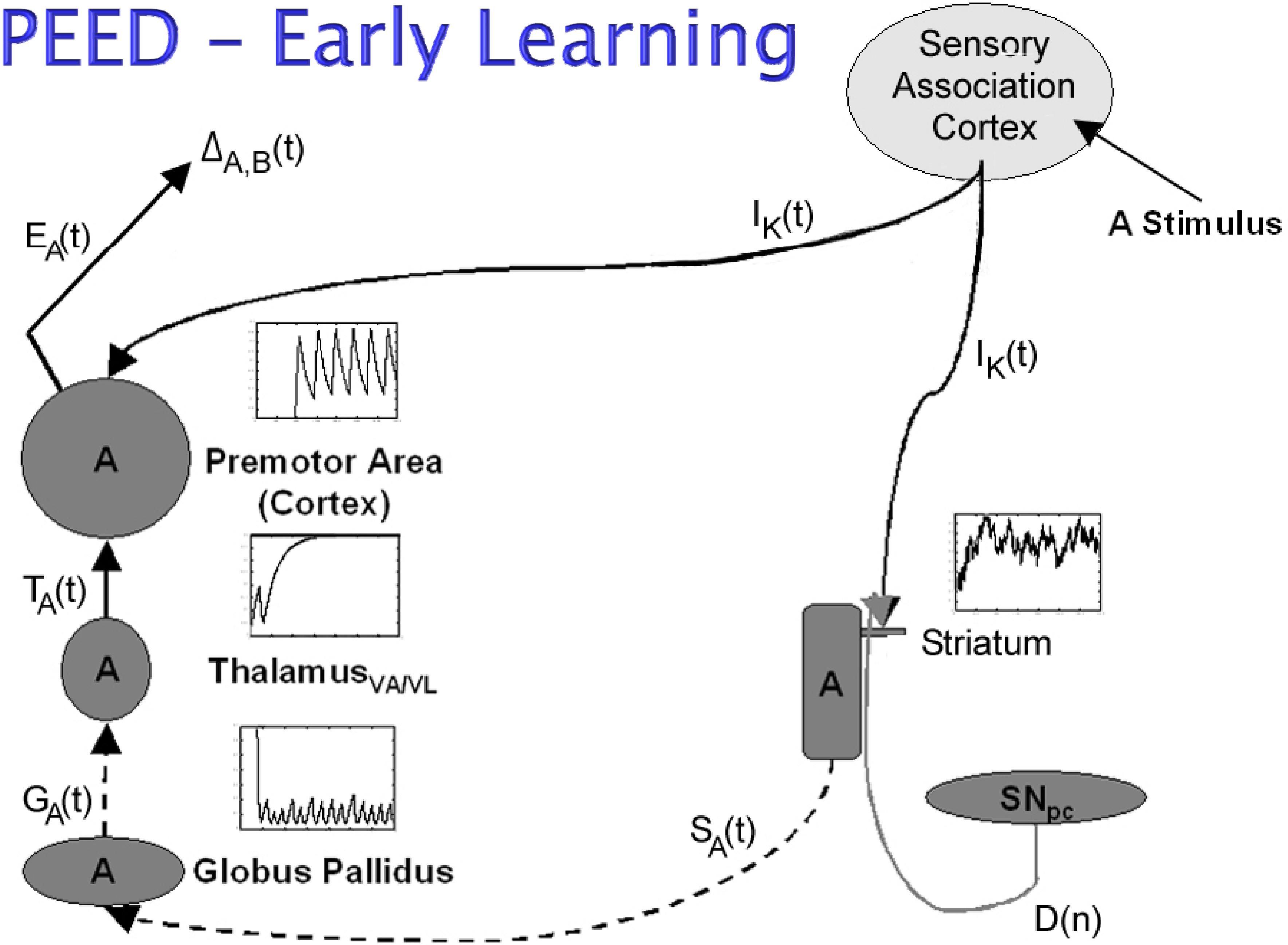
# Dopamine Release



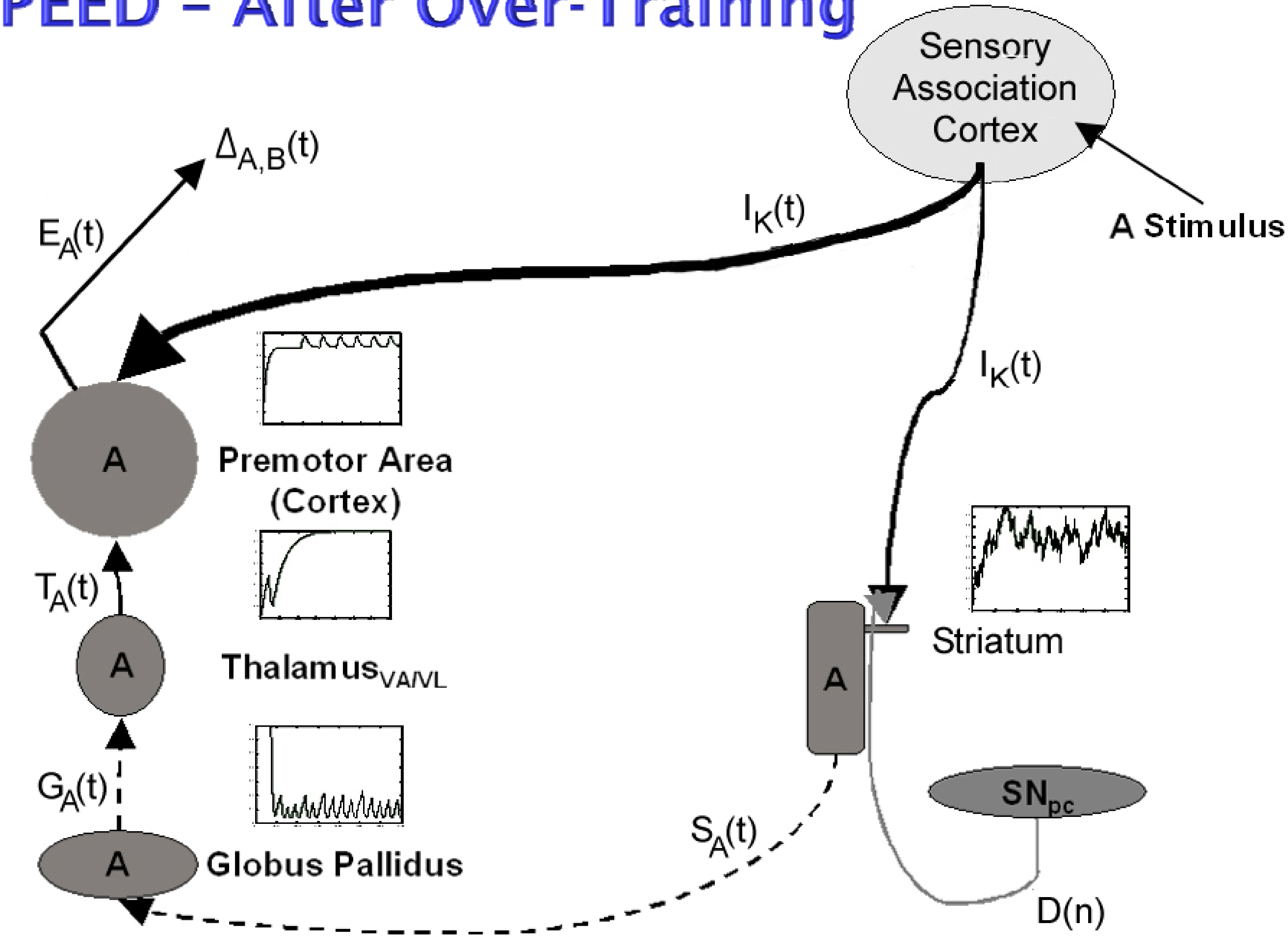
# II Category Learning



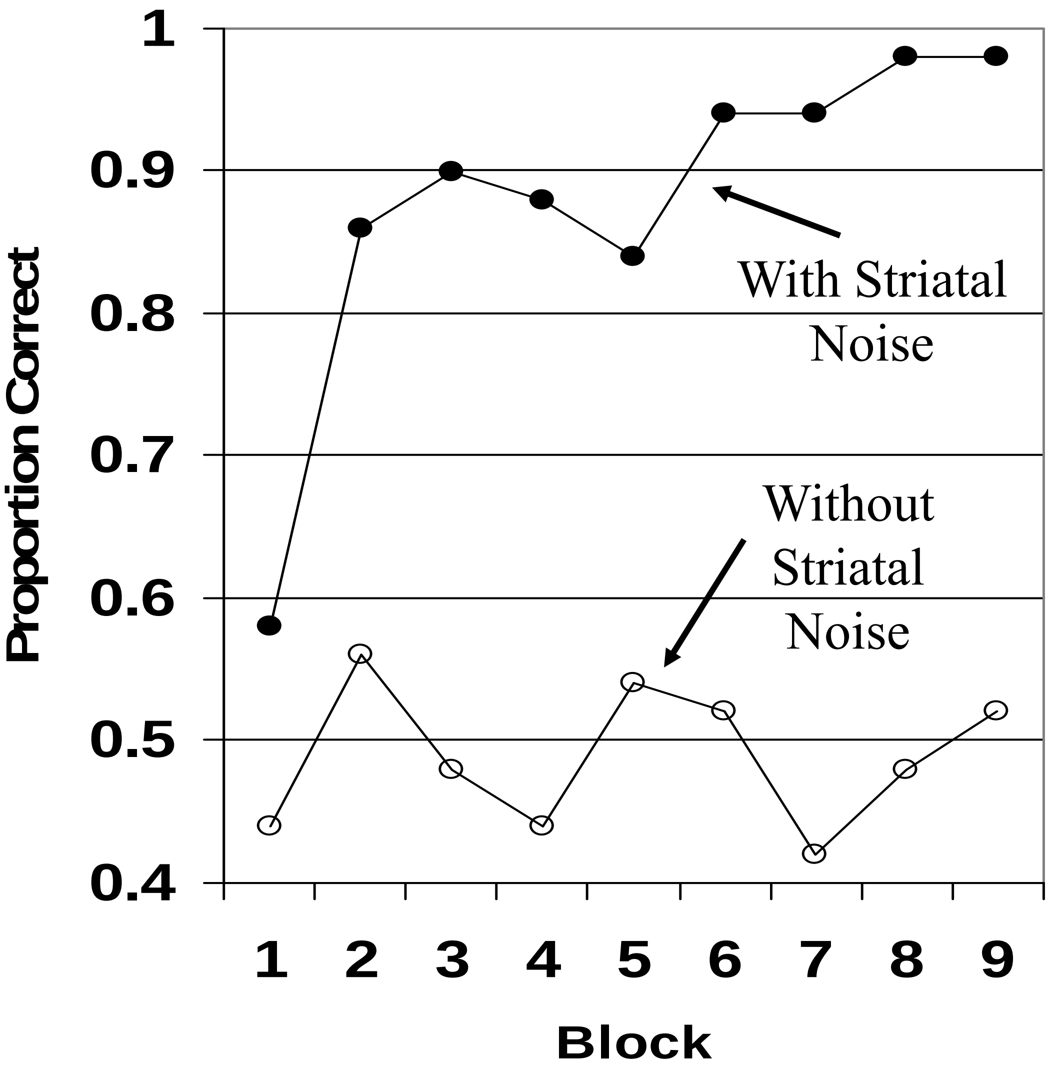
# SPEED – Early Learning



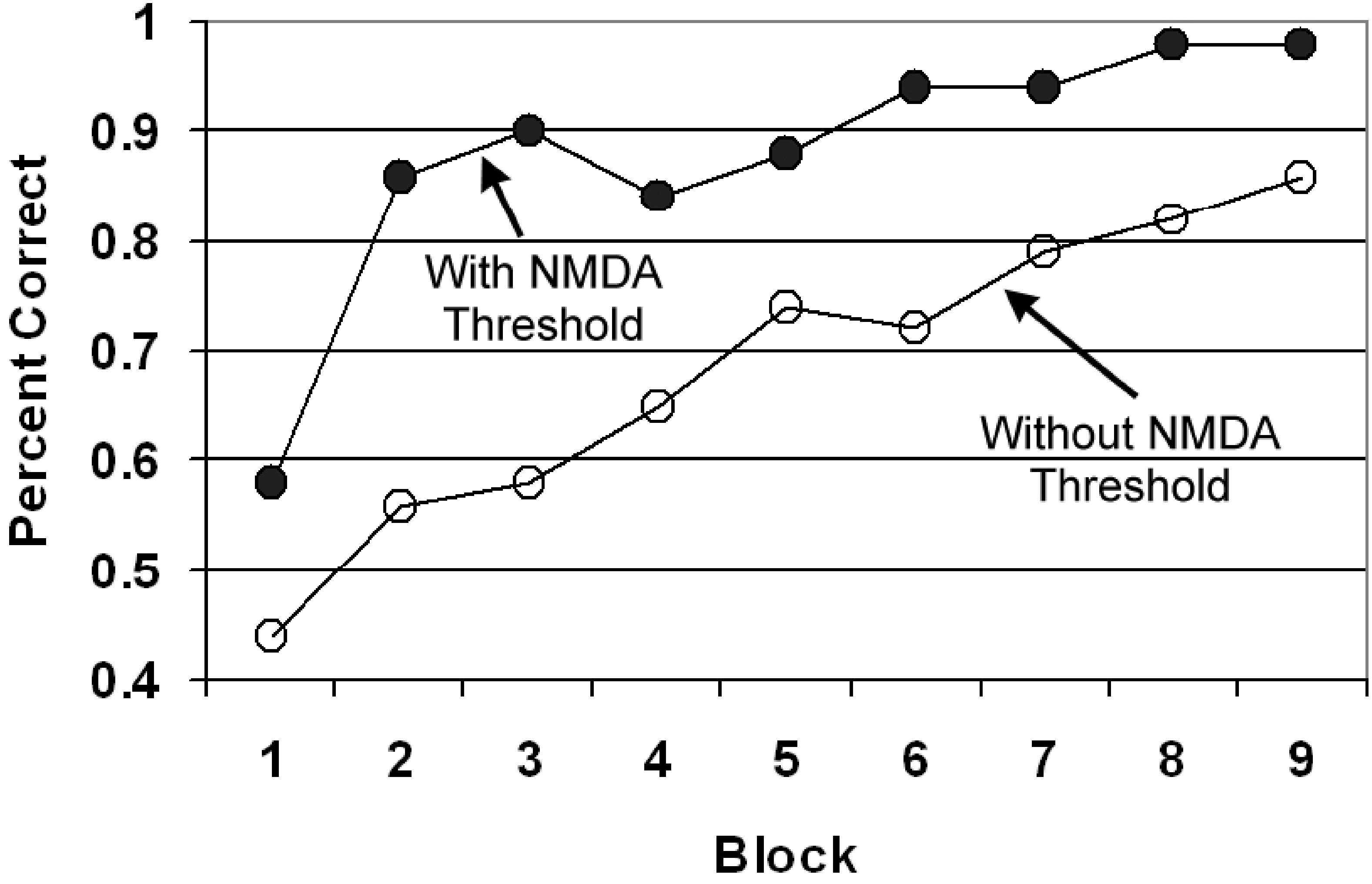
# SPEED – After Over-Training



# II Learning With and Without Striatal Noise



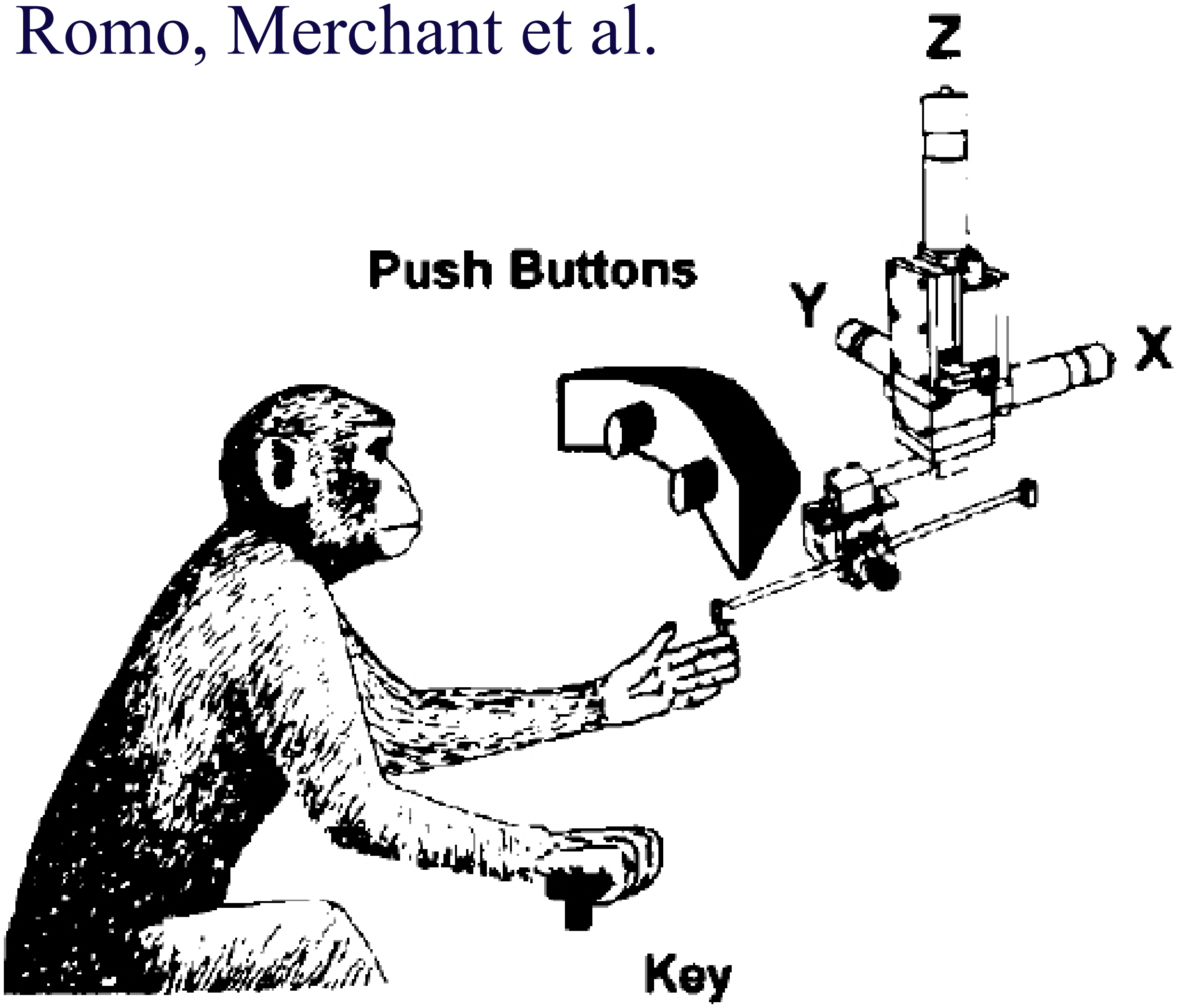
# II Learning With and Without NMDA Threshold



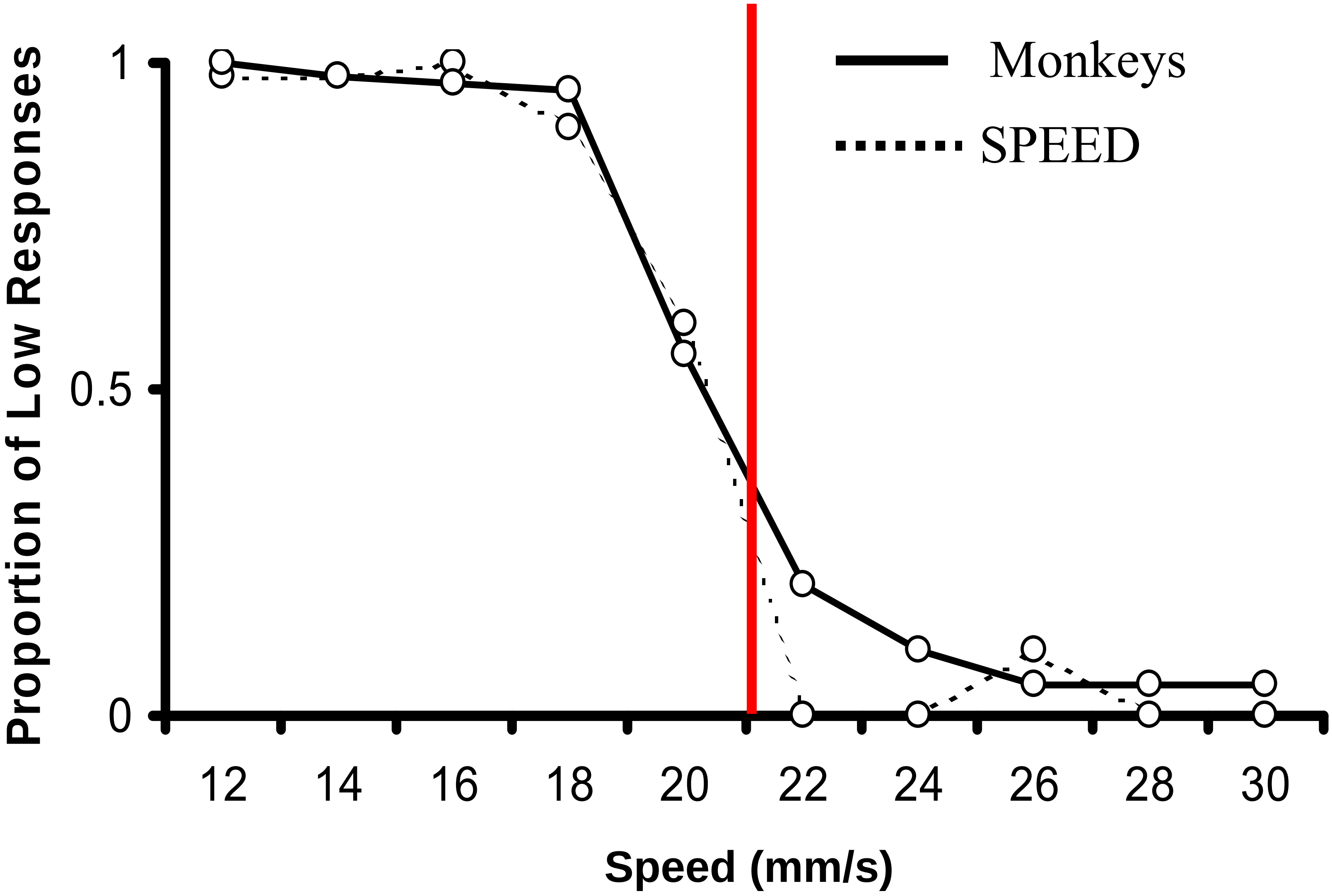
# Experimental Tests

# Tactile Category Learning

Romo, Merchant et al.



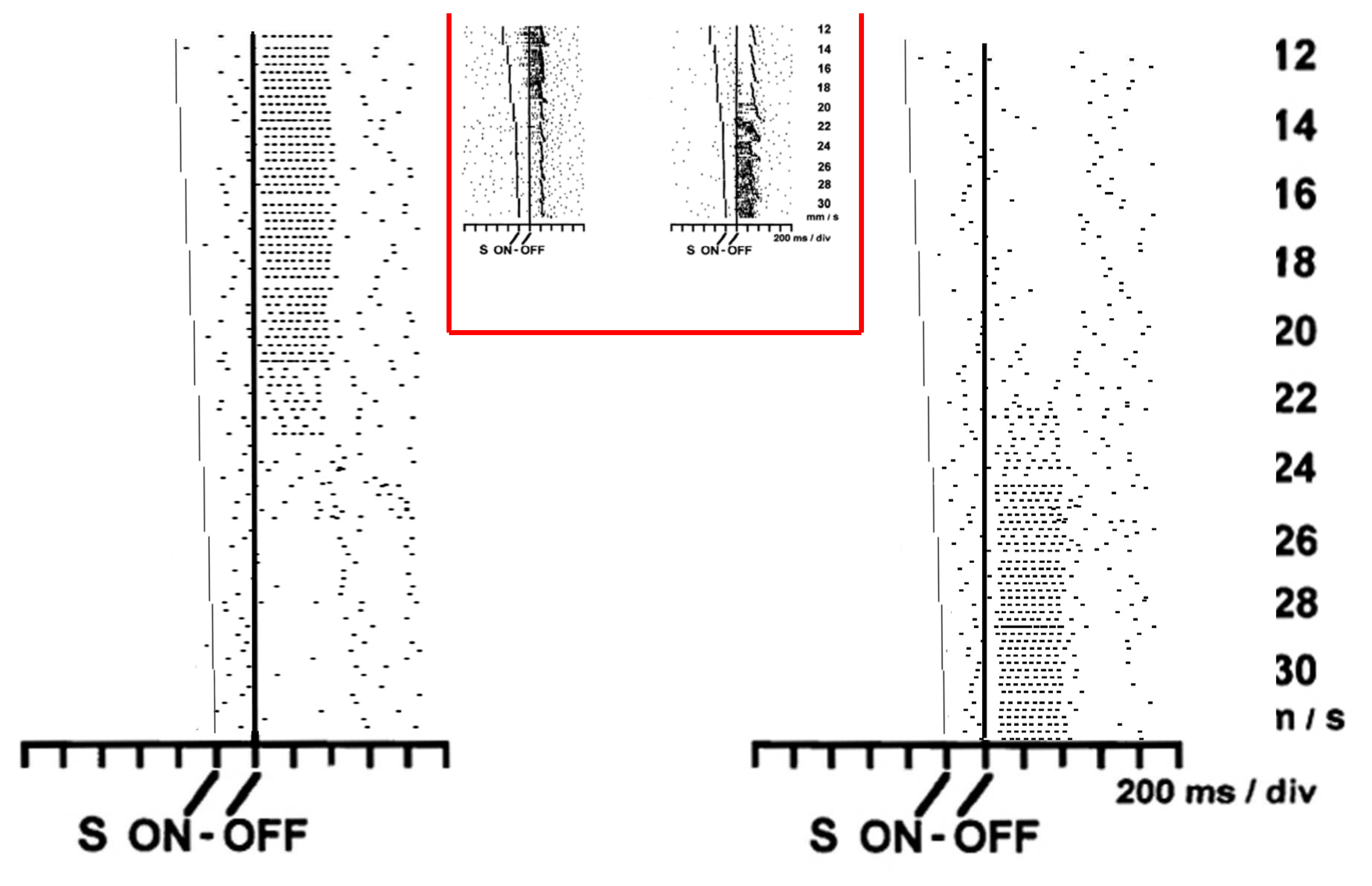
# Model Fits


Proportion of Low Responses
1
0.5
0
12
14
16
18
20
22
24
26
28
30
Speed (mm/s)
Monkeys
SPEED

# SPEED's Single Cell Responses –Putamen

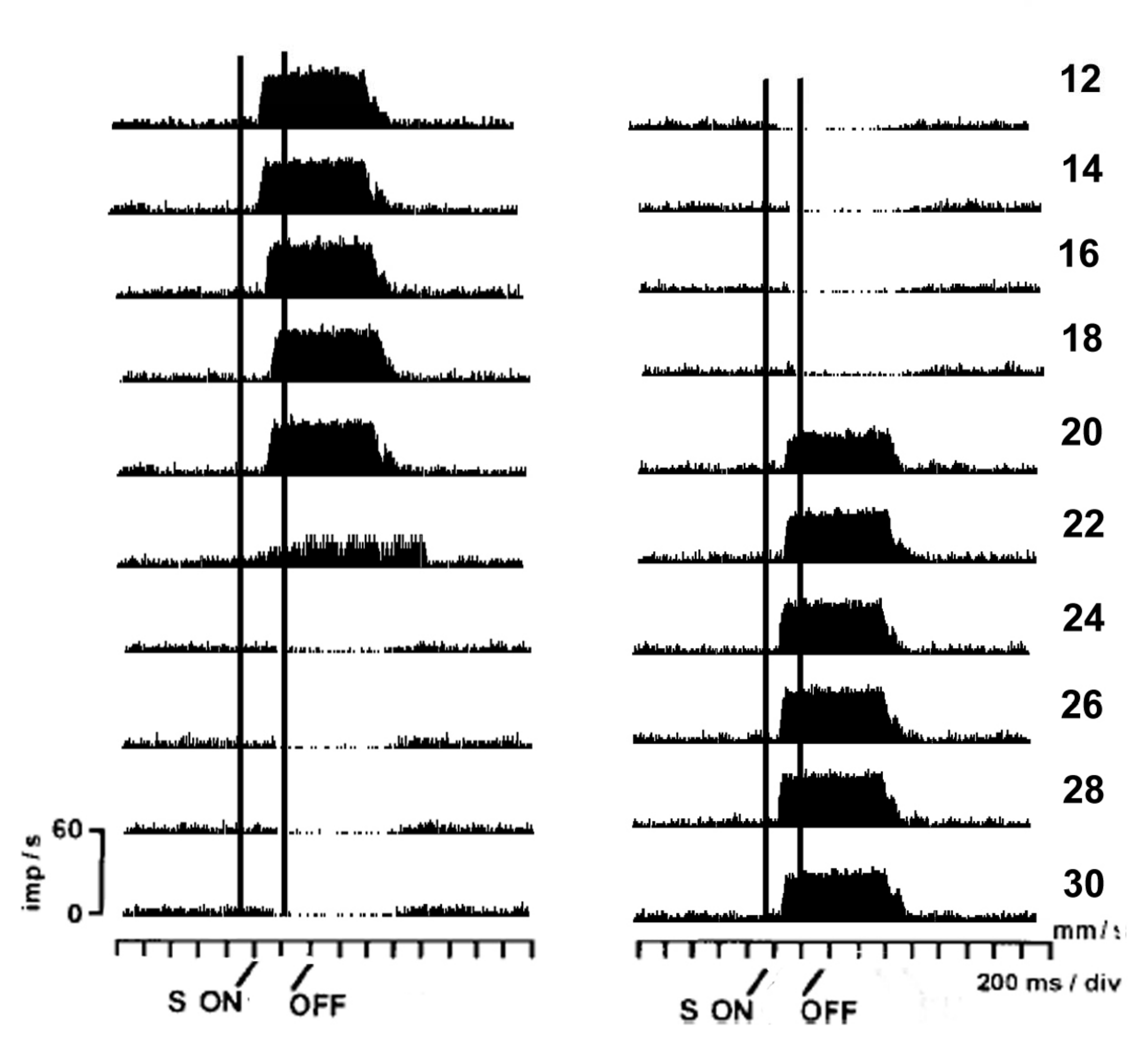
Low Speed Cell

High Speed Cell

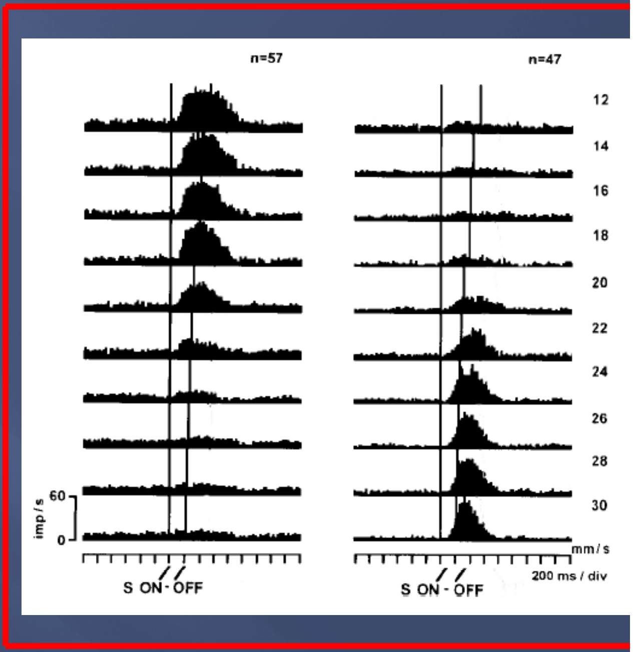


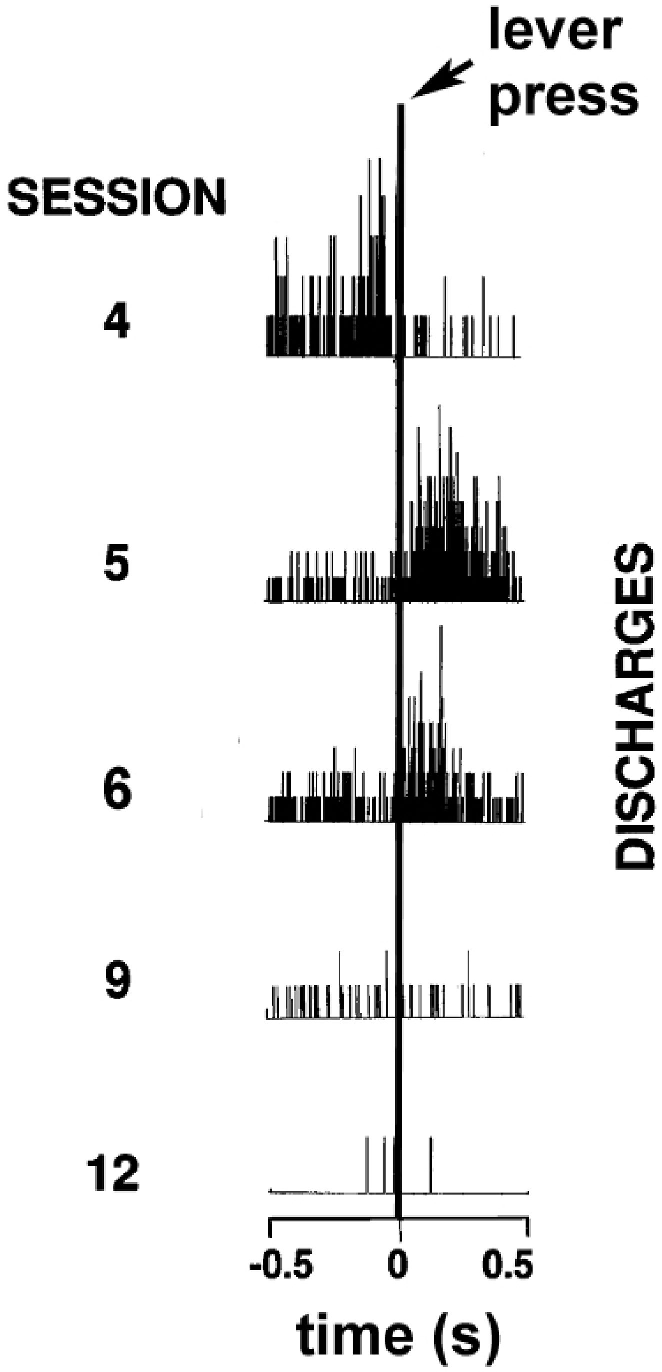
# SPEED's Responses – Premotor Cortex

Low Speed Cells High Speed Cells



Romo et al., 1997





# Carelli, Wolske, & West

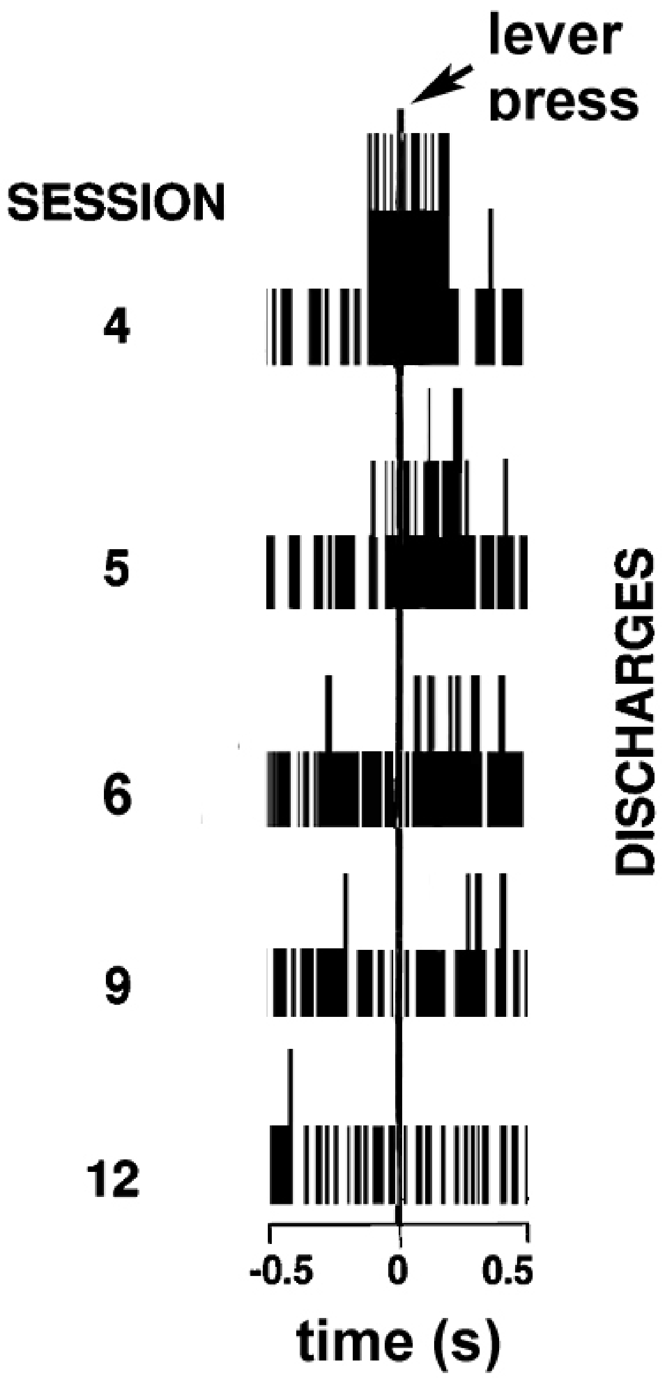
(1997, J. of Neuroscience)

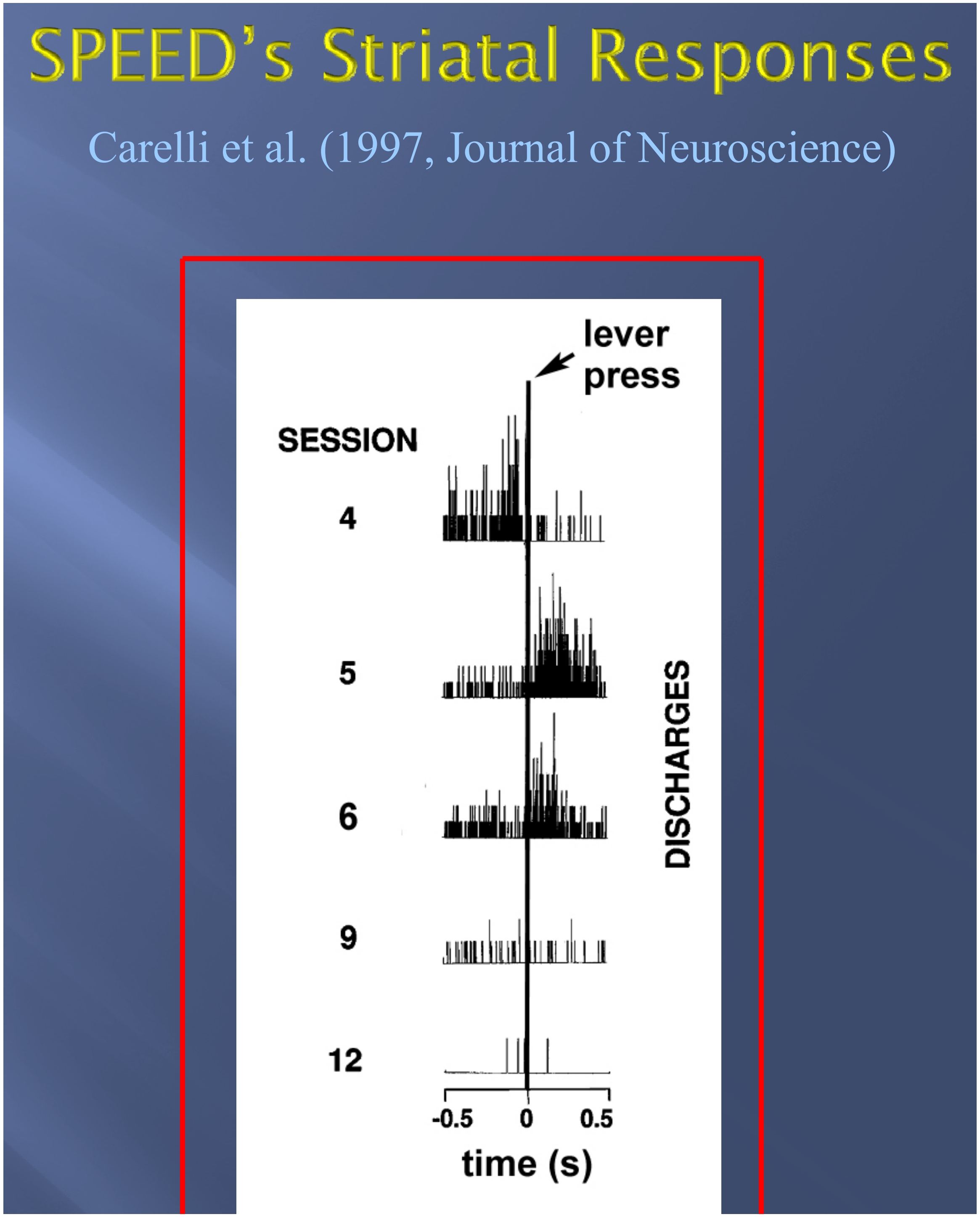
Lever press to tone

70 trials/day

18 days

## Striatal Response

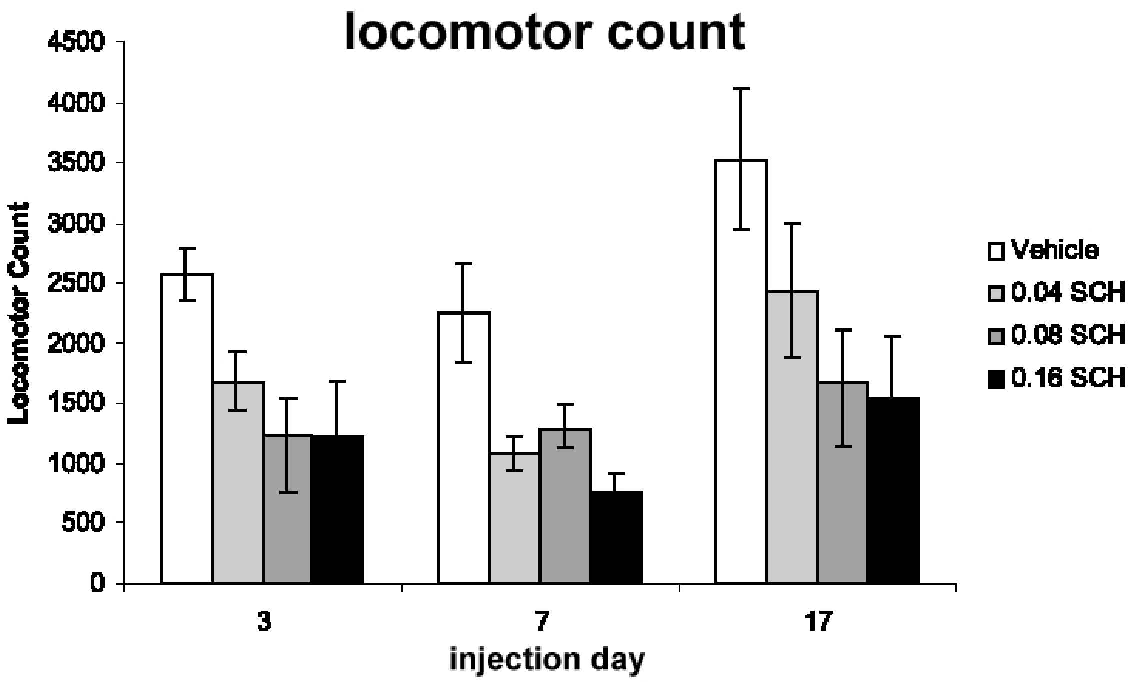




# SPEED's Striatal Responses

Carelli et al. (1997, Journal of Neuroscience)

proportion of trials missed



locomotor count

# Choi, Balsam, & Horvitz

(2005, J. of Neuroscience)

Food pellet dropped into compartment

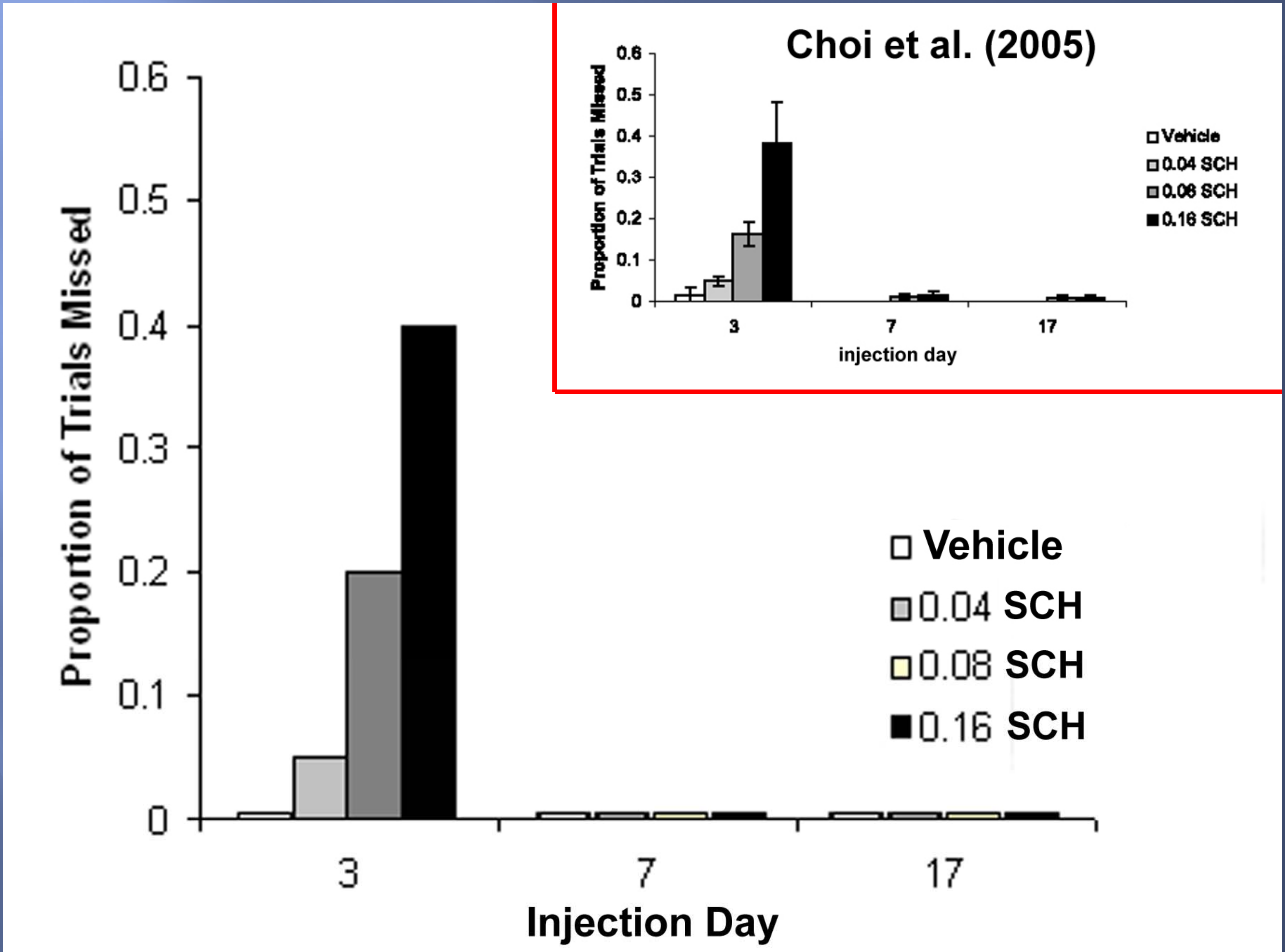
Minimum 30 s between trials

28 trials/day

17 days

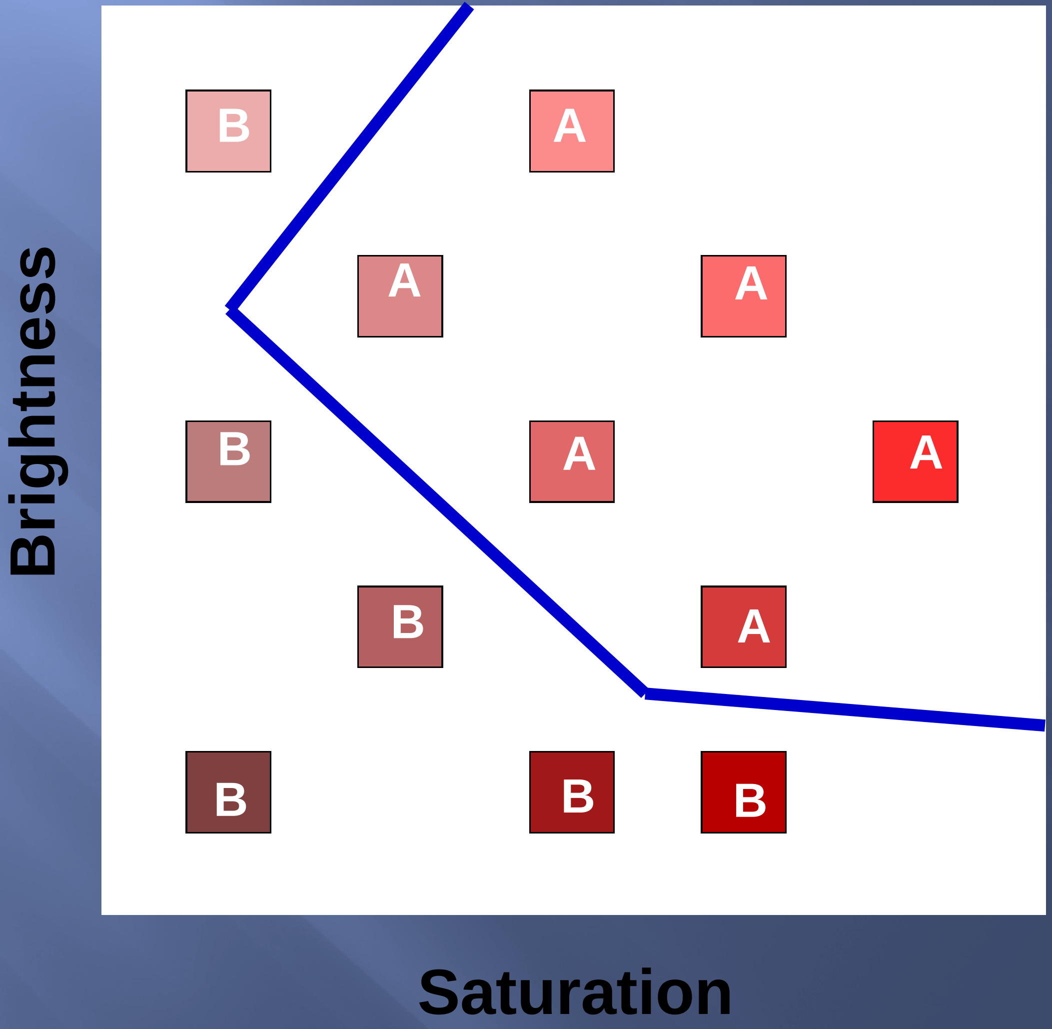
Injected with dopamine (D1) antagonist

# SPEED Fits to Choi et al. (2005) Data

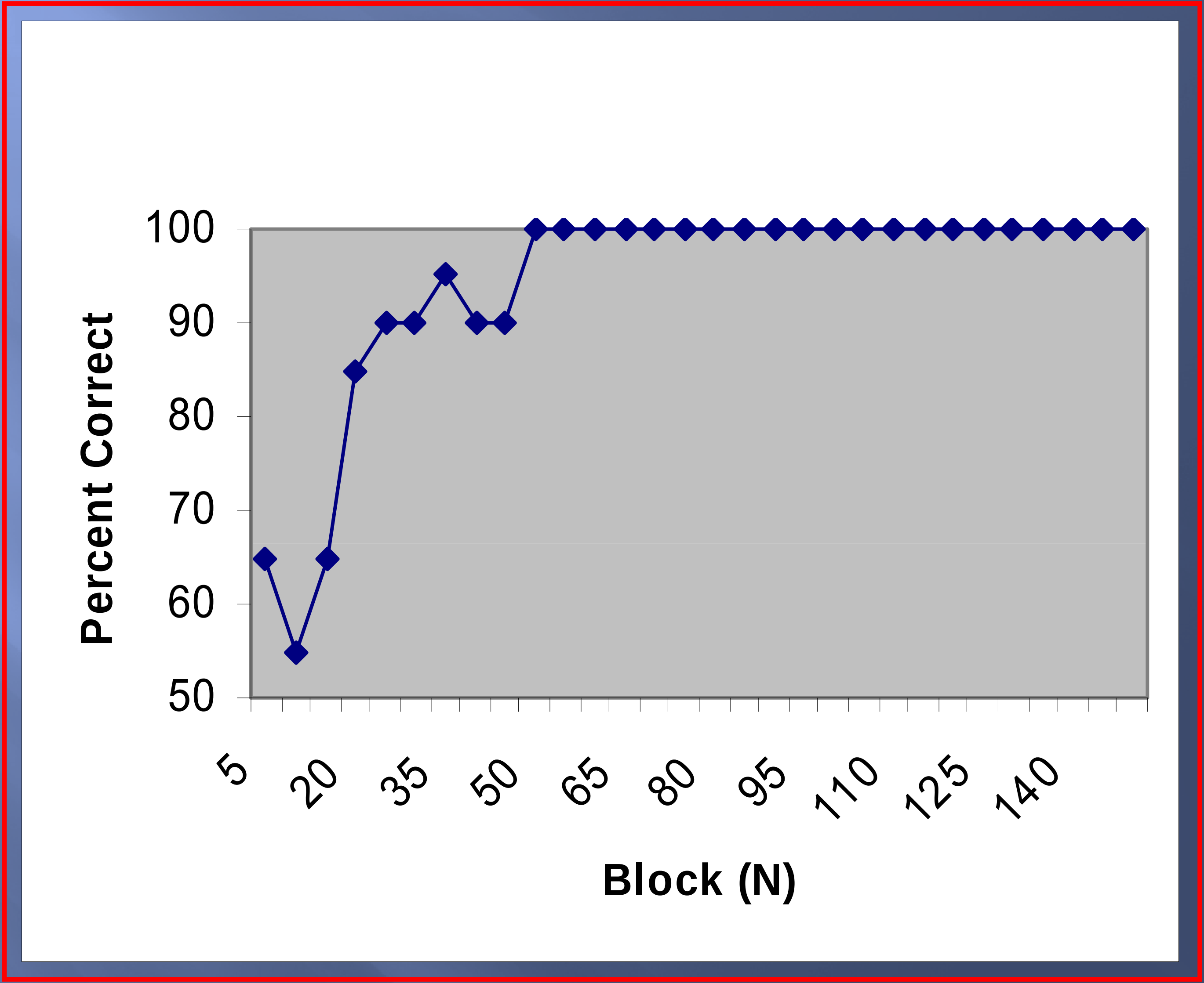


# Nosofsky & Palmeri (1997, Psych Review)

Munsell Color Patches – 3 Subjects – 1800 Trials

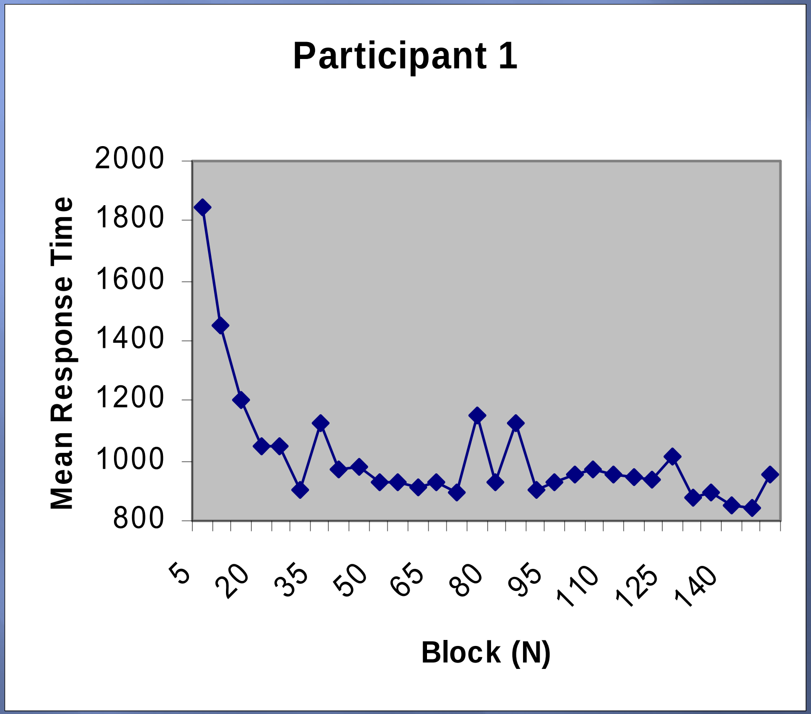


# SPEED Accuracy

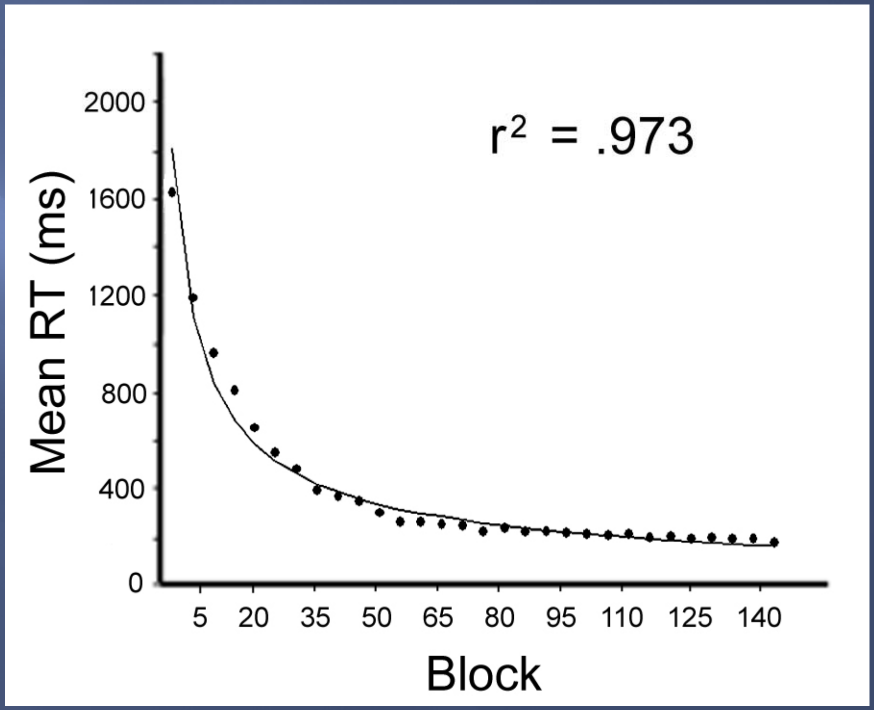


# Mean Response Time

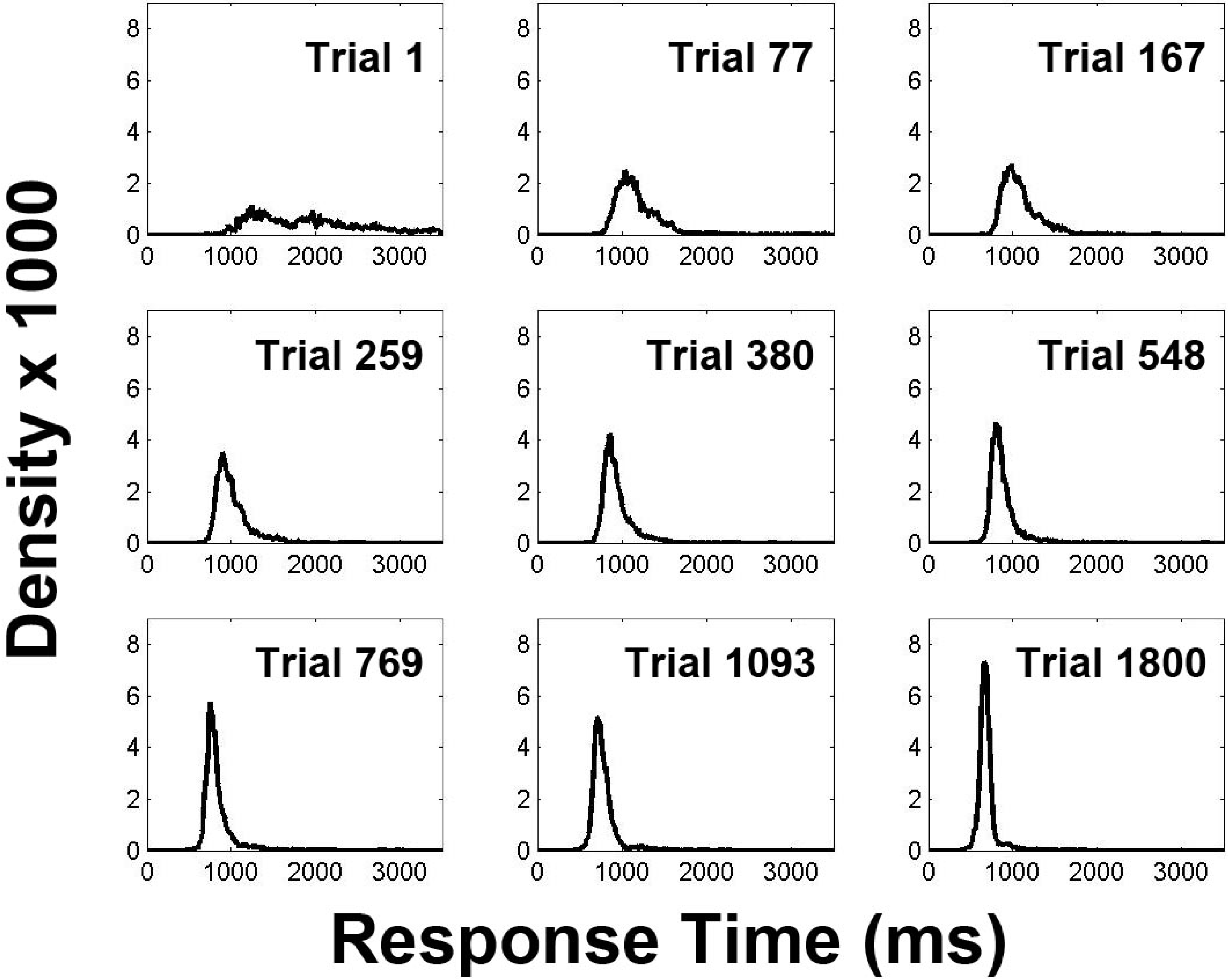
Nosofsky & Palmeri (1997)



SPEED



# SPEED RT Density Functions



# Future Directions

- fMRI
- Model automaticity development in:
    - -- neuropsychological populations
    - -- subjects under influence of drugs
- Automaticity in rule-based tasks

# Conclusions

- Two category learning systems

- Explicit, logical reasoning system
  - -- Uses working memory & executive attention
  - -- Frontal cortex

- Procedural learning system
  - -- Striatum

- Learning systems train long-term cortical representations

# ACKNOWLEDGMENTS

Collaborators:

Learning

Leola Alfonso-Reese, Michael Beran, Robert Cook, Shawn Ell, Vince Filoteo, Todd Maddox, Alan Pickering, David Smith, And Turken, Elliott Waldron, many others

Automaticity

John Ennis, Brian Spiering

Funding:

Public Health Services Grant MH3760-2