Learning and Memory

Lecture 11

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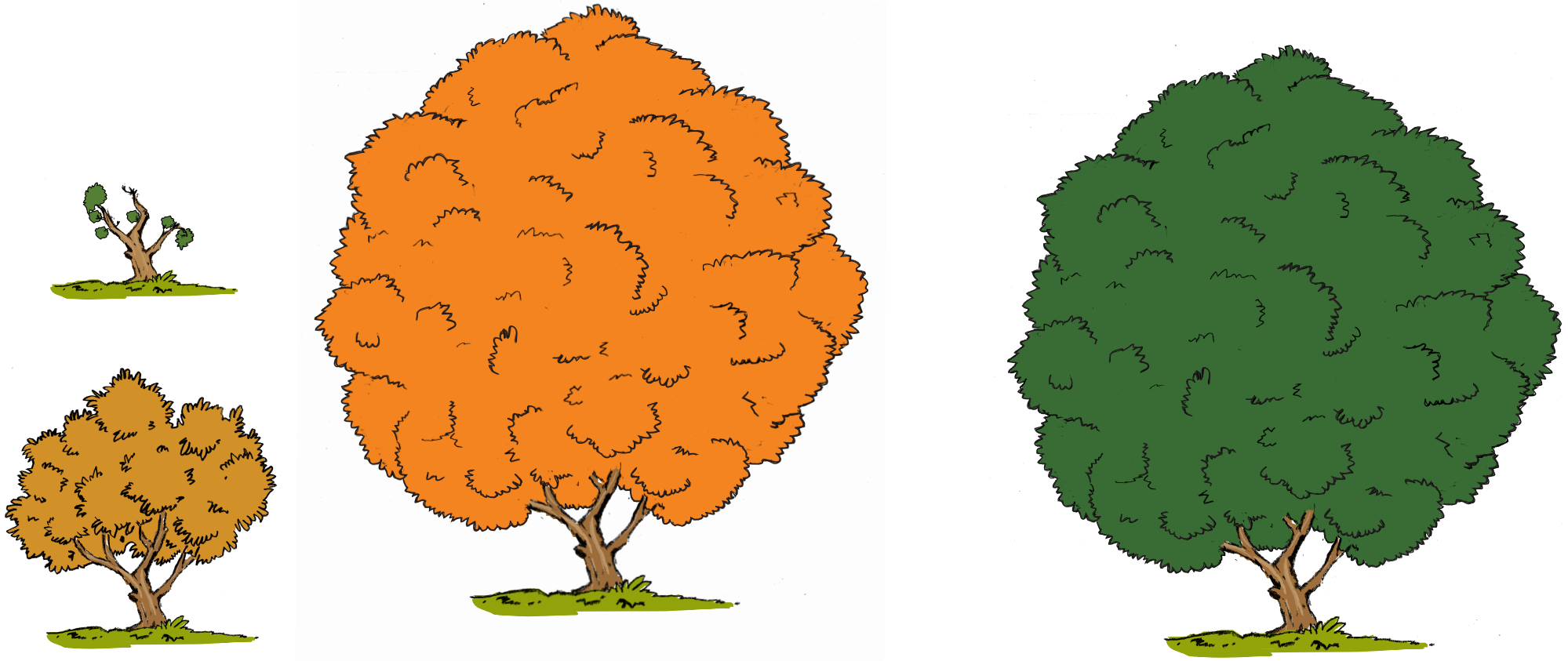
Agenda for Today

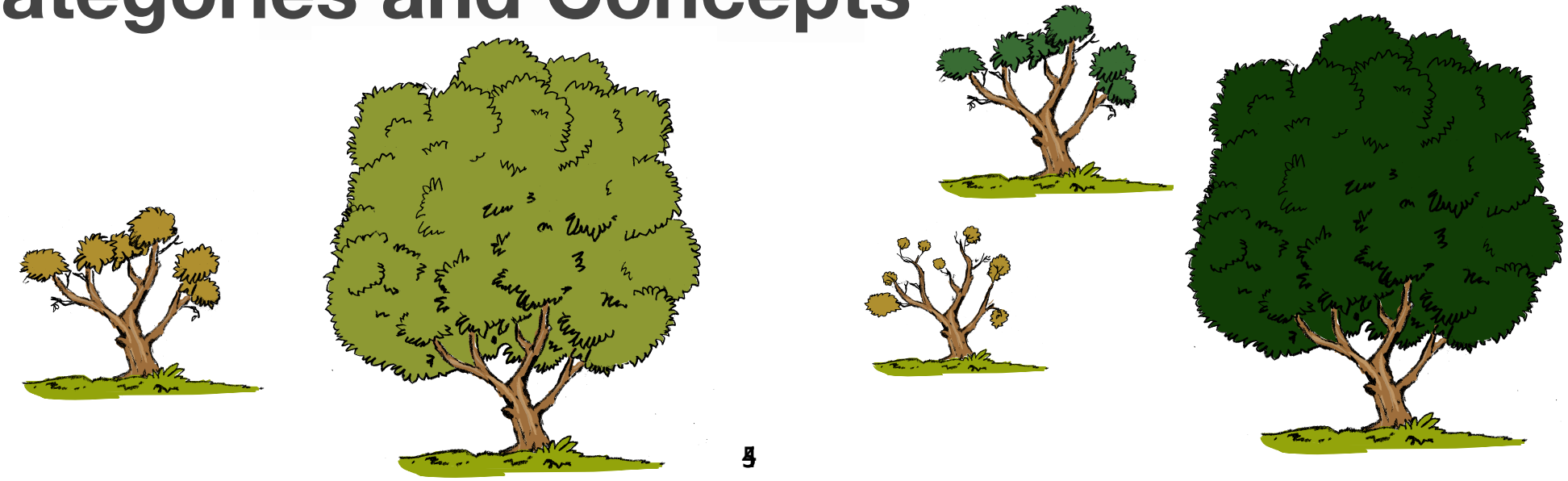
- More complex forms of generalization: Categorization
  - Basic models: similarity and attention
  - Advanced models: Abstraction and multiple representations
  - Cognitive neuroscience approaches

1 Categorization

Basic Models



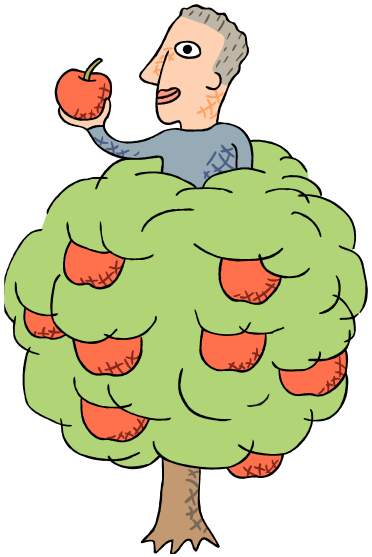
Categories and Concepts



Functions of Concepts

- Categories have many functions:
  - **Classification** - allows us to treat different things as the same
  - **Communication** - we communicate using words that refer to more abstract ideas/concepts
  - **Prediction and reasoning** - we can use categories to make predictions about unknown or unseen parts of the world

Example



What you see:

Red
Shiny → **Apple**
In a tree

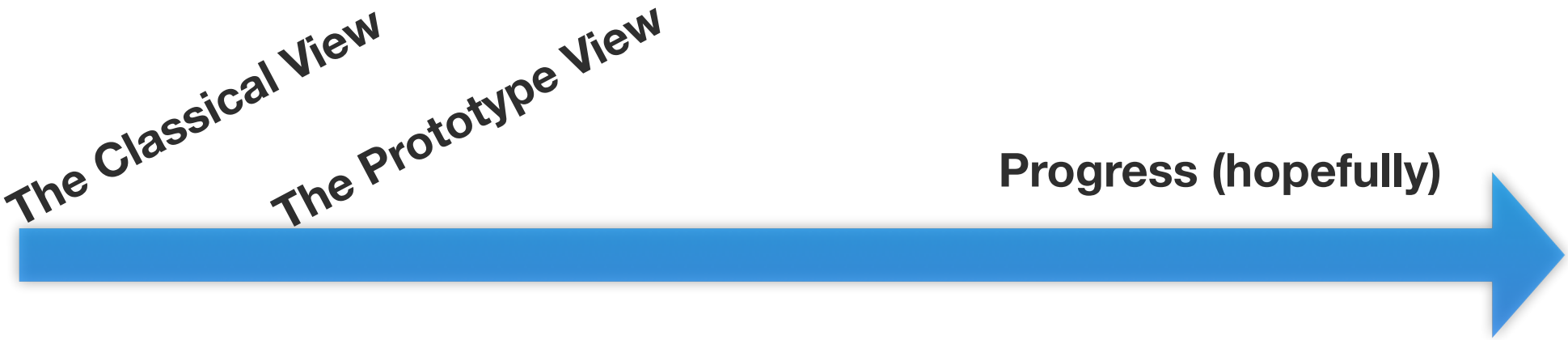
What you can then infer:

Has seeds
Sweet
Edible
Healthy

A little history....

A little history....

A little history....



A little history....

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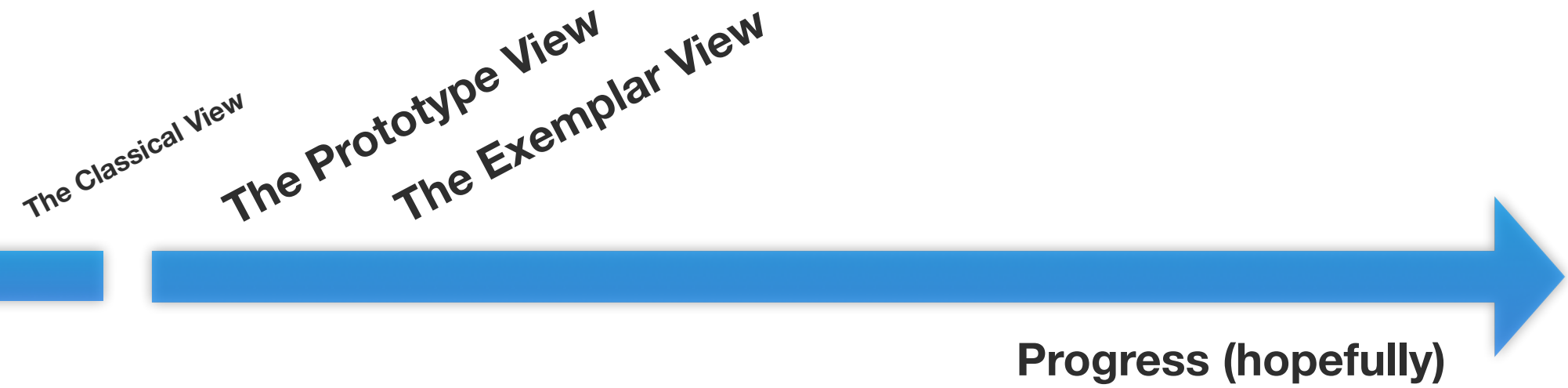

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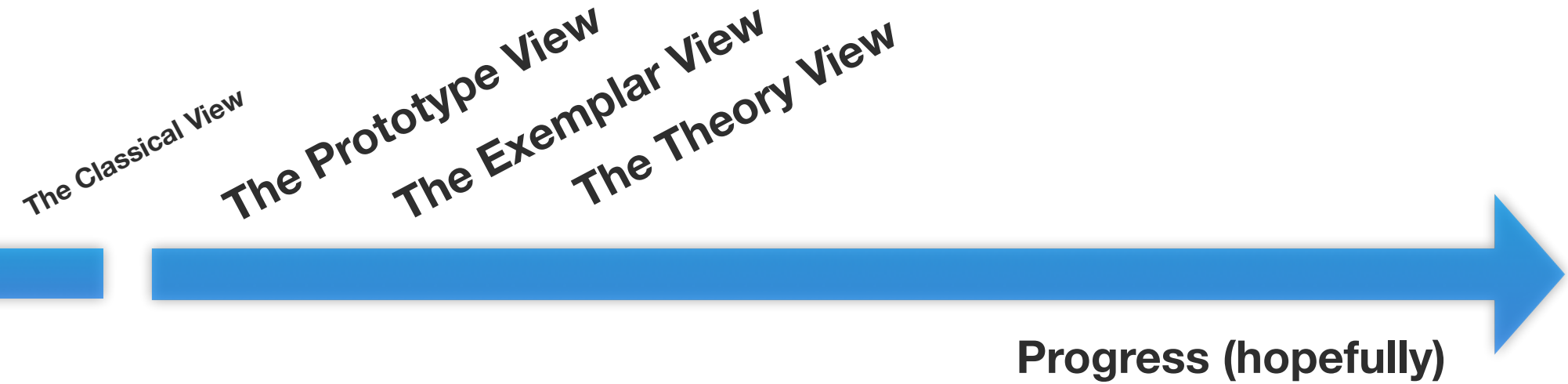

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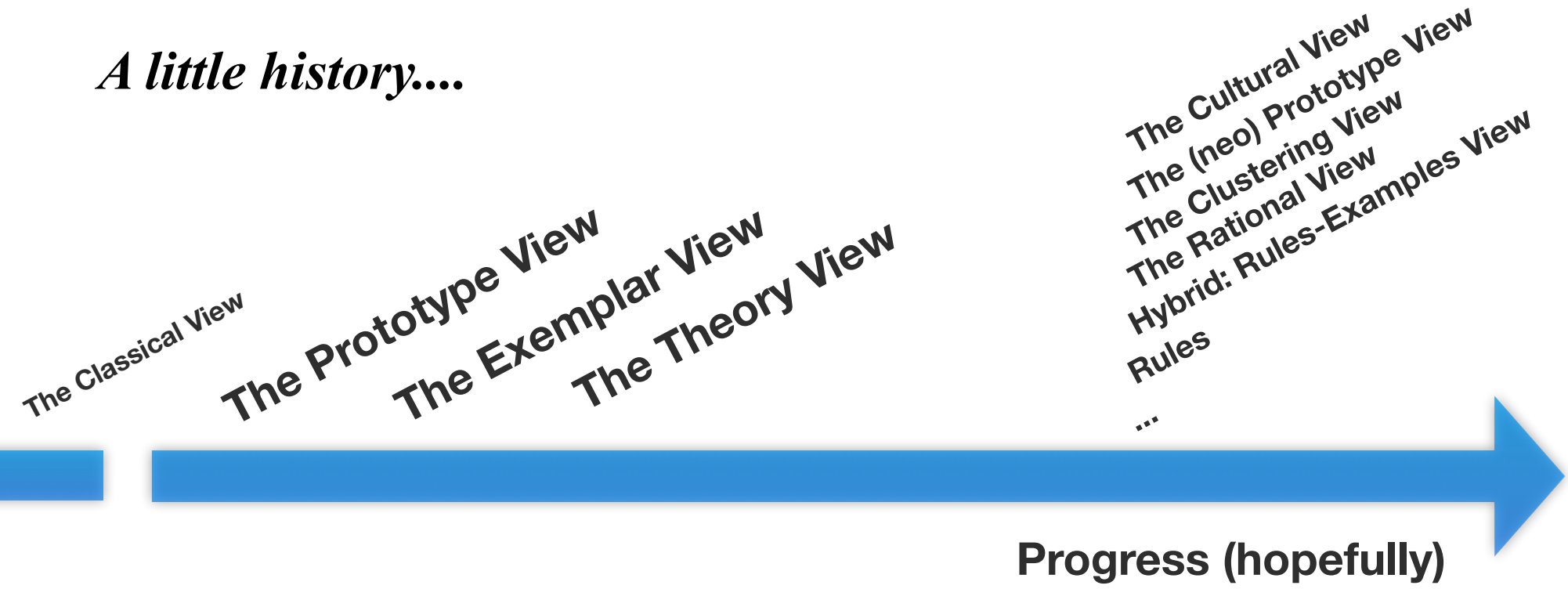


The Classical View

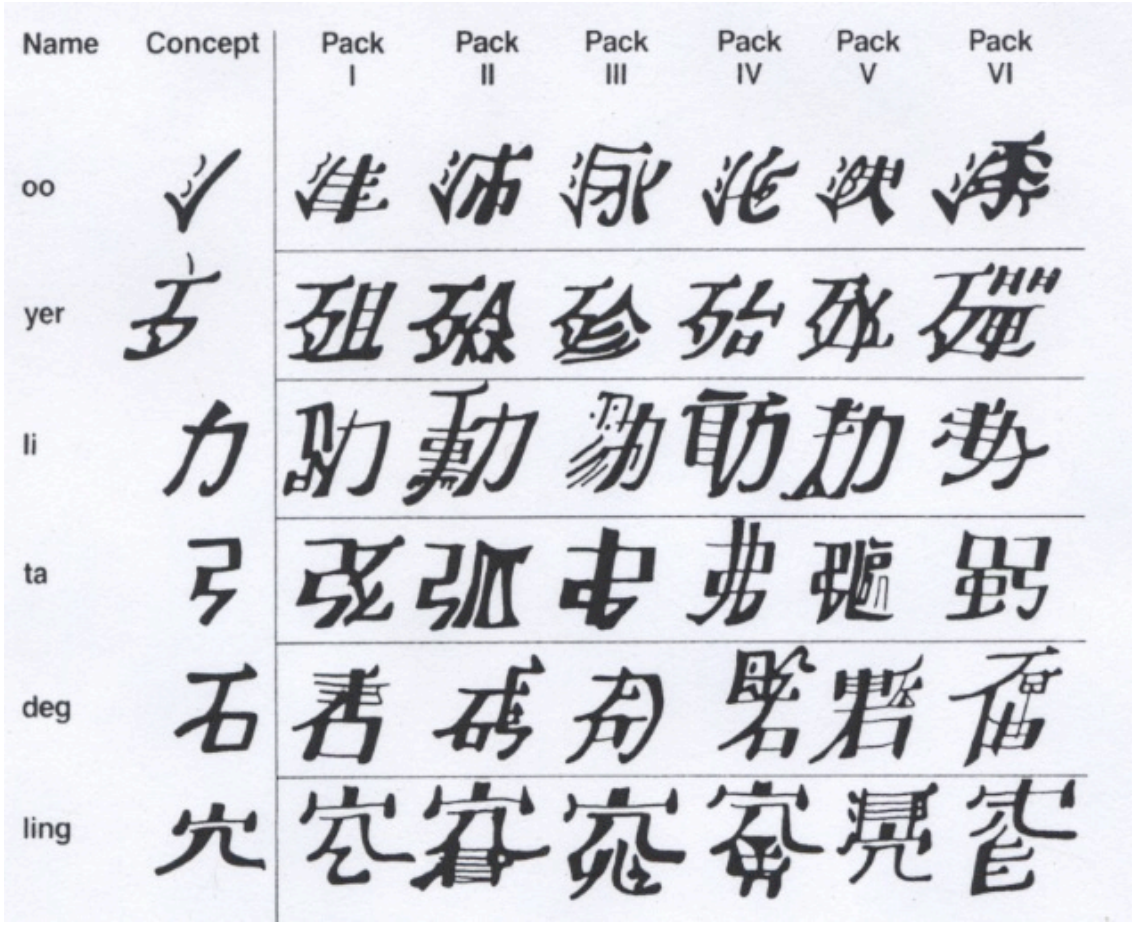
- According to the **classical view**, concepts are like definitions
- The defining features of are both necessary and sufficient
  - **Necessity:** If something is a category member, it has the defining features
  - **Sufficiency:** If something has the defining features, it is a category member

Example

- **Defining features:**
  - Closed figure, three sides, interior angles sum to 180 degrees
- **Sufficiency:**
  - If something is a closed figure, has three sides and angles sum to 180 degrees it is a triangle
- **Necessity:**
  - If something is a triangle, it is a closed figure, has three sides, and the angles sum to 180 degrees

Learning Classical Concepts

- **According to the classical view, category learning usually involves hypothesis testing or rule discovery:**
  - A search for the defining features



Hull, 1920 - phd thesis

Studied learning concepts defined by simple features

Learning Classical Concepts

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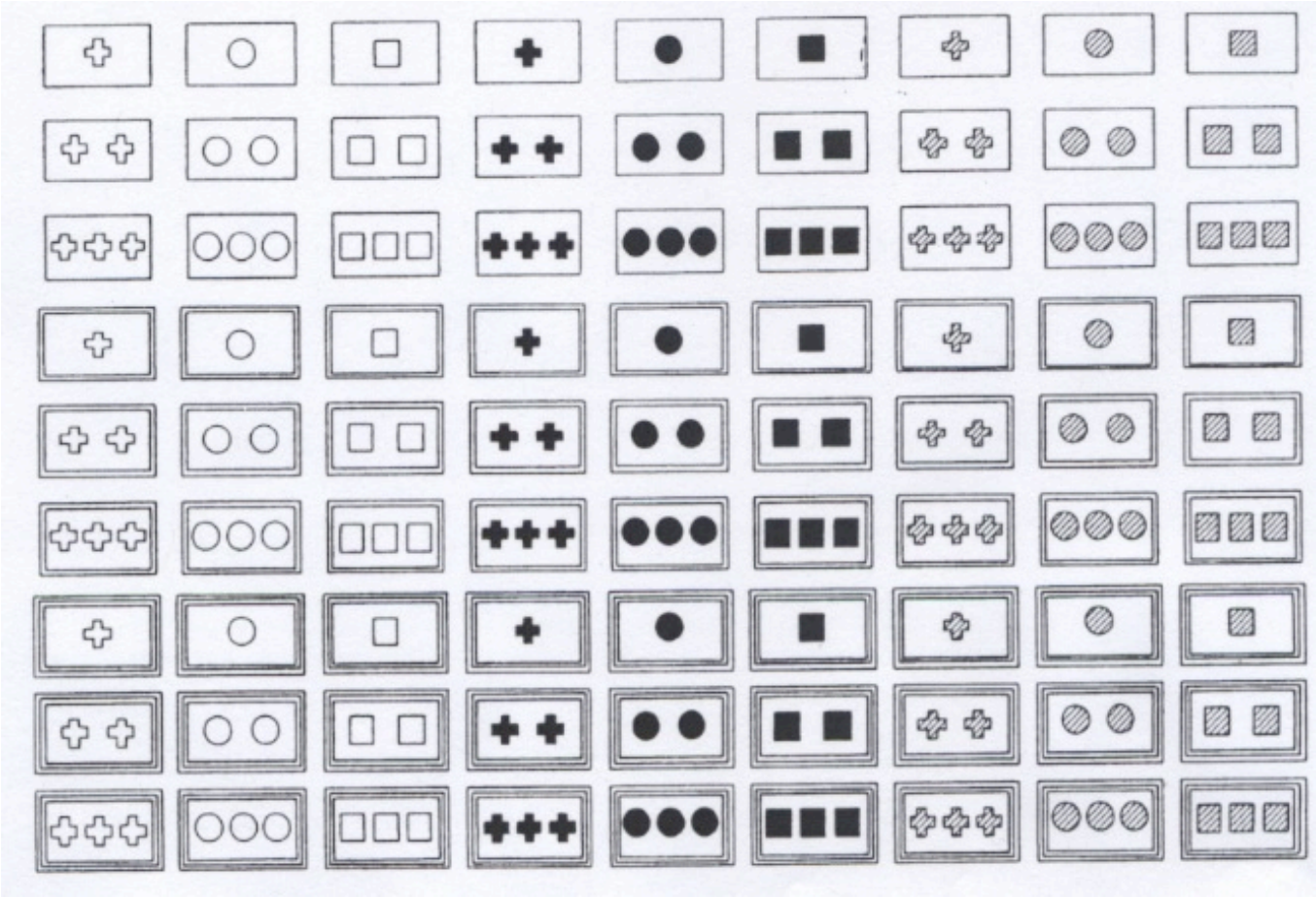
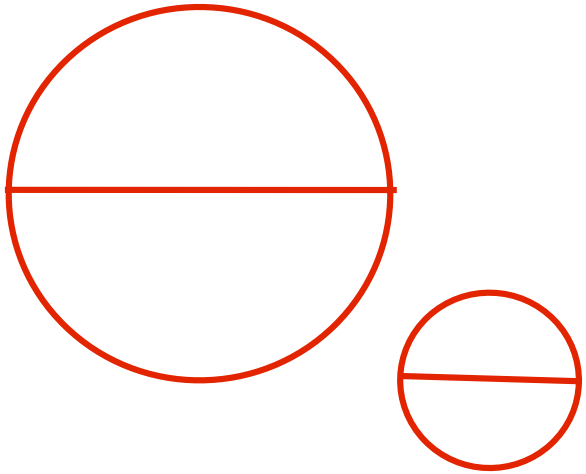
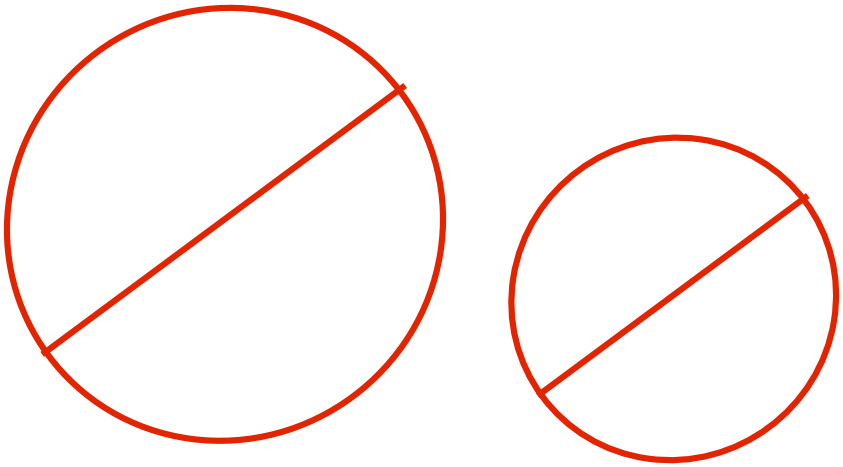


Bruner, Goodnow, & Austin, 1956

Four dimensional concepts involving conjunctions of features, disjunctions, etc...

Rules are one basis for complex forms of generalization





... but, problems for the classical view

- Are all concepts represented in terms of rules? In the 70s there became strong philosophical and empirical arguments against this

One prediction

1: Do defining feature exist?

- Hampton (1979): Asked subjects for necessary and sufficient features of everyday categories (sofas, cars, dogs, chairs, birds, etc...)
- There was little agreement about what the defining features were
- However, people might not explicitly know the features and agreement between individuals doesn't seems problematic per-se (although perhaps a little surprising)

One prediction

2: Category membership should be unambiguous

- McClosky & Glucksberg (1978): Asked subjects to judge category membership of several everyday categories.

A shelf	**76%**
A rug	**52%**
A lampshade	**63%**
Bookends	**57%**
Candlestick	**28%**

Many borderline cases

One prediction

2: Category membership should be unambiguous

- McClosky & Glucksberg (1978): Asked subjects to judge category membership of several everyday categories.

A shelf	**76%**
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Many borderline cases

came back 1 week later... changed their minds about 22% of borderline cases!

One prediction

3: Ungraded category membership. All members are equally good

Rosch (1973): Asked people to rate "how good" different items are as a example of a category (1-7 scale)

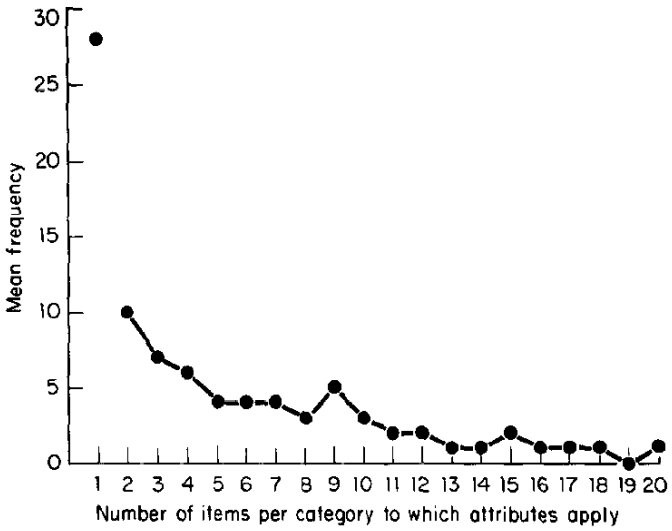
Robin	**1.4**
Eagle	**1.8**
Wren	**2.4**
Chicken	**2.8**
Ostrich	**3.2**

Members vary in how good they are!

One prediction

3: Ungraded category membership. All members are equally good

What makes something typical? Rosch & Mervis (1975) investigated what makes an item typical by having subject list features of instance of many categories, other people rated typicality.



Hardly any examples of features that were in all category members!

One prediction

3: Ungraded category membership. All members are equally good

Typical features appear in many category members. # of typical features determines the typicality of a category member.

	Examples					
Properties	**Robin**	**Cardinal**	**Eagle**	**Penguin**	**Bat**	**Feature Score (a.k.a. "Weight")**
Has wings	Yes	Yes	Yes	Yes	Yes	5
Flies	Yes	Yes	Yes	No	Yes	4
Has feathers	Yes	Yes	Yes	Yes	No	4
Sings	Yes	Yes	No	No	No	2
Builds nests in trees	Yes	Yes	Yes	No	No	3
Eats worms/insects	Yes	Yes	No	No	Yes	3
Family Resemblance Score	5+4+4+2+3+3= **21**	5+4+4+2+3+3= **21**	5+4+4+3= **16**	5+4= **9**	5+4+3= **12**	

~~The Classical View~~

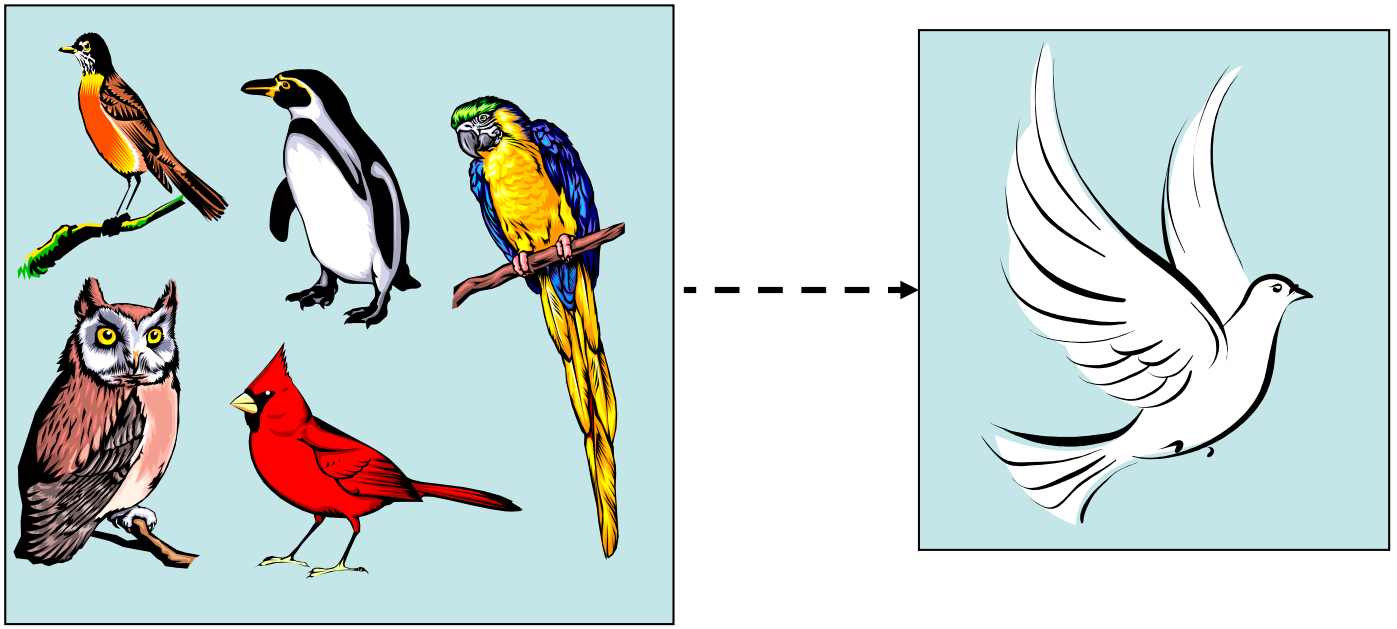
Probabilistic Approaches

- Category membership is a matter of **degree**. There can be better or worse members of a category!
- Two main theories - prototype models, exemplar models

Prototype Theory

- According to **prototype theory,** the mental representation of a category consists of a prototype or central tendency of the examples

- Learning is about abstracting this schema or prototype across all the examples you have see so far.



Birds
You've Seen

Prototypical
Bird

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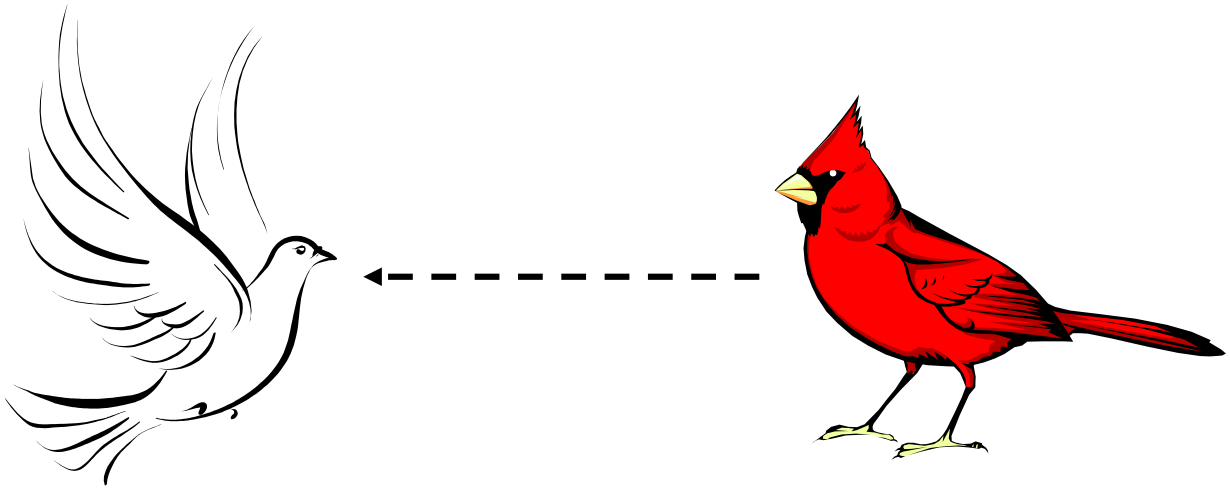
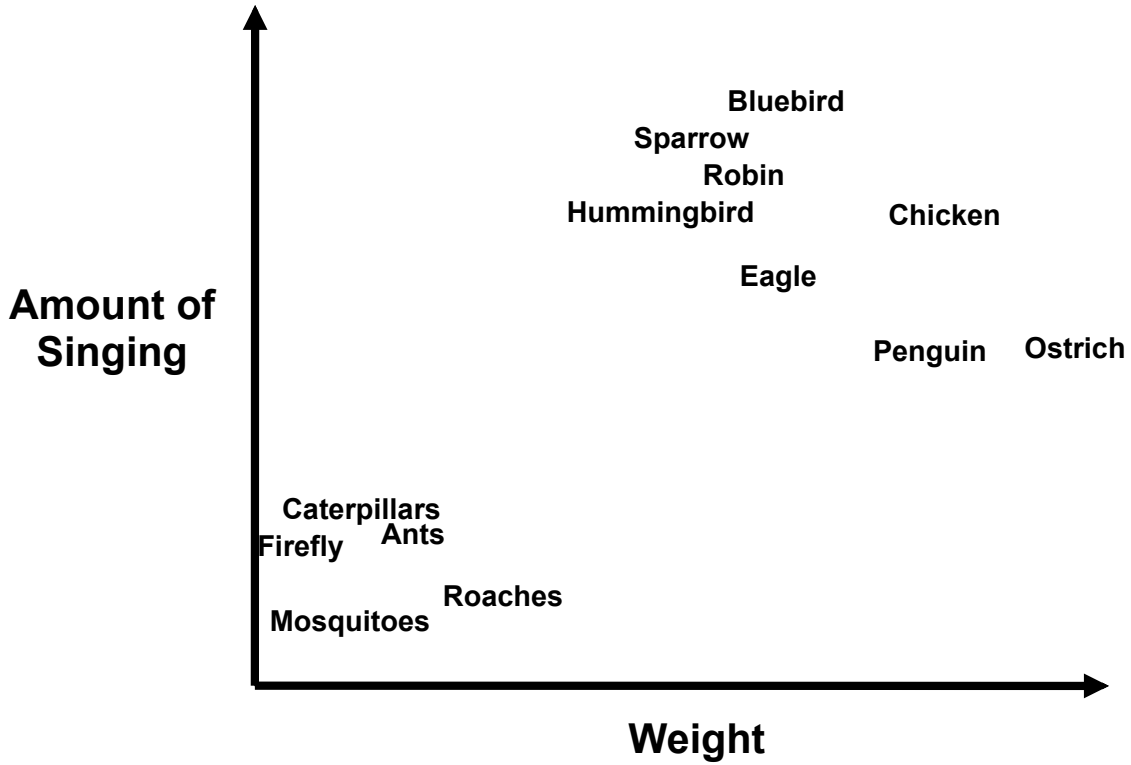


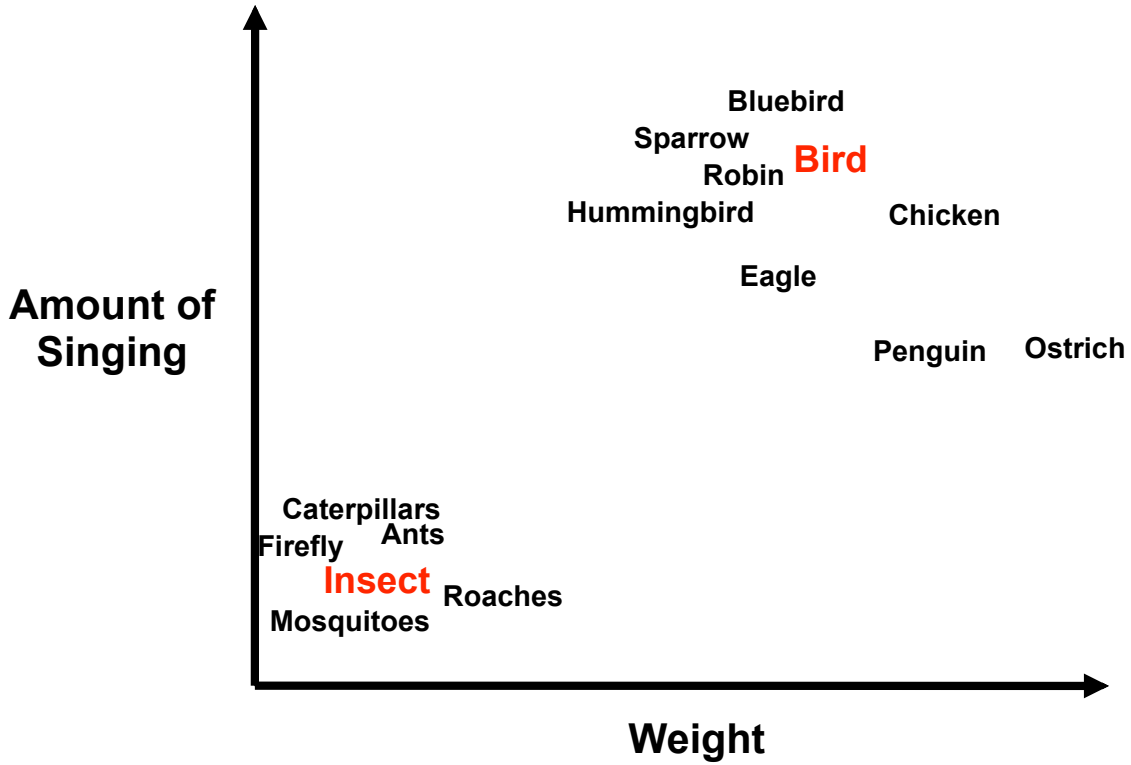
Prototypical Bird

Bird?

How Most Models of Categorization Work (Psychological Similarity Spaces)

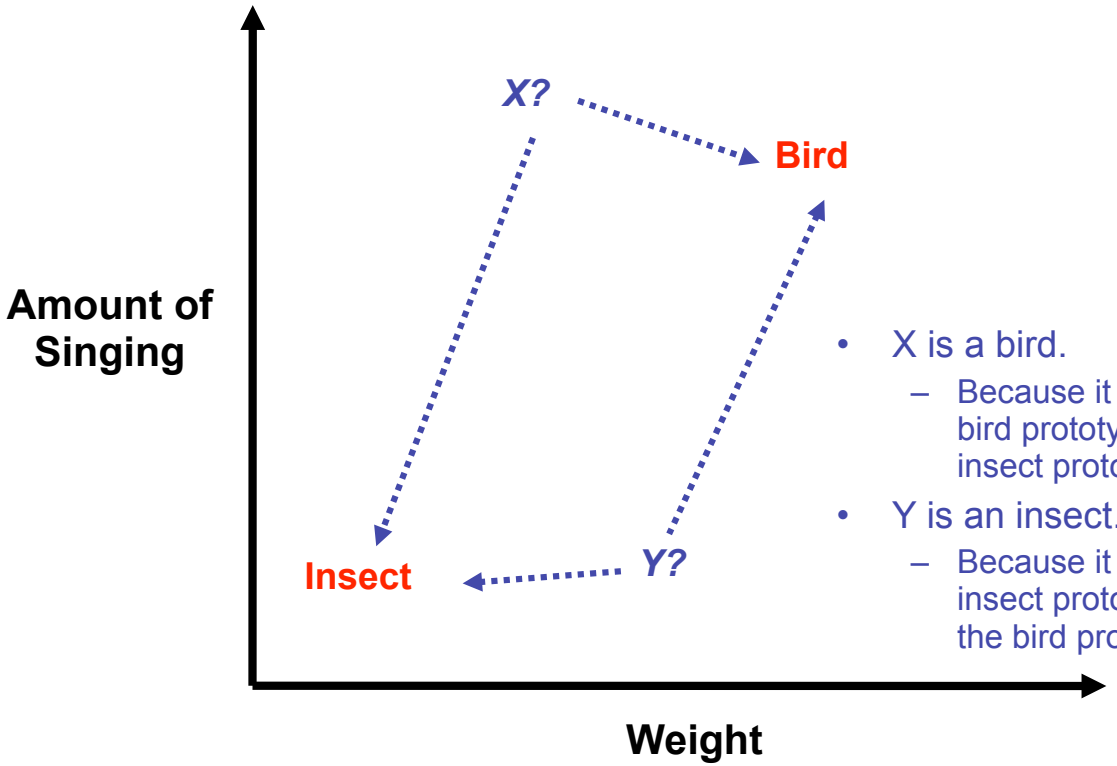


How Most Models of Categorization Work (Prototype Theory)



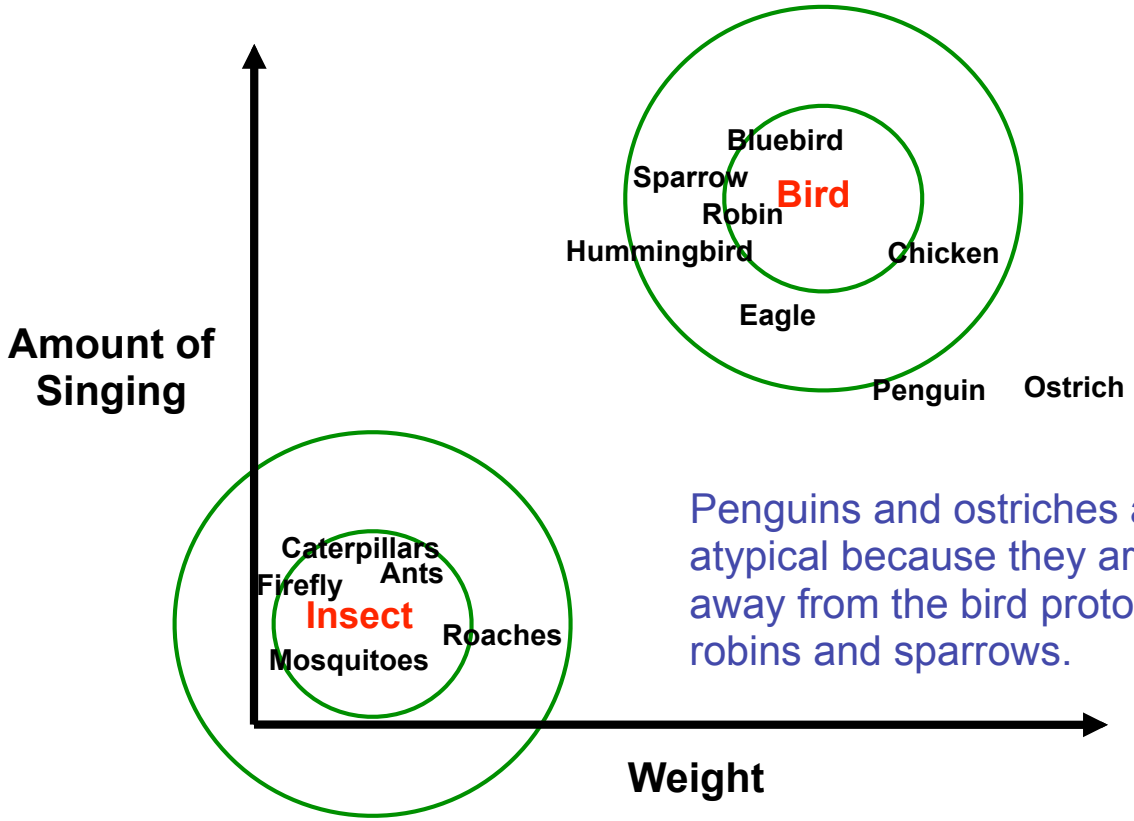
Two key effects: prototype enhancement and borderline cases/graded structure

How Most Models of Categorization Work (Prototype Theory)



- X is a bird.
  - Because it closer to the bird prototype than to the insect prototype.
- Y is an insect.
  - Because it closer to the insect prototype than to the bird prototype.

How Most Models of Categorization Work (Prototype Theory)



Penguins and ostriches are atypical because they are farther away from the bird prototype than robins and sparrows.

...but, do people really abstract away?

- People remember many of the bird they have actually seen. People are influenced even in categorization contexts by the specific examples they've seen
- **Brooks & Allen (1991)**
  - Asked subjects to discriminate between two animals (Diggers and Builders)
  - Two kinds of animals could be distinguished in two different ways ("two-out-of-three" rule or based on animals environments context)

Classification rule:

2 of (long legs, angular body, spots) => *Builder*

2 of (short legs, curved body, not spots) => *Digger*

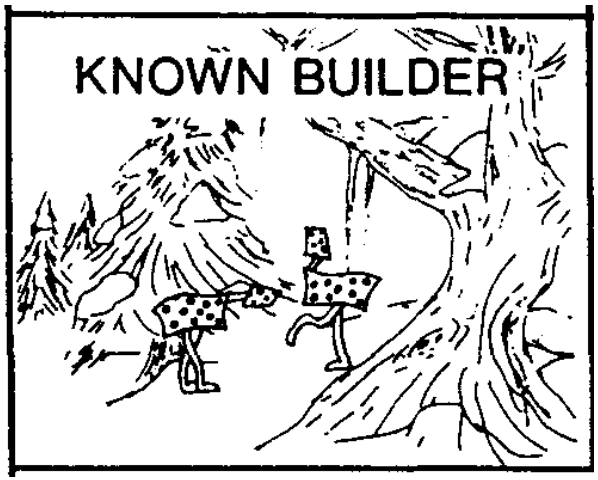
Example of *Builder*

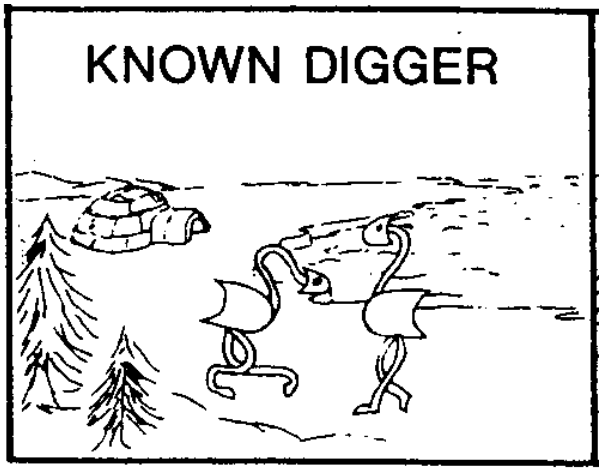
Example of *Digger*

Environmental context

Forest scene => *Builder*

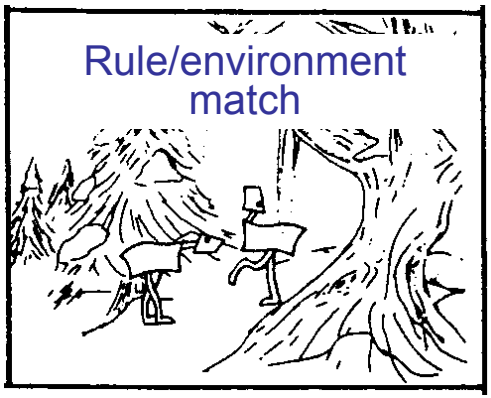
Arctic scene => *Digger*



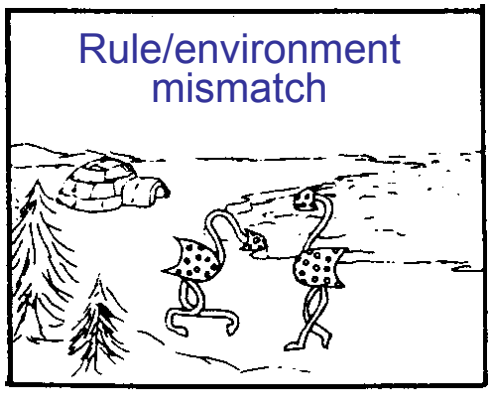


Brooks and Allen (1991)

- Two conditions: memory group, or rule group
- **Memory group -** not given the rule (told would have to guess), learn incrementally based on feedback which is digger or builder
- **Rule group -** just told the rule from the outset
- At test, classified new items as Diggers or Builders

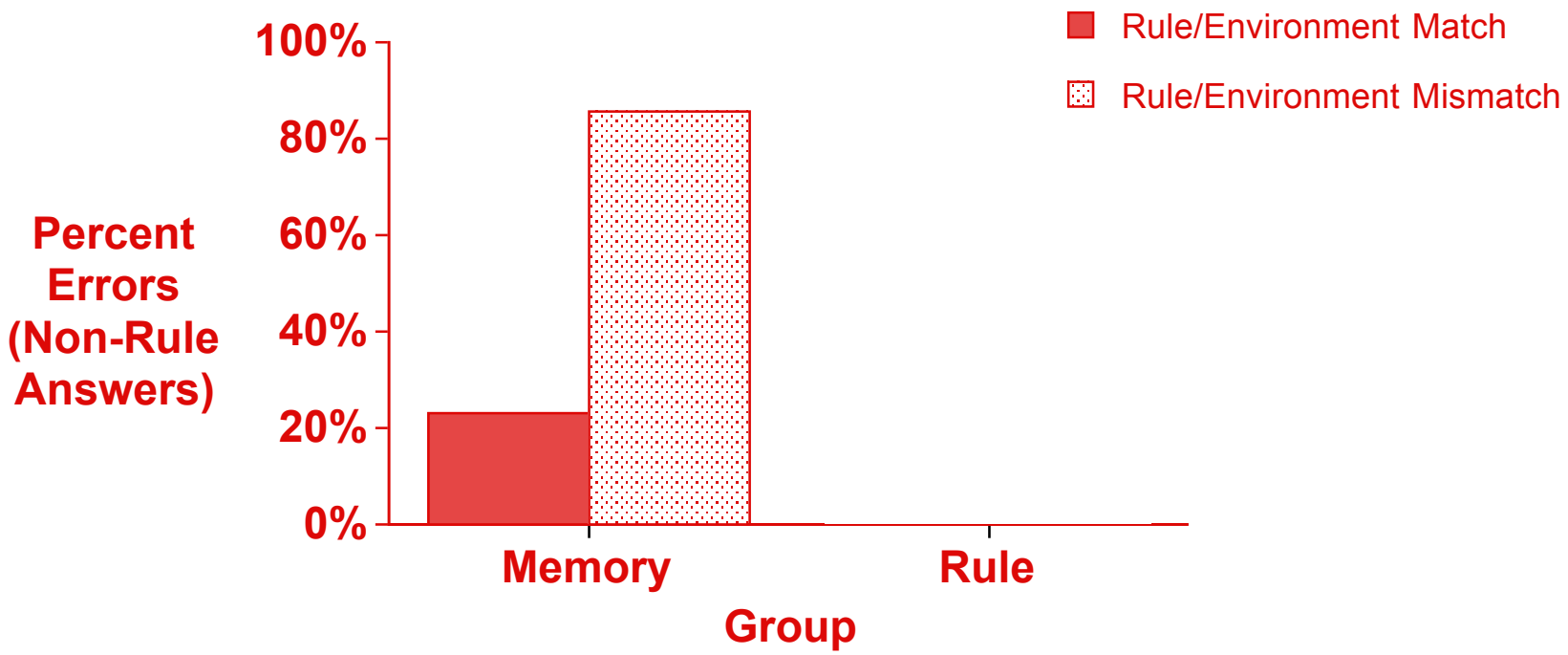


E.g., *Builder* in *Builder* context.



E.g., *Builder* in *Digger* context.

Brooks and Allen (1991)



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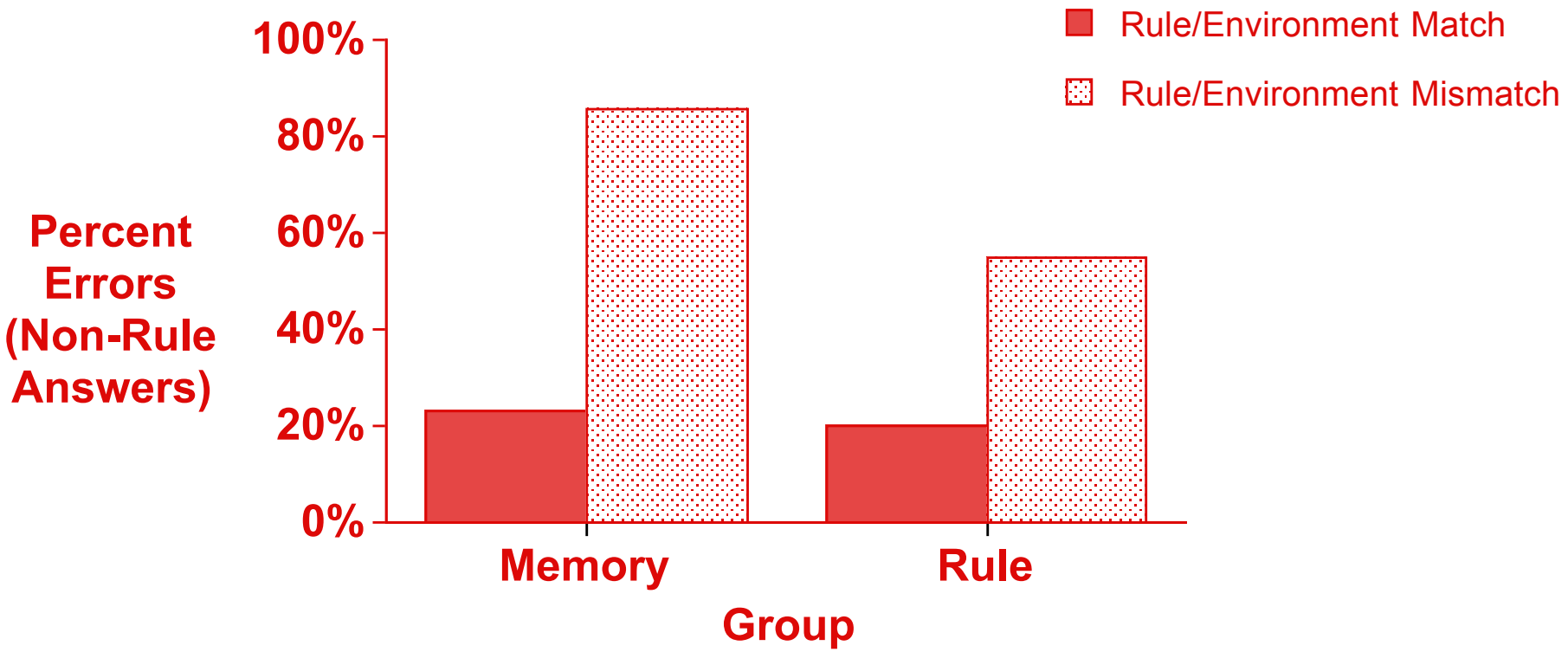

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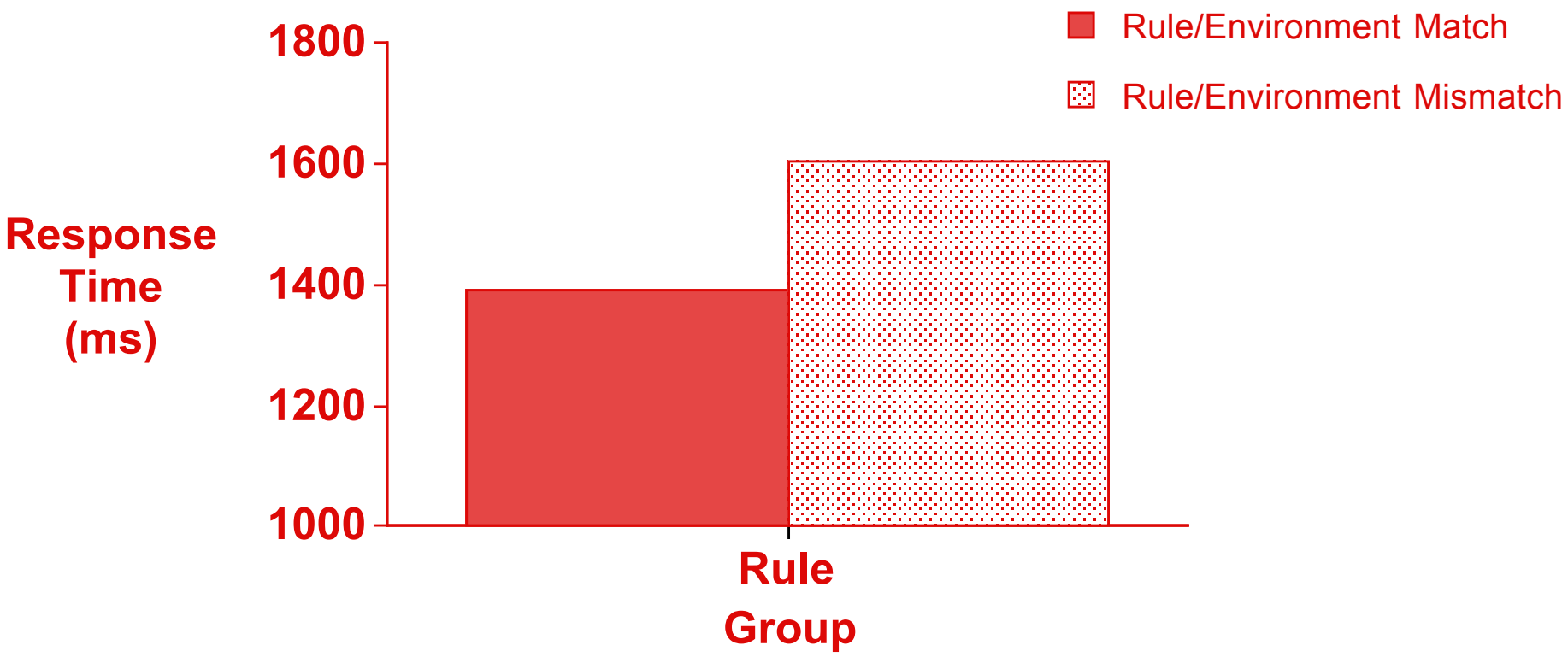


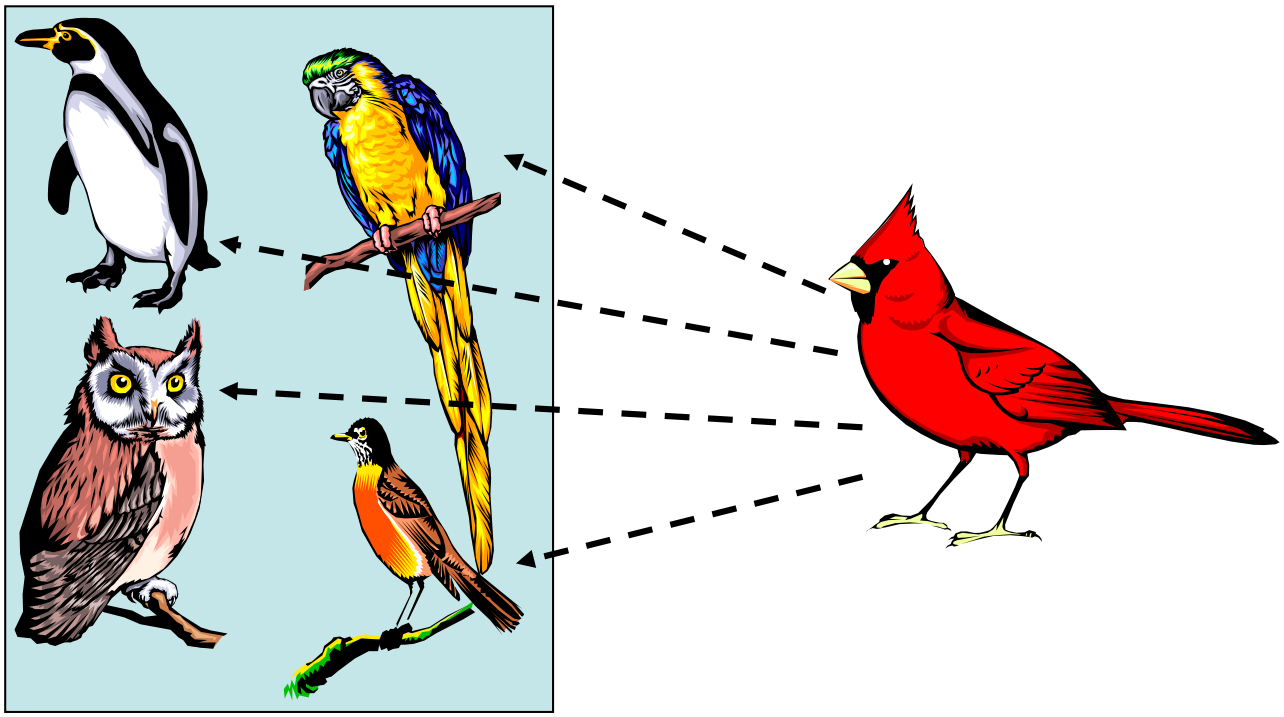
Brooks and Allen (1991)

- Even when an individual in the rule group responds correctly, they take longer if the environment is “telling them” to respond differently!

- Even when subjects new the correct “featural rule” their classification decisions were affected by context.

- Exemplar-based interference - **even when a rule is known and easy to articulate, past examples can override application of the rule**

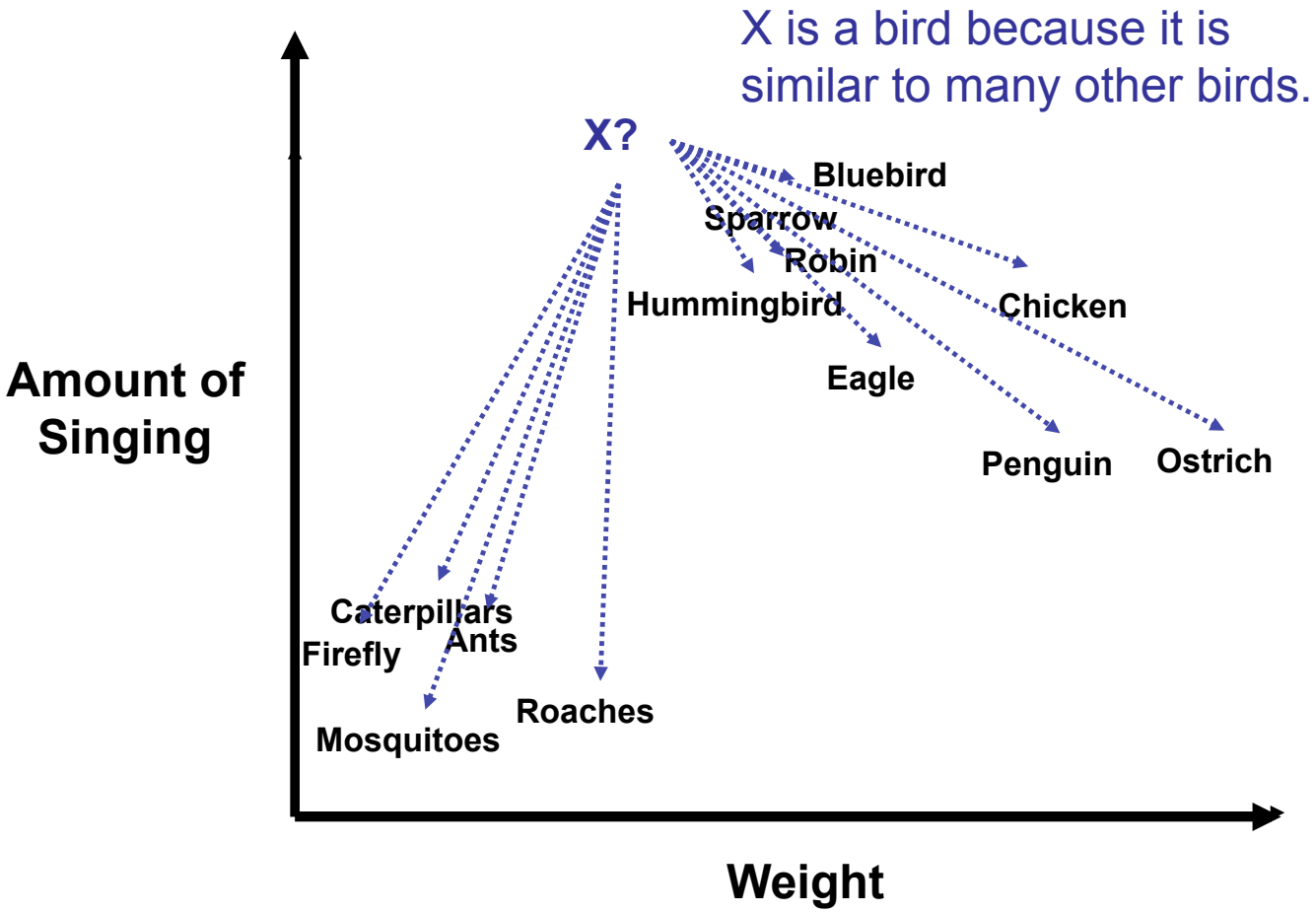
Exemplar Theory



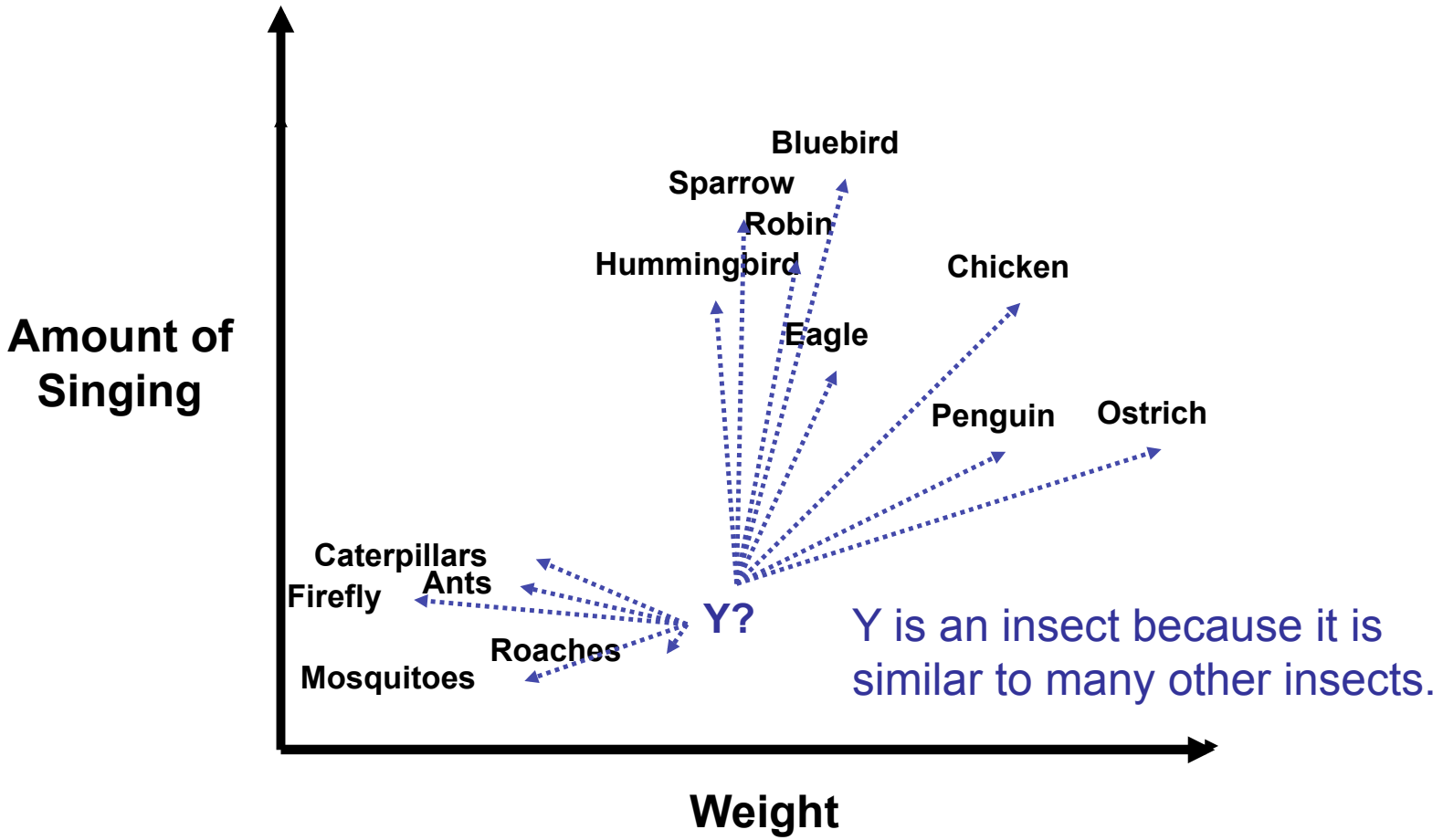
Birds
You've Seen

Bird?

Exemplar Theory

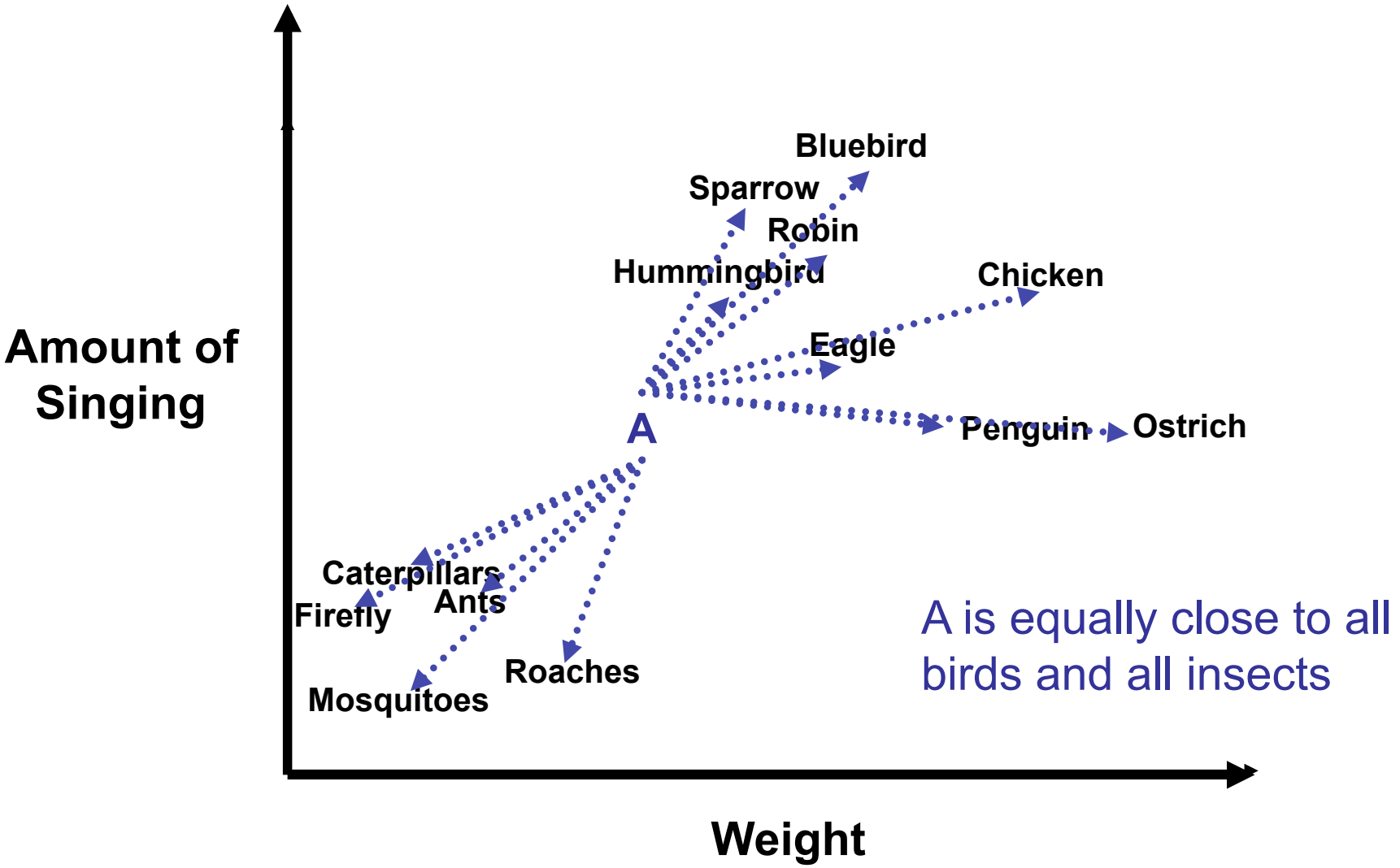


Exemplar Theory



Empirical Effect	Classical View	Prototype Model	Exemplar Model
No defining features		√	√
Borderline cases		√	√
Graded typicality		√	√
Prototype effect		√	√
Exemplar effects			√

Exemplar Theory



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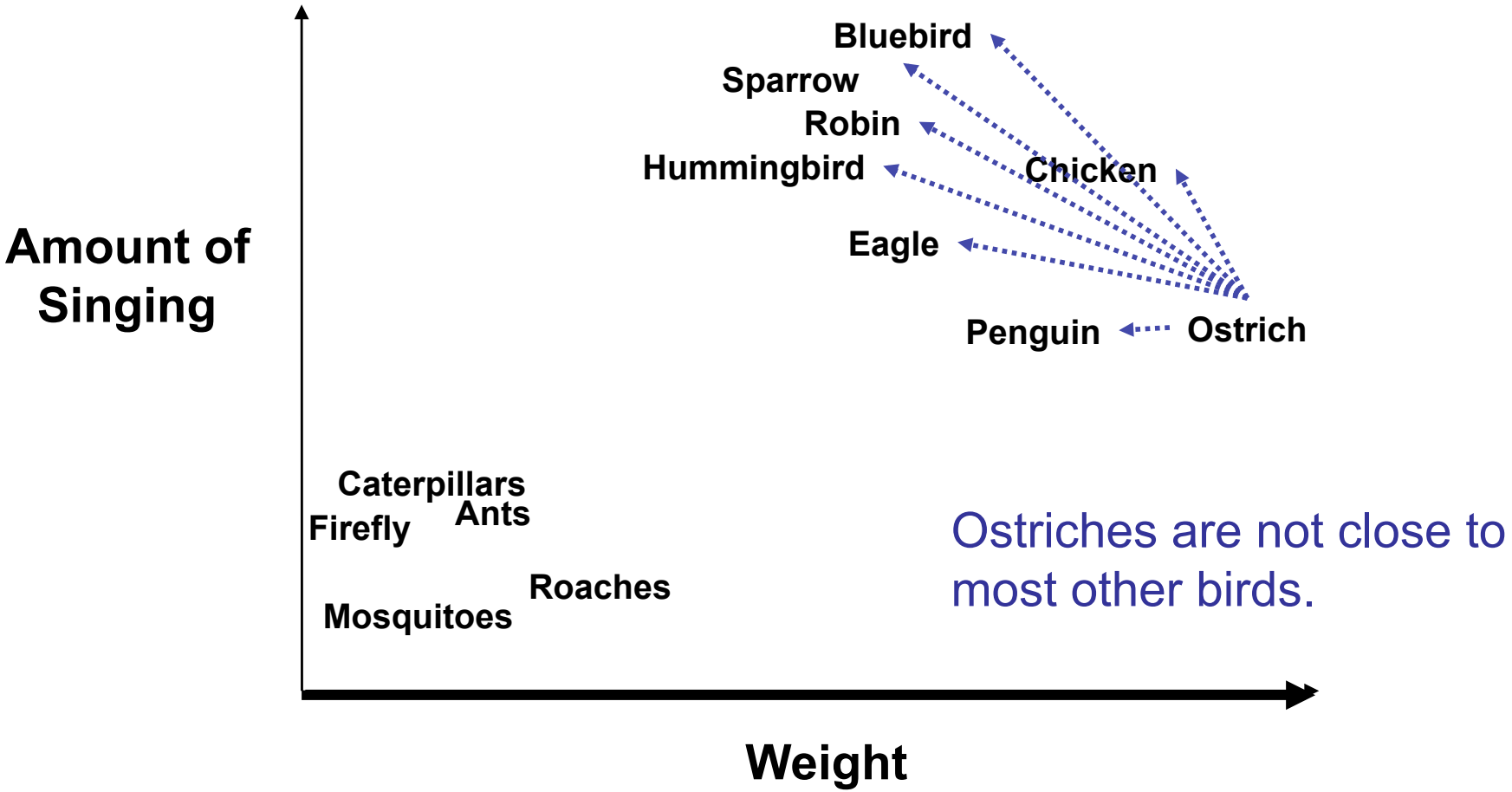
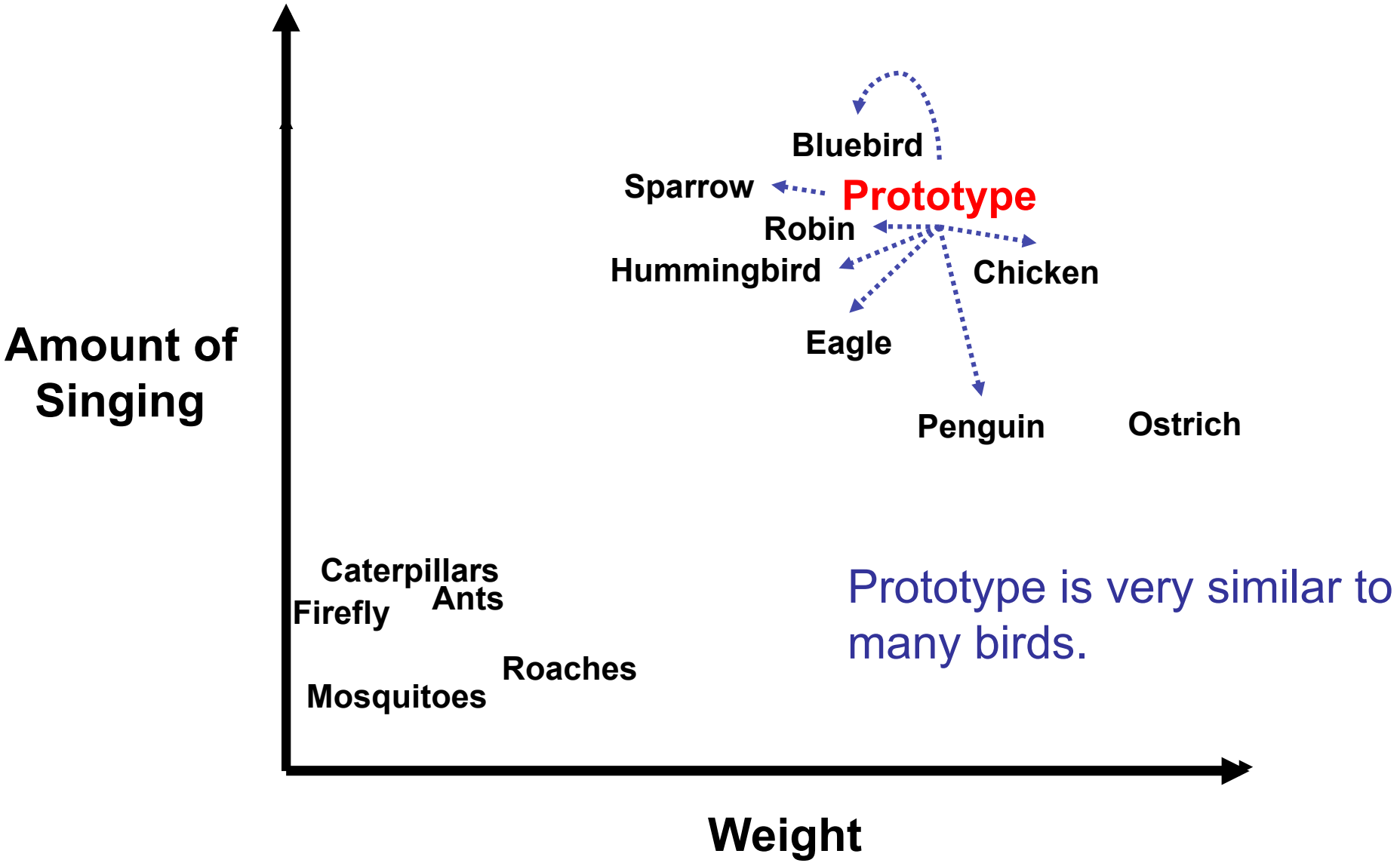


Ostriches are not close to most other birds.

Exemplar Theory



Prototype is very similar to many birds.

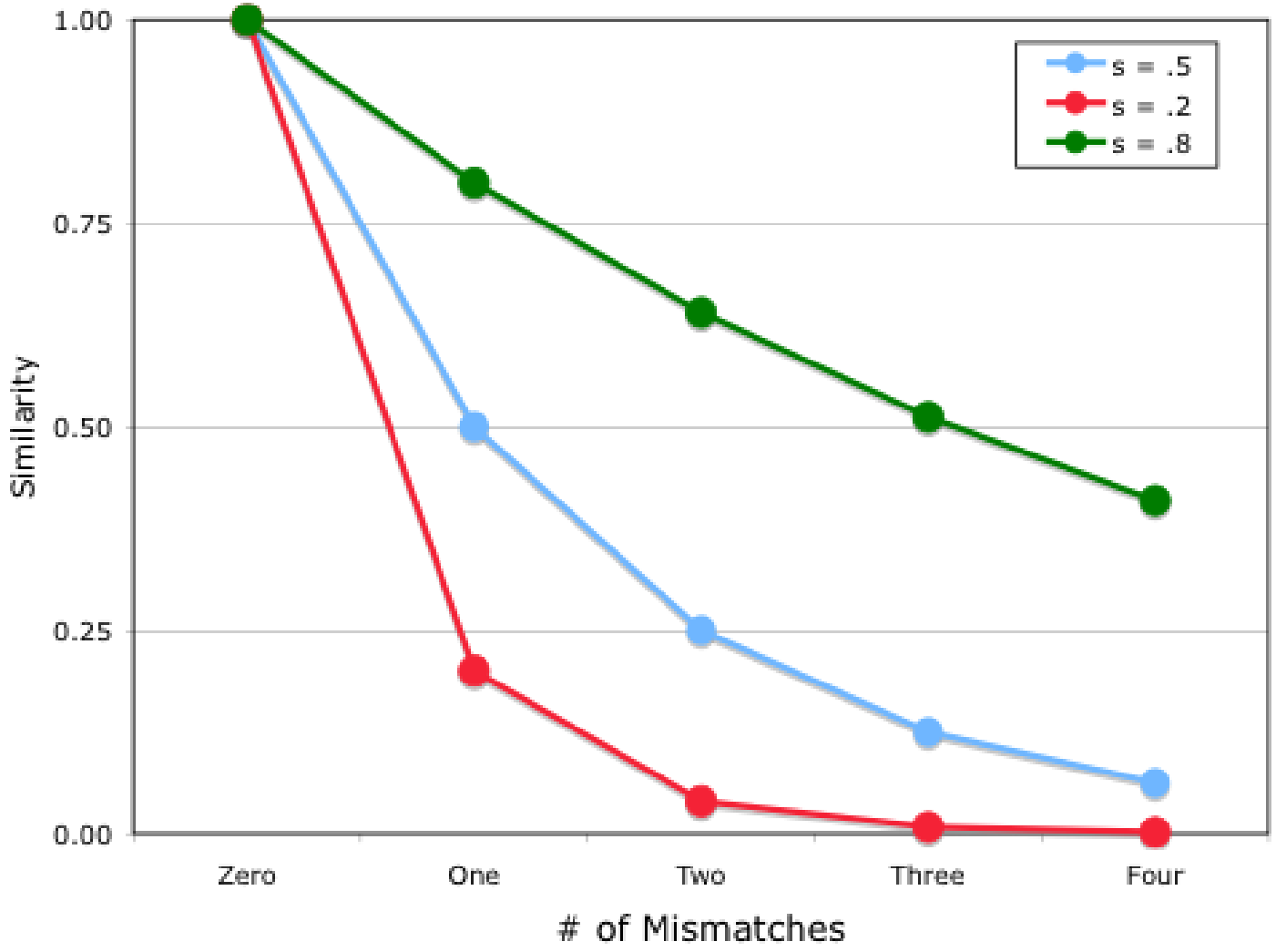
Similarity and Exemplar Models

- How is similarity to the stored examples computed?
- Medin & Schaffer (1978) proposed the **context model** of classification
  - A model of similarity for binary dimensions
  - A simple model of evidence accrual
  - A simple model of decision making

Similarity and Exemplar Models

- Each dimension has an associated importance or weight
  - An **s** parameter (0-1) which controls importance
- When comparing two items, compute a match score, **m**, on each dimension
  - m_i = 1 if values on dimension i match
  - m_i = s_i i values on that dimension mismatch
- Overall similarity is is the product of the m values

Similarity and Exemplar Models



Evidence Accrual

- Similarity of item S_i to a category C_j is the sum of its similarities to the category's exemplars
  - $$sim(C_j, S_i) = \sum_k sim(S_k, S_i)$$

Decision Making

- The probability of classifying S_i as a C_j is the ratio of its evidence relative to other categories
  - $$p(C_j|S_i) = \frac{sum(C_j, S_i)}{\sum_k sim(C_k, S_i)}$$

The Generalized Context Model

Nosofsky (1984; 1986)

- The **generalized context model (GCM)**
  - Application of the context model to continuous dimensions.
  - Unification of Luce's work on choice behavior and Shepard's work on stimulus generalization
- Similarity is a function of the **distance** between two objects in psychological space (Shepard!!).

$$d_{ij} = c(\sum_{k=1}^{N} w_k |x_{ik} - x_{jk}|^r)^{1/r} \qquad d_{ij} = (\sum_{k=1}^{K} |x_{ik} - x_{jk}|^r)^{1/r}$$

The Generalized Context Model

Nosofsky (1984; 1986)

- Actual similarity of two objects is a function of their distance:

Exponential

$$\eta_{ij} = e^{-d_{ij}}$$

Gaussian

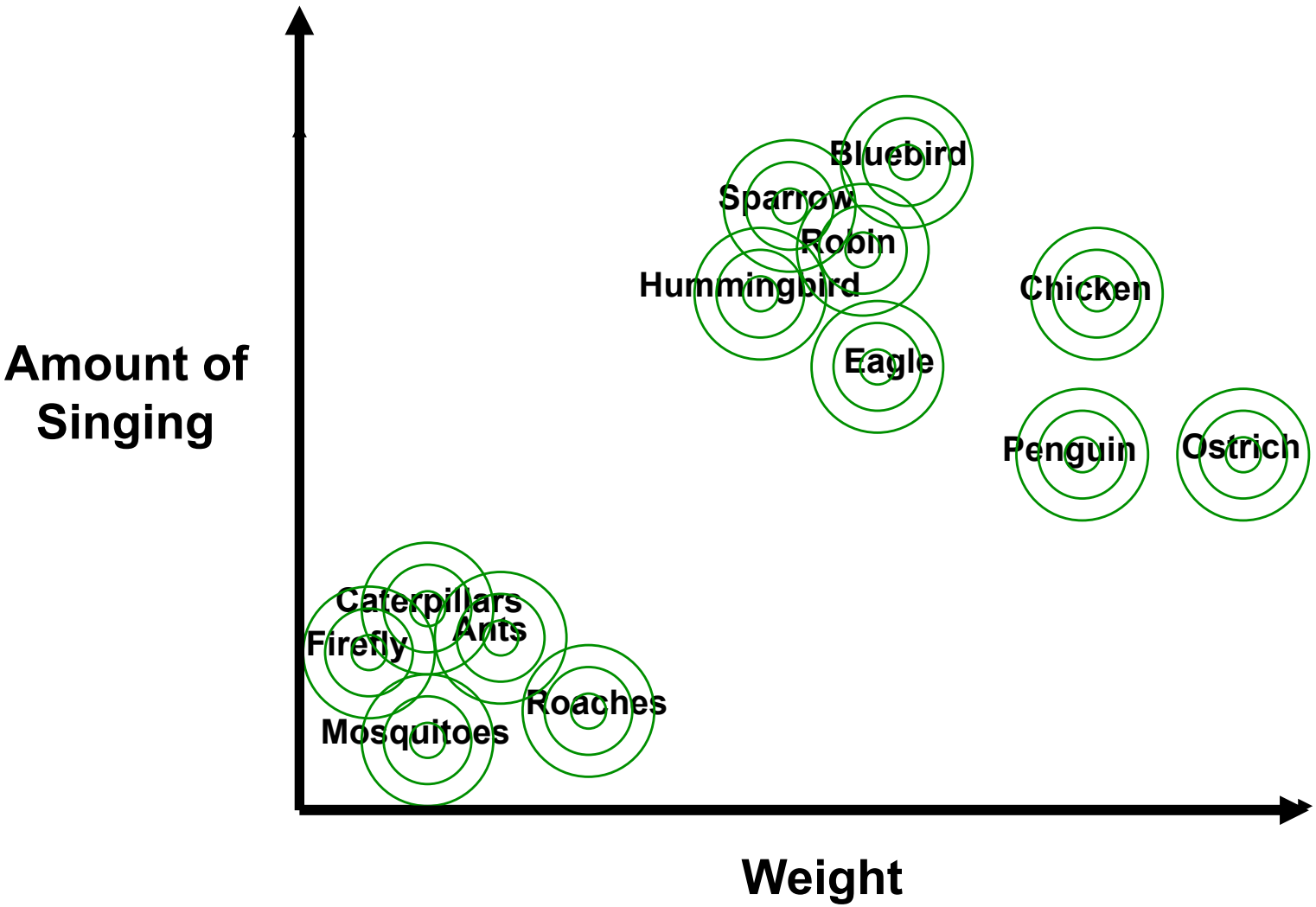
$$\eta_{ij} = e^{-d_{ij}^2}$$

- Response rule

$$p(R_j|S_i) = \frac{b_j \sum_{j \in C_j} n_{ij}}{\sum_{k=1}^{m} (b_k \sum_{j \in C_k} n_i k)}$$

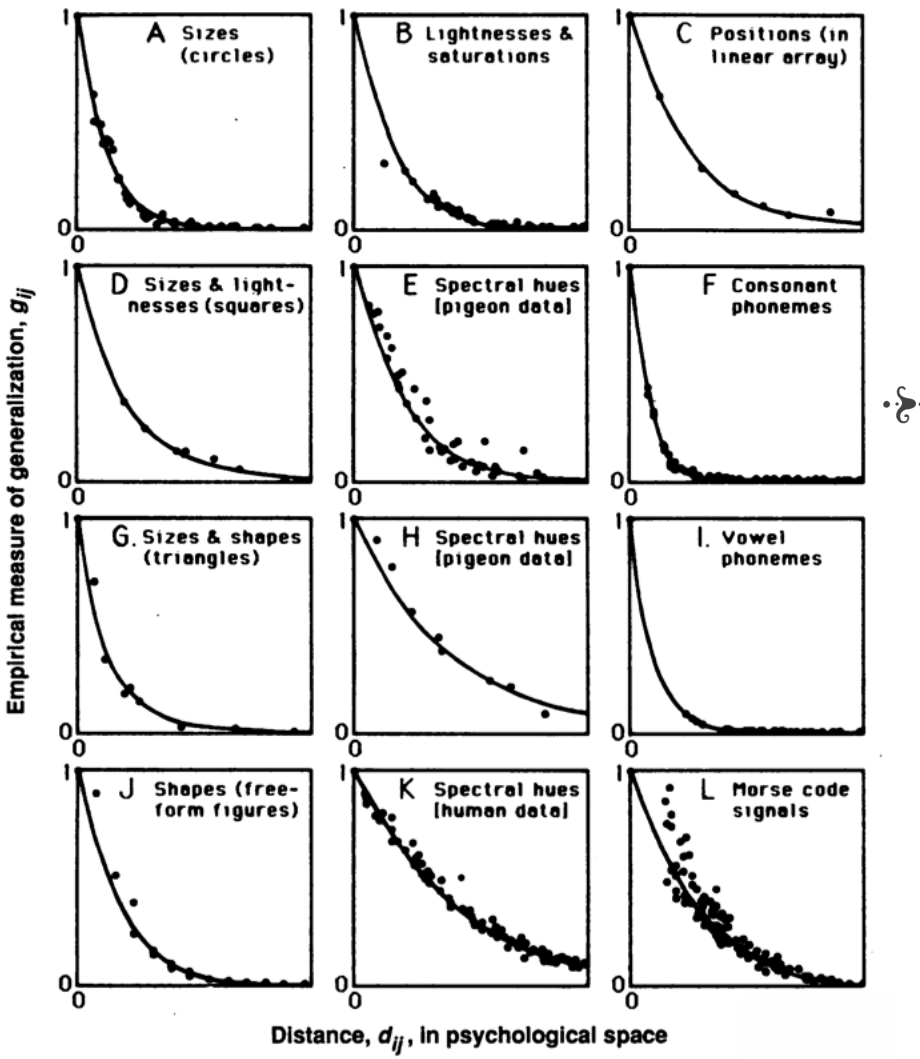
The Generalized Context Model

Nosofsky (1984; 1986)



The Generalized Context Model

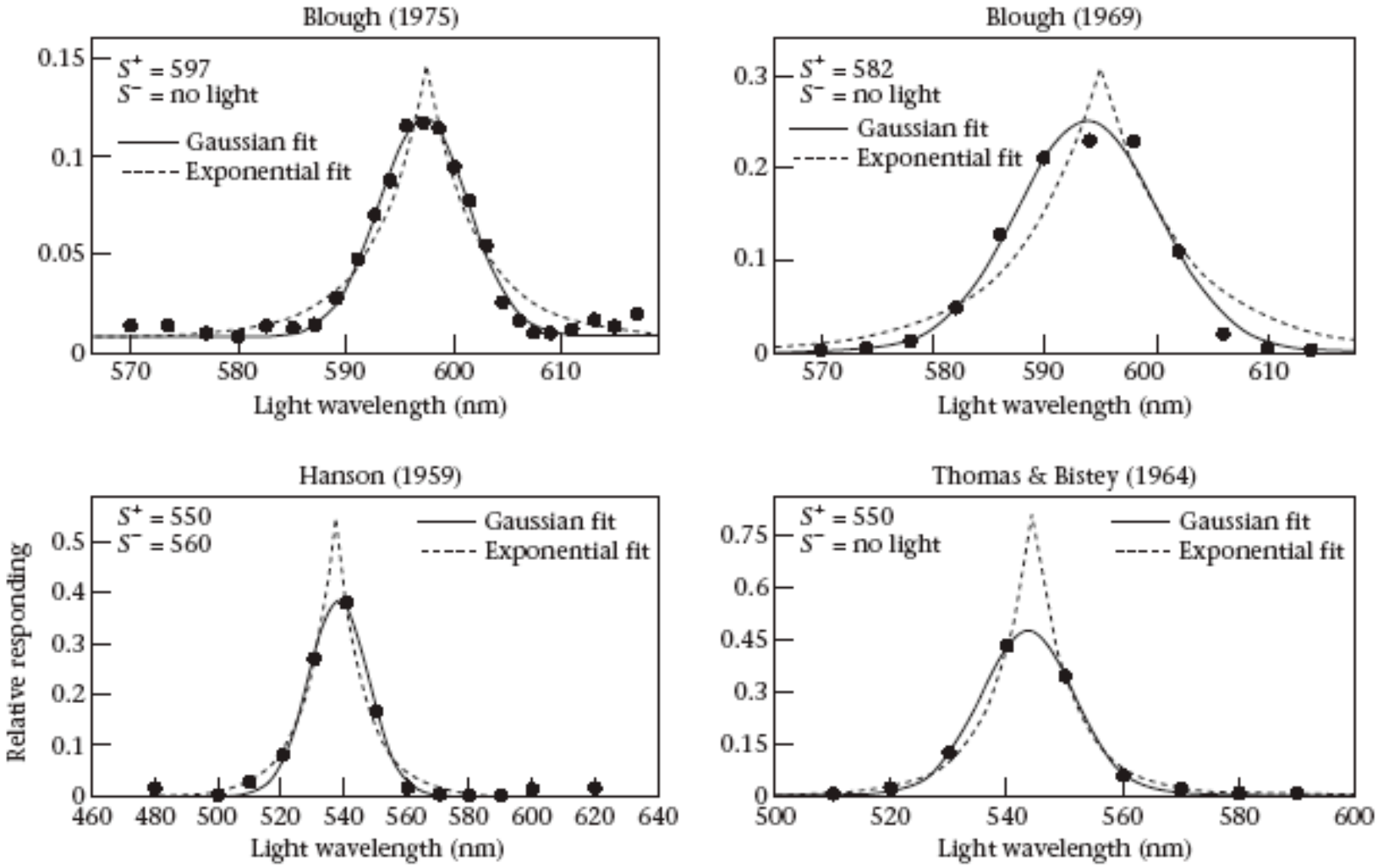
Nosofsky (1984; 1986)



- The **c** parameter in the model matches the exponential generalization gradient in Shepard's work

The Generalized Context Model

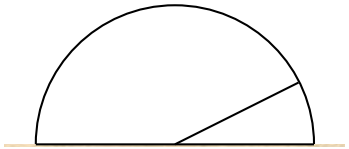
Nosofsky (1984; 1986)



Selective Attention

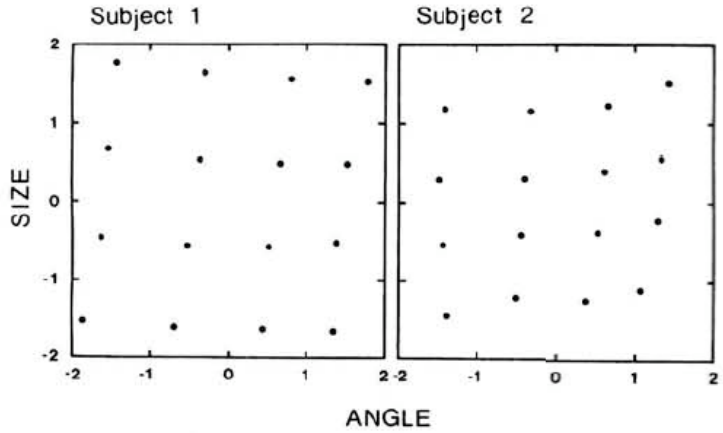
Nosofsky (1986)

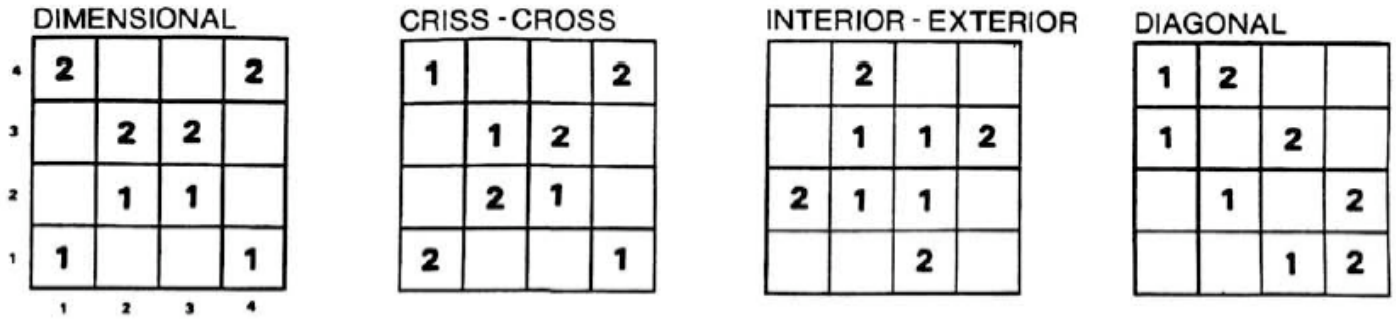
Stimuli



- Size and Angle
- Both size and angle varied along four levels

- Subject first made identification judgments (yielding a confusion matrix)
- MDS techniques from Shepard used to provide stimulus representation for each subject in appropriate “psychological space”

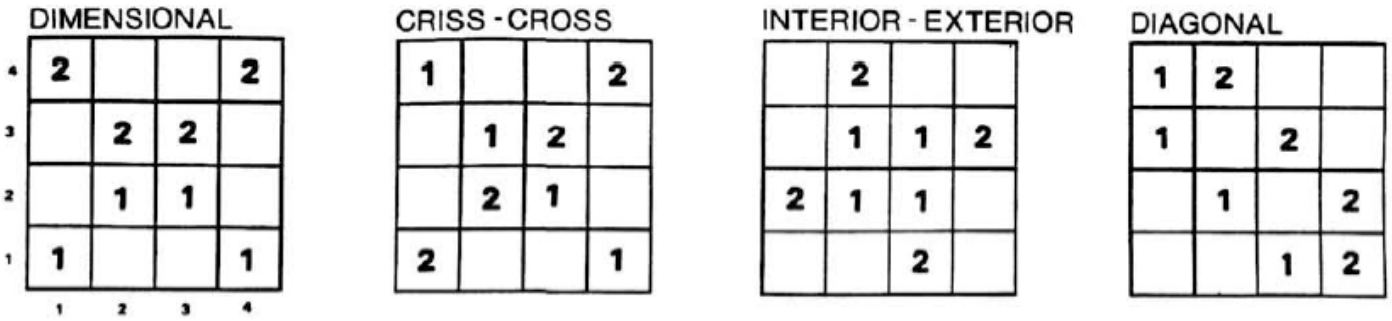




Selective Attention

Nosofsky (1986)

- GCM model fit to each subject to estimate best fit values of w's, c, etc...



w1	0	.58	.64	.60
w2	1	.42	.36	.40
w1	0.09	.66	.66	.56
w2	0.91	.34	.34	.44

The Exemplar and Prototype Debate

- Exemplar and Prototype Models are titans in the field of cognitive psychology.
- These model are important beyond just the categorization literature because the issues of memory representation and stimulus generalization come up in many areas
  - "Prototypical" or "Average" faces are rated as more attractive (Langlois & Roggman, 1990)
  - The E and P models share deep similarities to Bayesian template-matching models in visual perception (Gold, Cohen, Shiffrin, 2006)
  - In Memory literature: MINERVA (Hintzman, 1988)
  - Speech Perception: Fuzzy Logic Model is a "prototype"-like model (Massaro, 1989); The prototype-magent effect (Kuhl, 1991), "Rich Phonology" (Port, 2007)
- However, is this really all there is?

3 Categorization

Rules and Associations in Learning

Multiple Strategies in Categorization

- Once again, the story is a shift to exemplar-like processes with extensive training
- However, careful considering of the *dynamics* of learning, reveal a number of strategies and representations are in play
- Abstract, effortful, (potentially explicit) strategies give way to effortless, automatic, memory-based processes later in training.

Sloman (1996)

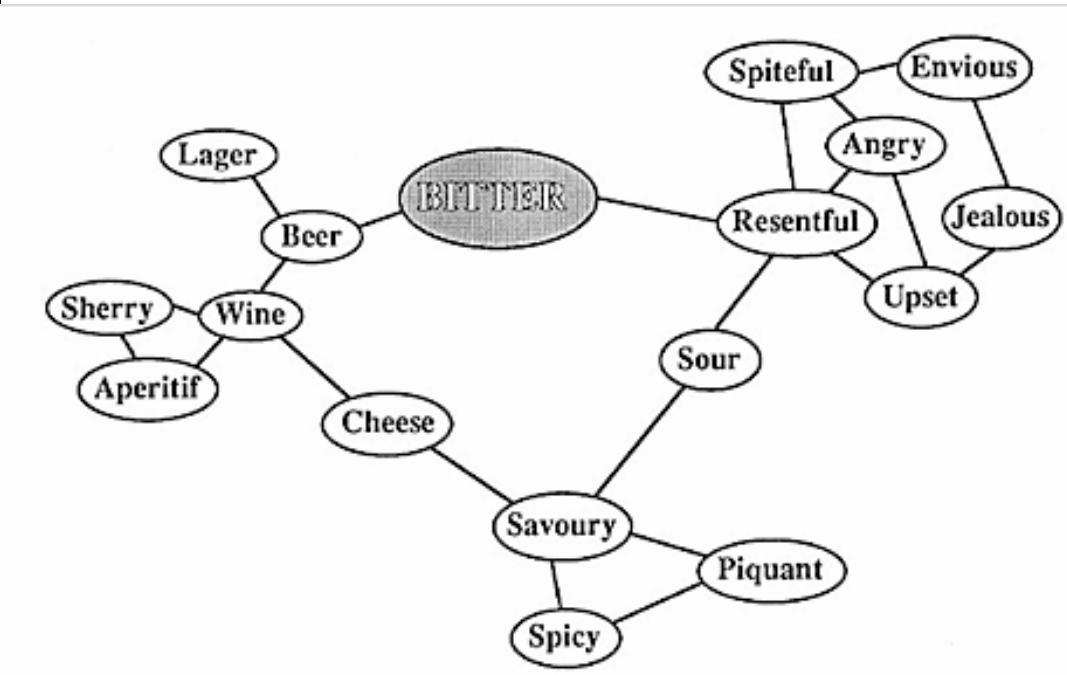
Associative vs. Rule-Based Systems

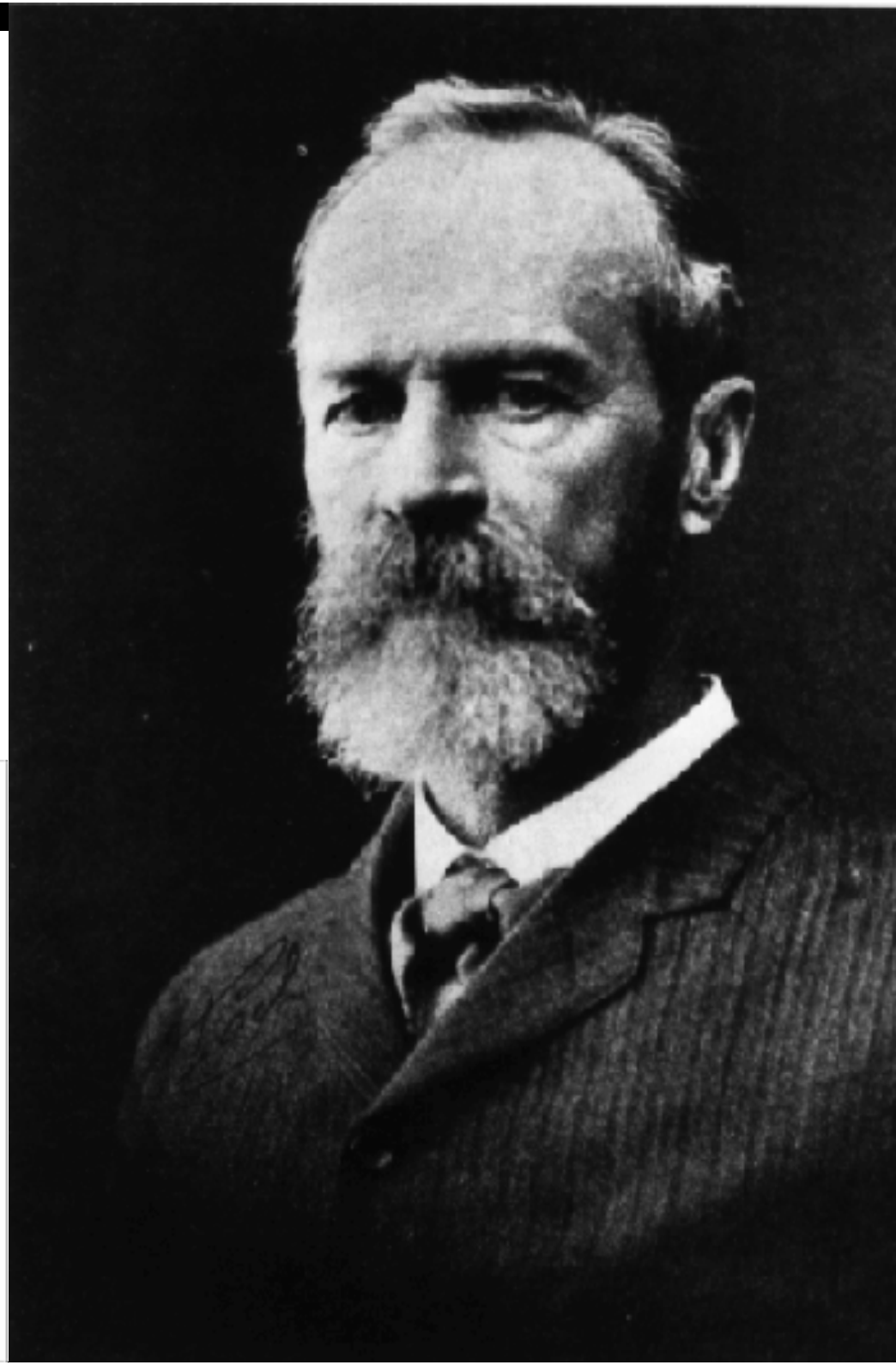
Table 1
Characterization of Two Forms of Reasoning

Characteristic	Associative system	Rule-based system
Principles of operation	Similarity and contiguity	Symbol manipulation
Source of knowledge	Personal experience	Language, culture, and formal systems
Nature of representation		
Basic units	Concrete and generic concepts, images, stereotypes, and feature sets	Concrete, generic, and abstract concepts; abstracted features; compositional symbols
Relations	(a) Associations	(a) Causal, logical, and hierarchical
	(b) Soft constraints	(b) Hard constraints
Nature of processing	(a) Reproductive but capable of similarity-based generalization	(a) Productive and systematic
	(b) Overall feature computation and constraint satisfaction	(b) Abstraction of relevant features
	(c) Automatic	(c) Strategic
Illustrative cognitive functions	Intuition Fantasy Creativity Imagination Visual recognition Associative memory	Deliberation Explanation Formal analysis Verification Ascription of purpose Strategic memory

William James

- **Associationism** elaborate the Aristotelian view of associations to include networks of interrelated concepts (precursor to connectionist "Rummelhart" networks)
- Initiated study of habits and automatic associations
- Aimed to eventually detail the nature of his networks directly in the brain





Hypothesis Testing in the Rat: Tolman

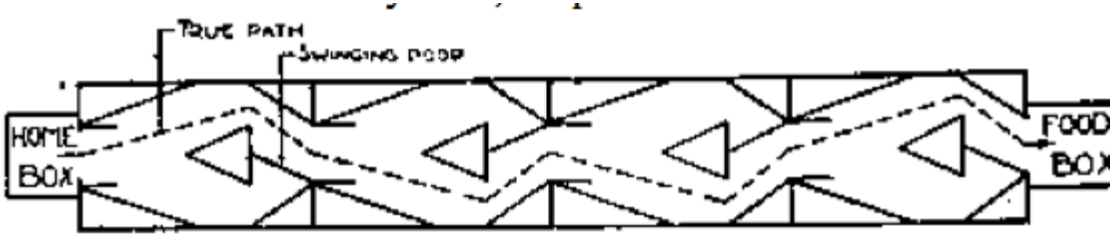
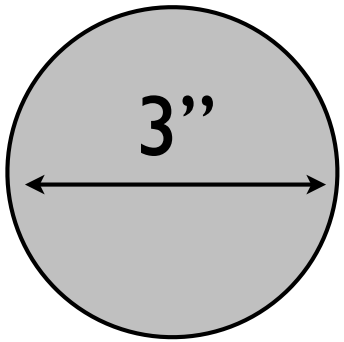


FIG. 14

(From I. Krechevsky (Now D. Krech), The genesis of "hypotheses" in rats. *Univ. Calif. Publ. Psychol.*, 1932, 6, No. 4, p. 46.)

Rips (1989)

- A central tenant of both the prototype and exemplar models is that similarity between representations stored in memory and to-be-categorized stimuli are the critical determinants of a response
- Lance Rips found an simple way to dissociate similarity and categorization:

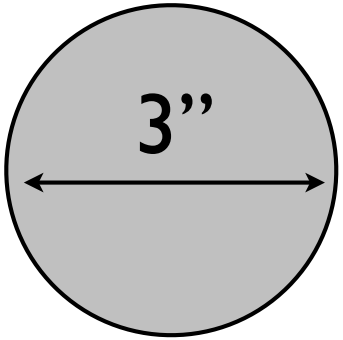


More Similar

More Likely

Rips (1989)

- The idea is that the rule ***if diameter is not almost exactly .25 inches then it is not a quarter*** overrides this "similarity" response



Sloman (1996)

- **Criterion S:** cases where one, presumably rule or logic based response, is held simultaneously with another associative response but are in conflict.
- An example: Tversky and Kahneman (1983)'s Linda the Bank Teller:

> Linda is 31 years old, single, outspoken and very bright. She majored in philosophy. As a student, she was deeply concerned with issues of discrimination and social justice, and also participated in anti-nuclear demonstrations.

Rank order the following according to the statement's probability:

-- Linda is a bank teller.
-- Linda is a bank teller and is active in the feminist movement.

The "logical"/"rule-based" response overwhelmed by the "representative heuristic" (a similarity based response).

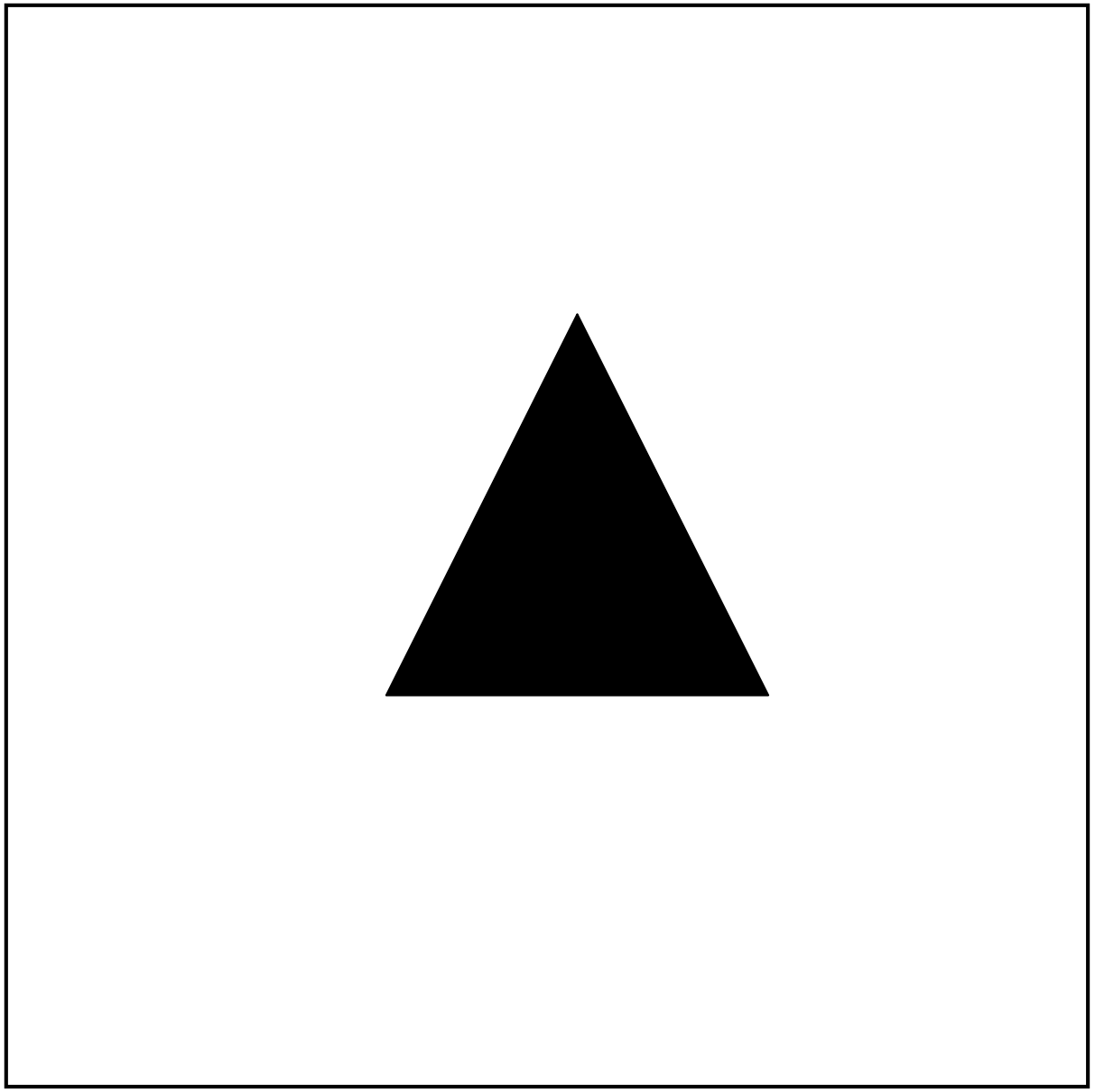
Rules and the classical view of concepts

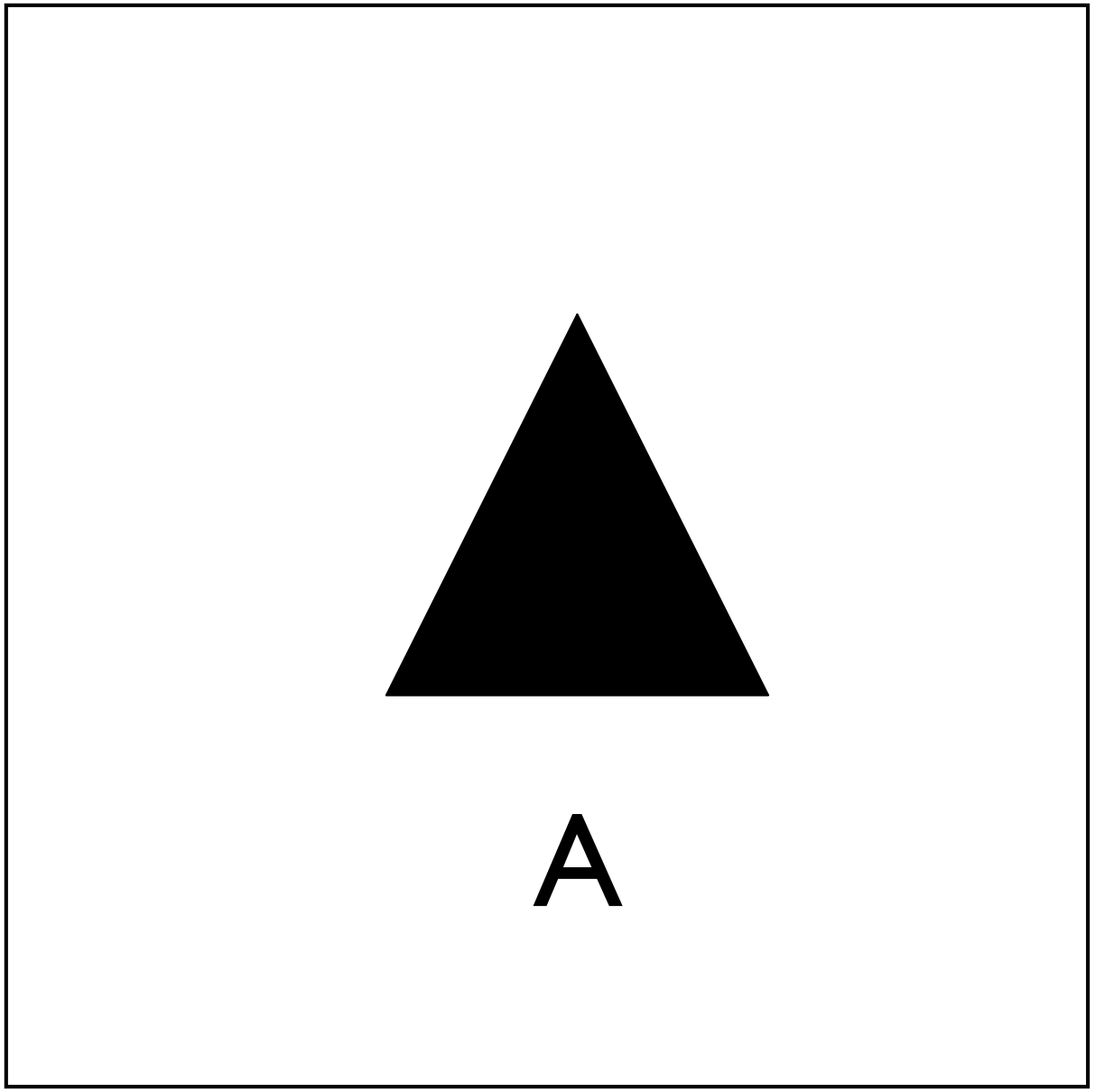
- The Allen & Brooks (1991) study described last week is consistent with this as well (even subjects in the rule condition were influence by exemplar similarity in both their judgements and response times)

- As the last lecture showed, the classical view of concepts was sorely damaged if not destroyed by findings of graded category structure.

- However, one way to view the general point in Sloman's article is to appreciate the role of logical "reasoning"-based processes in categorization.

- Again, multiple ways of learning are engaged in any situation possibly in parallel

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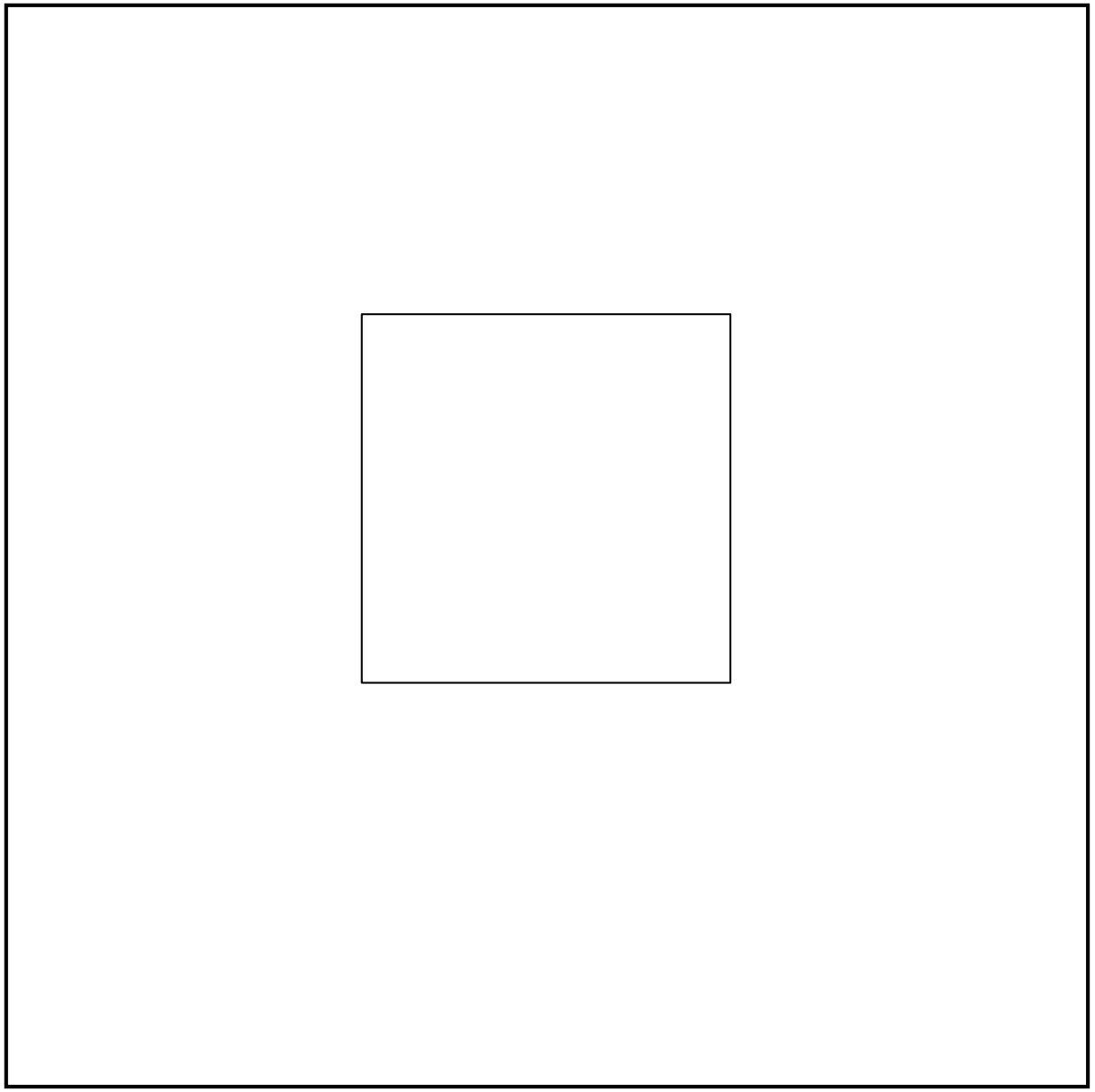

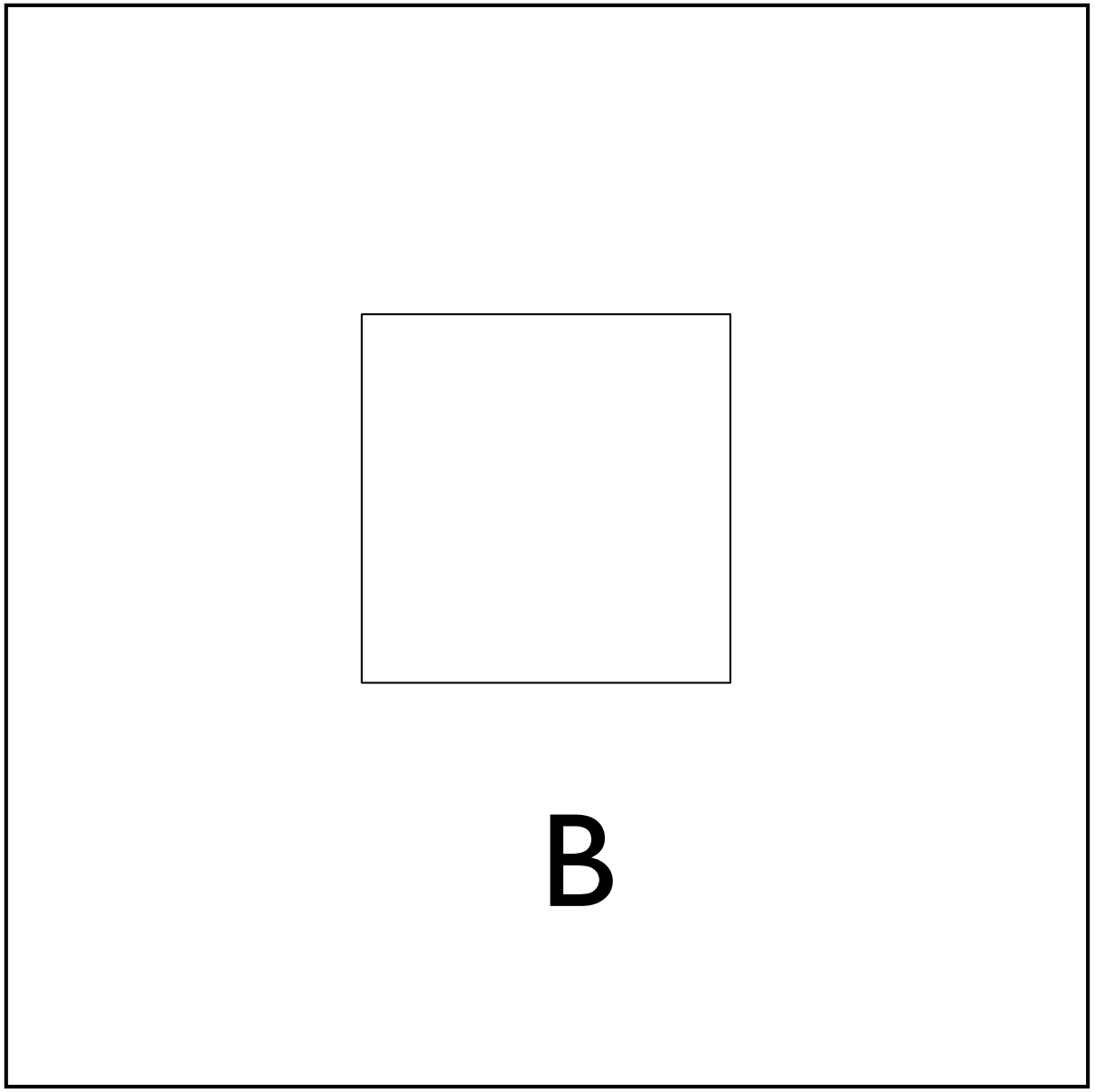
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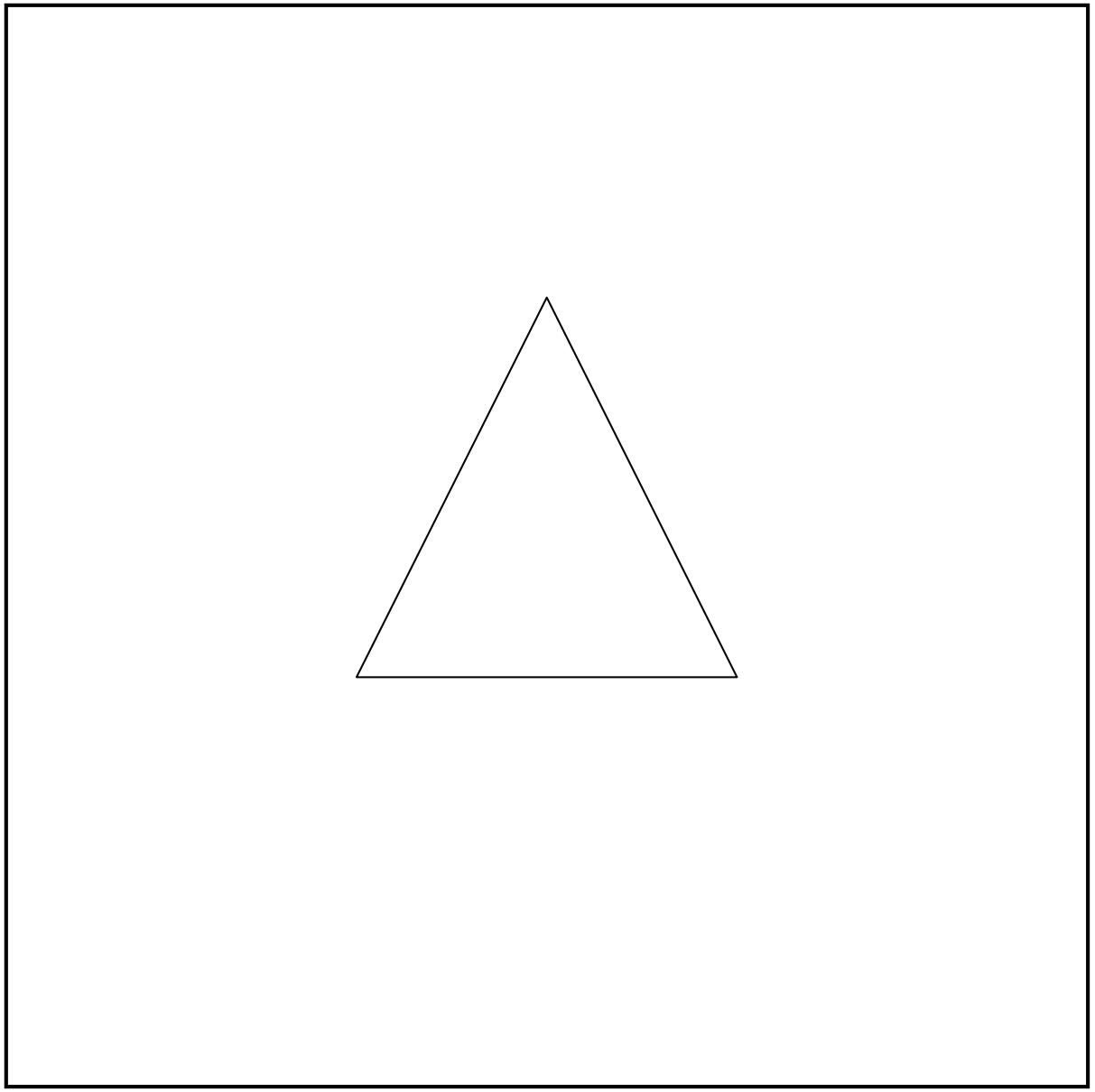

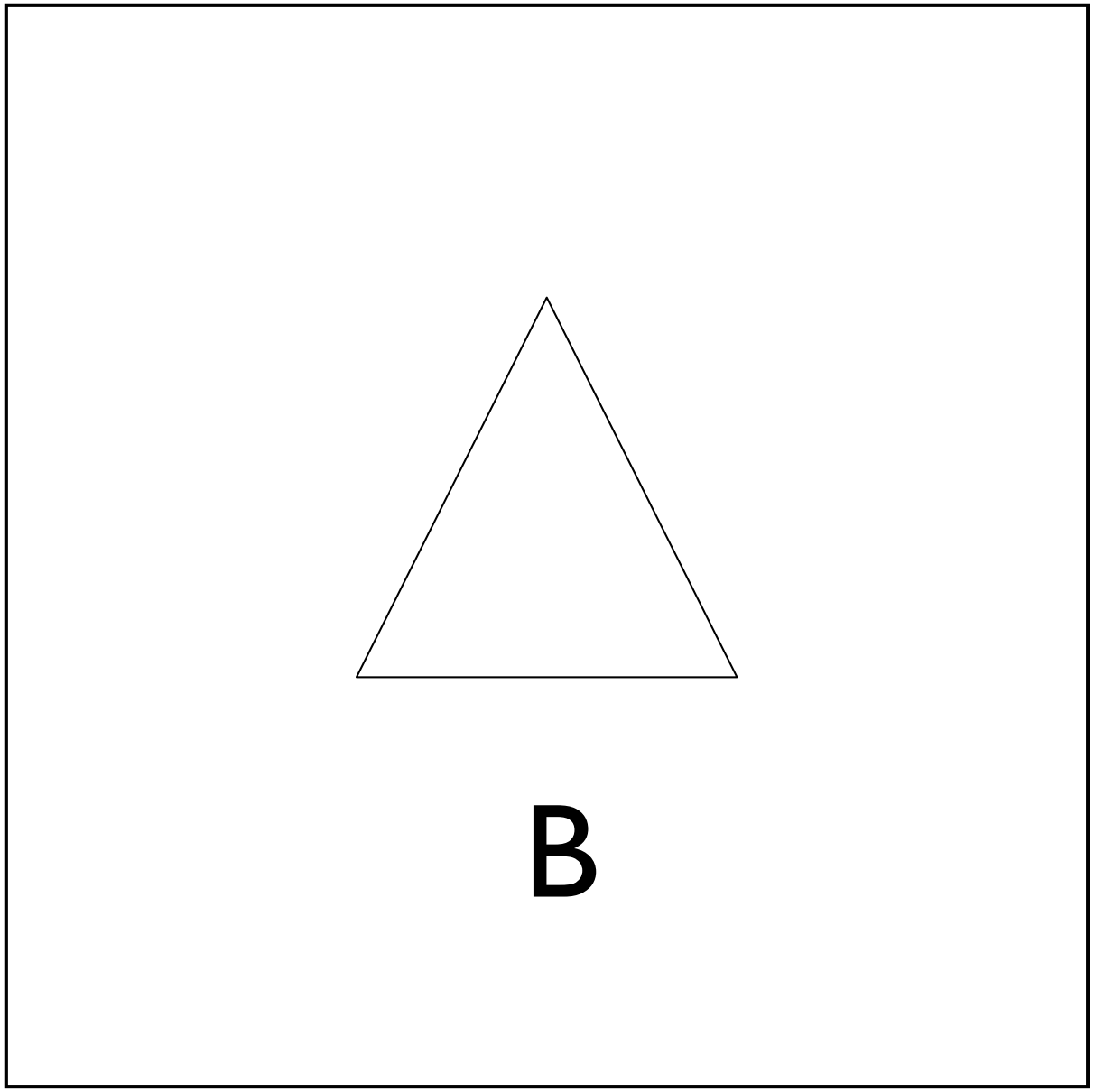
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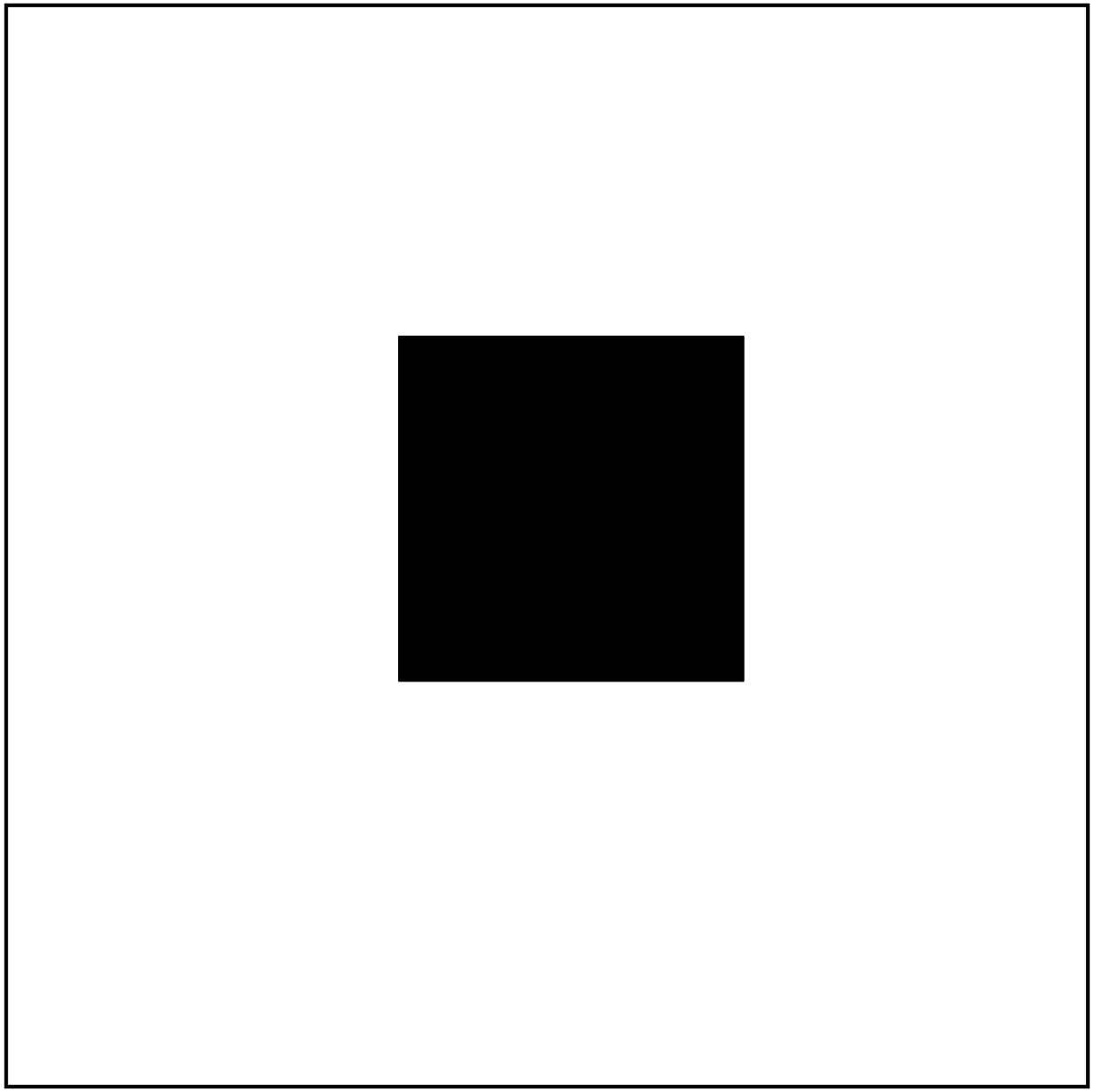

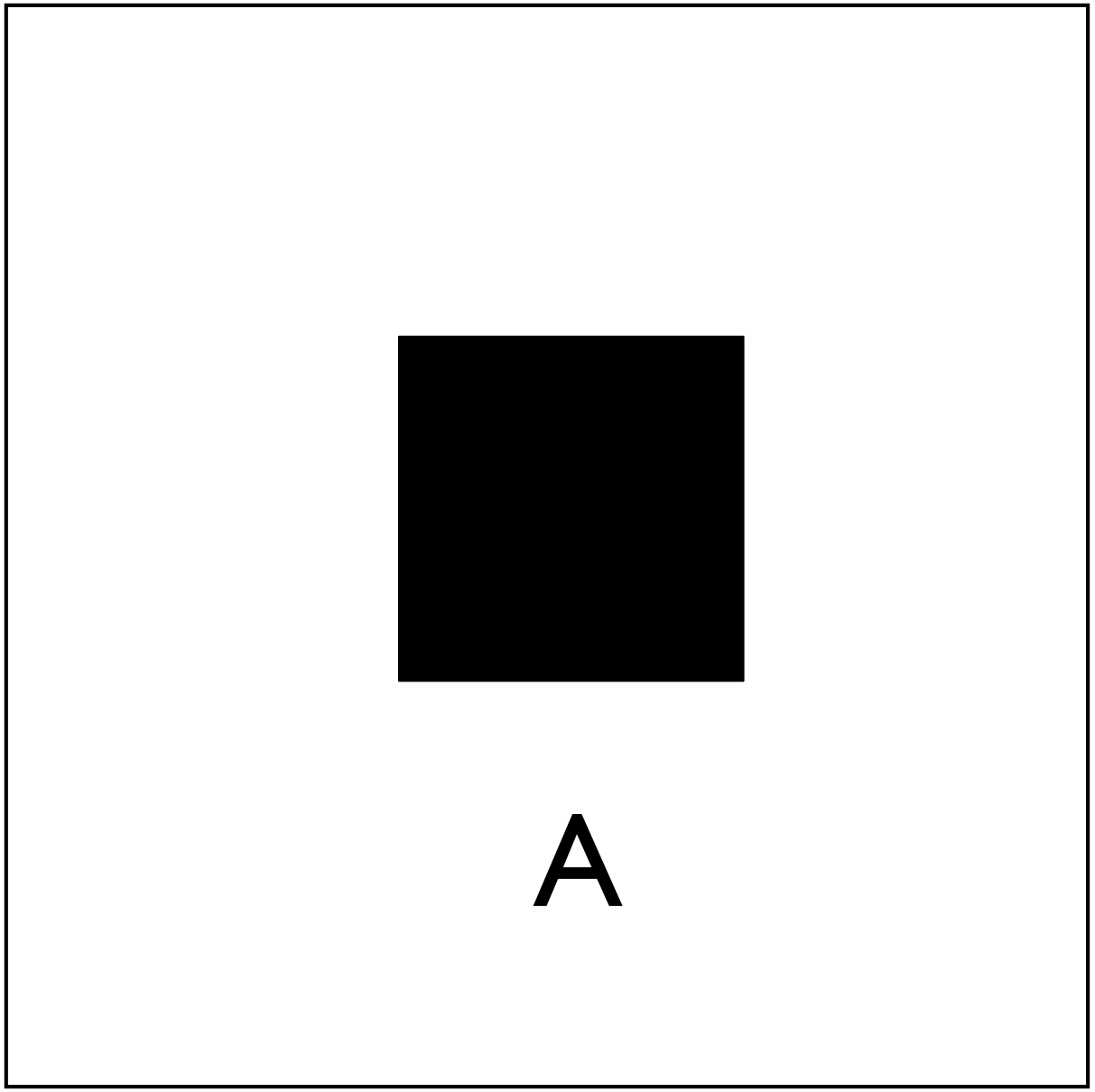
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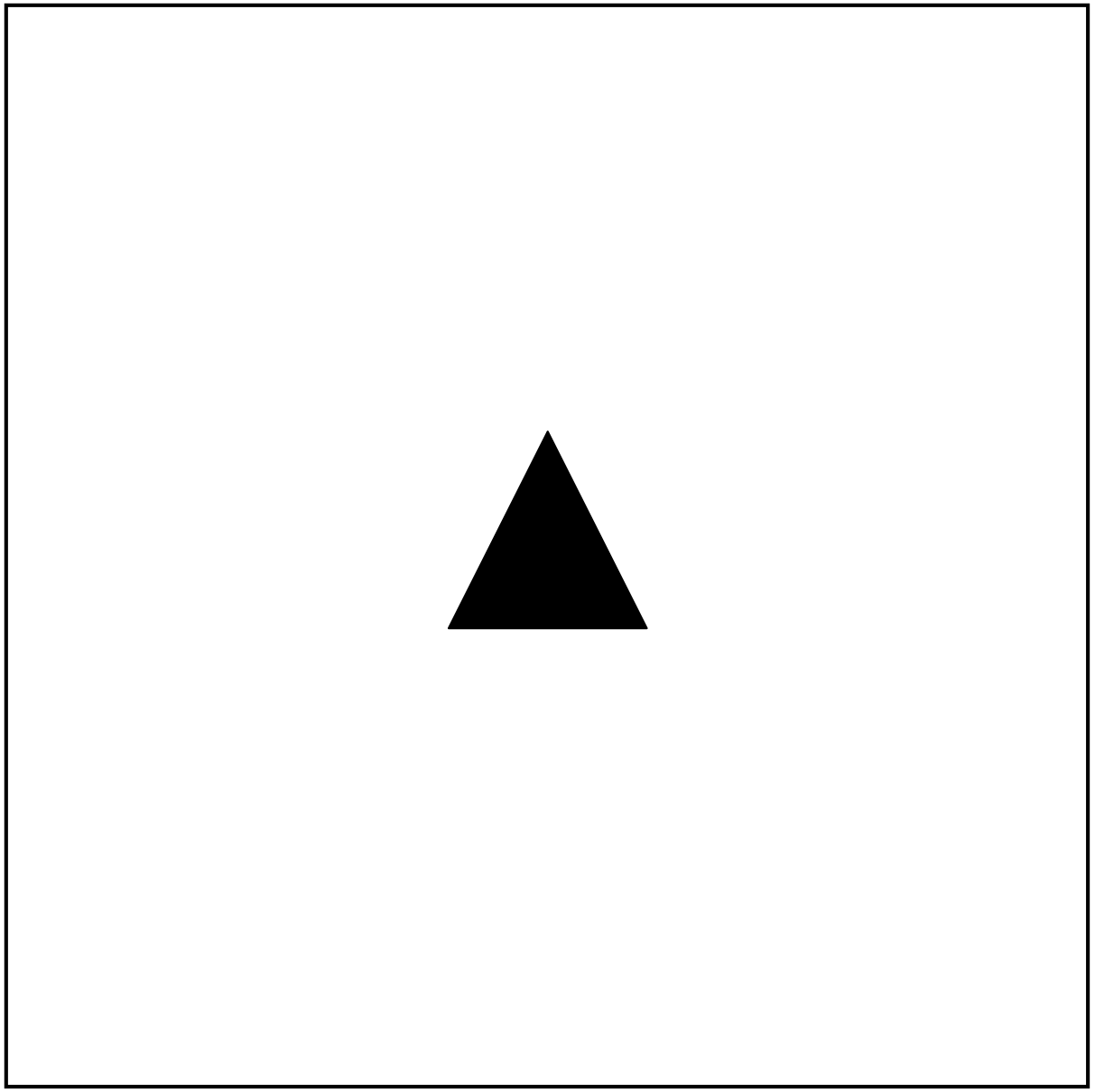

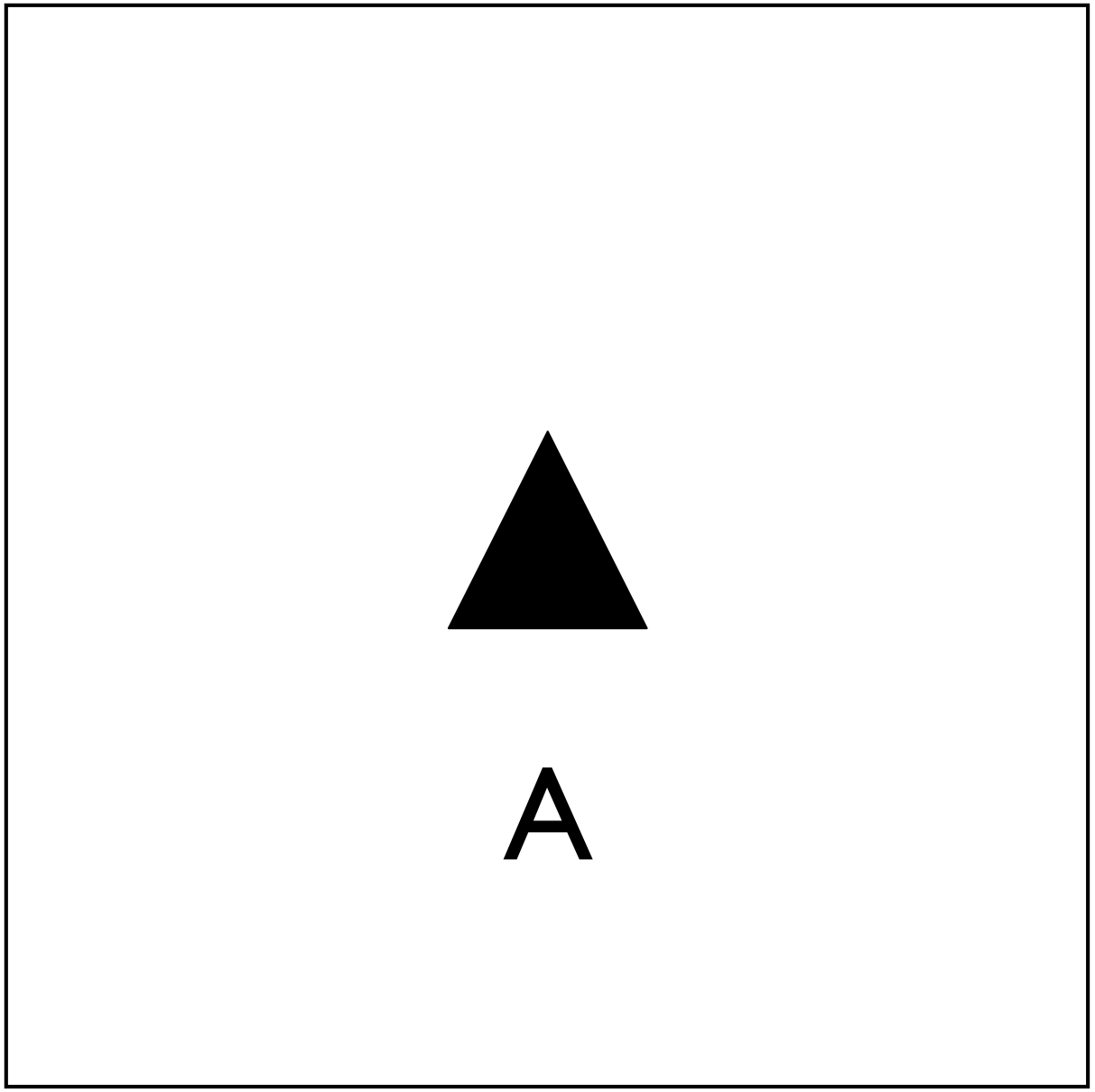
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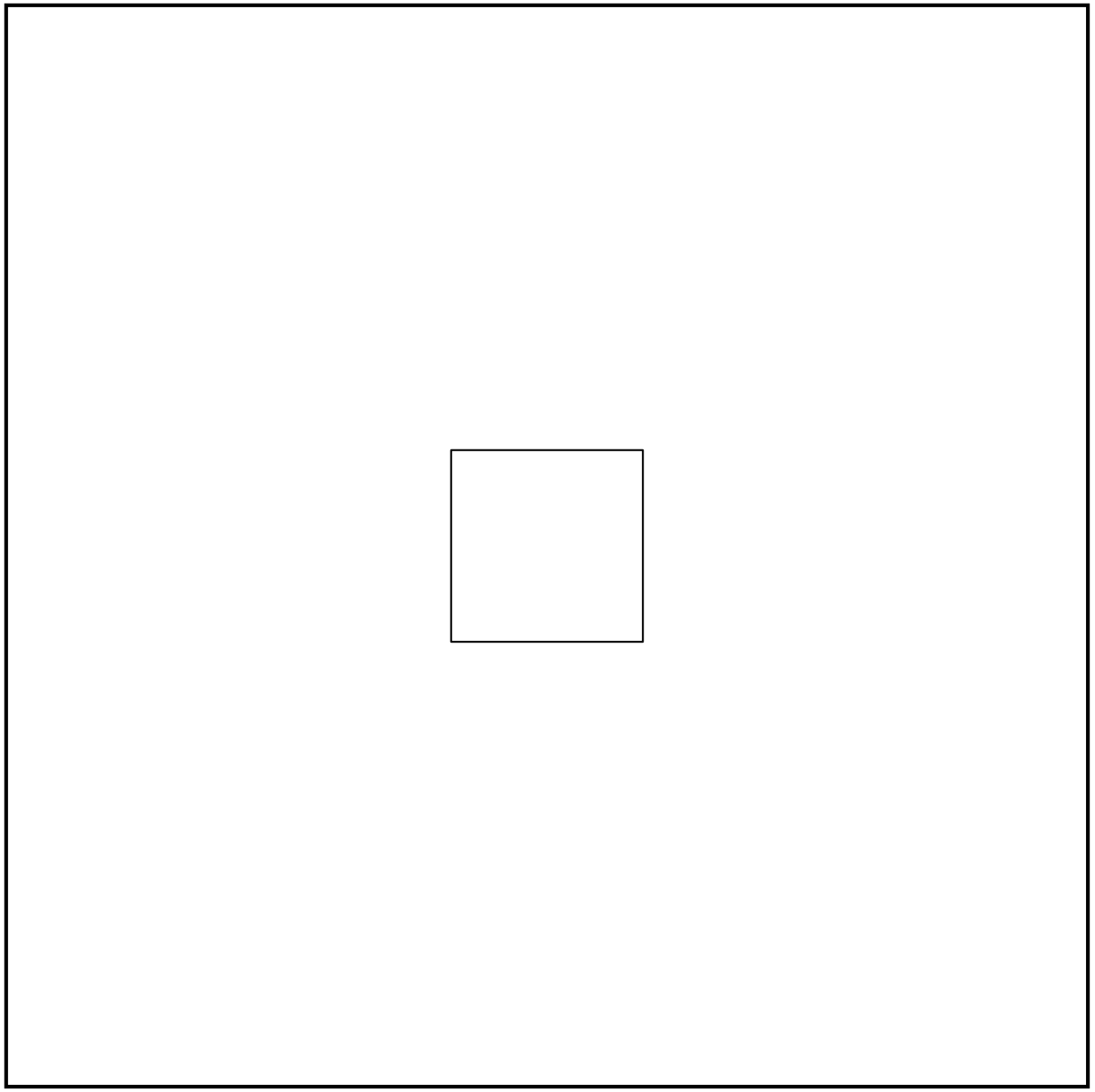

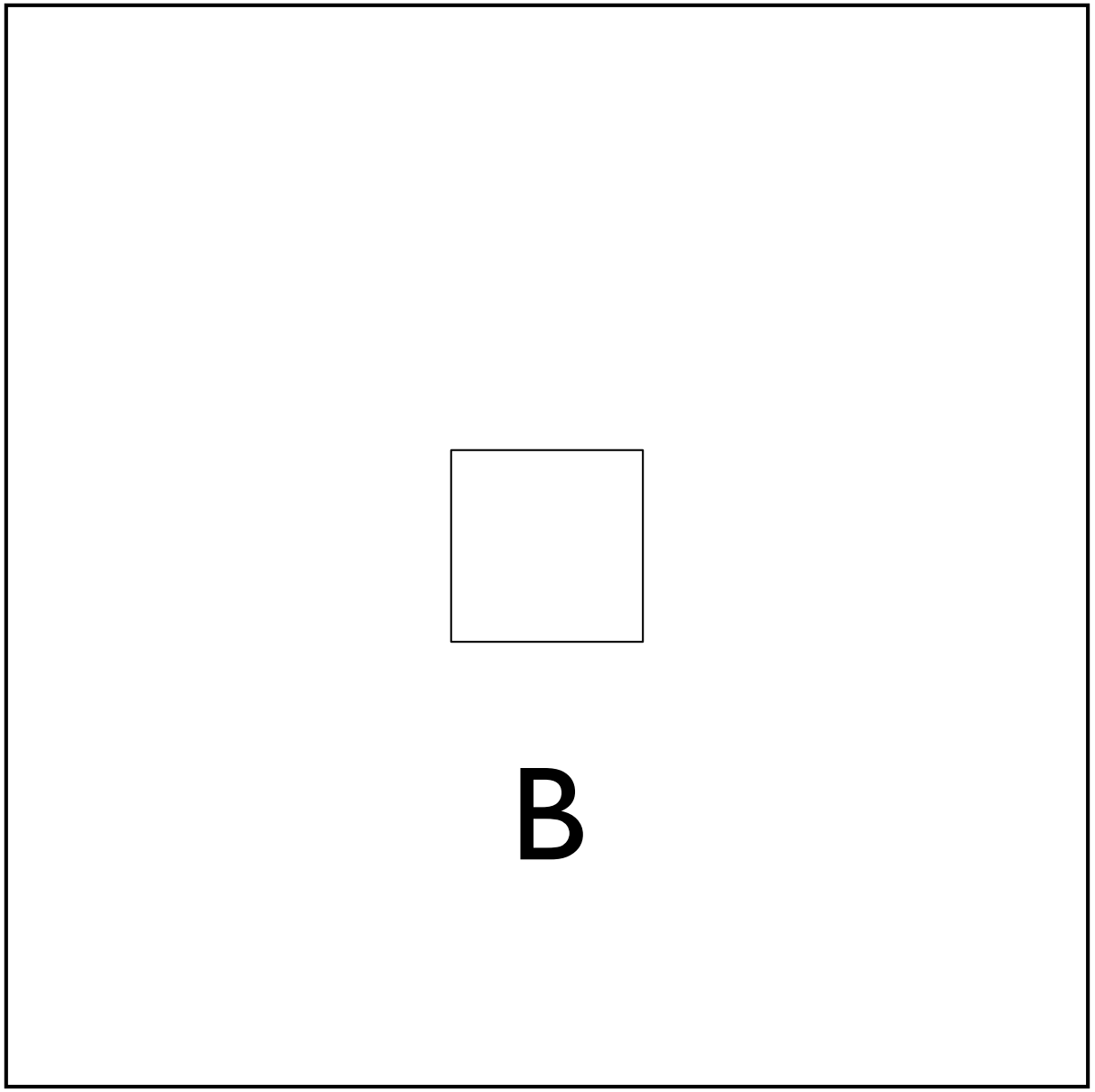
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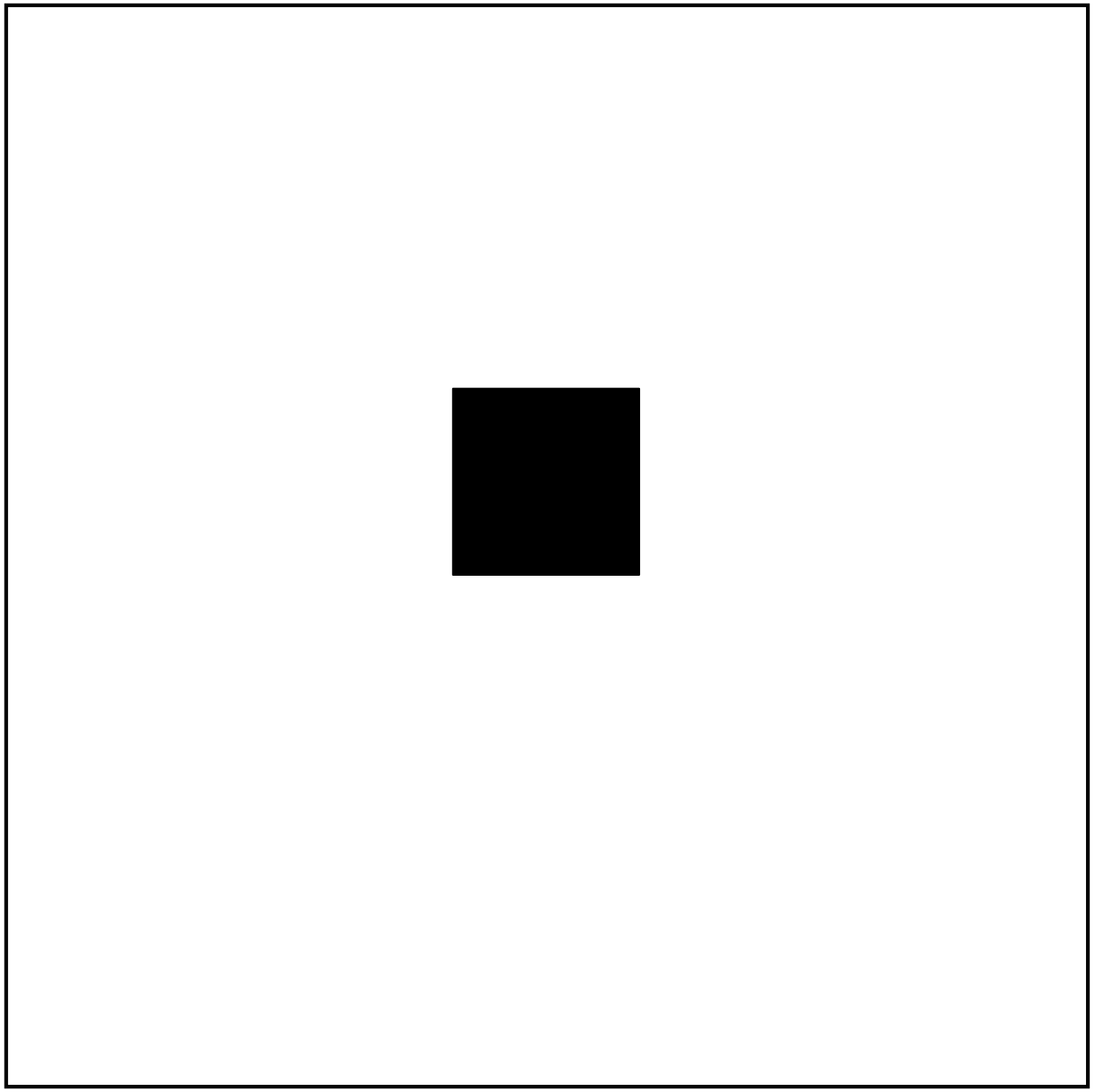
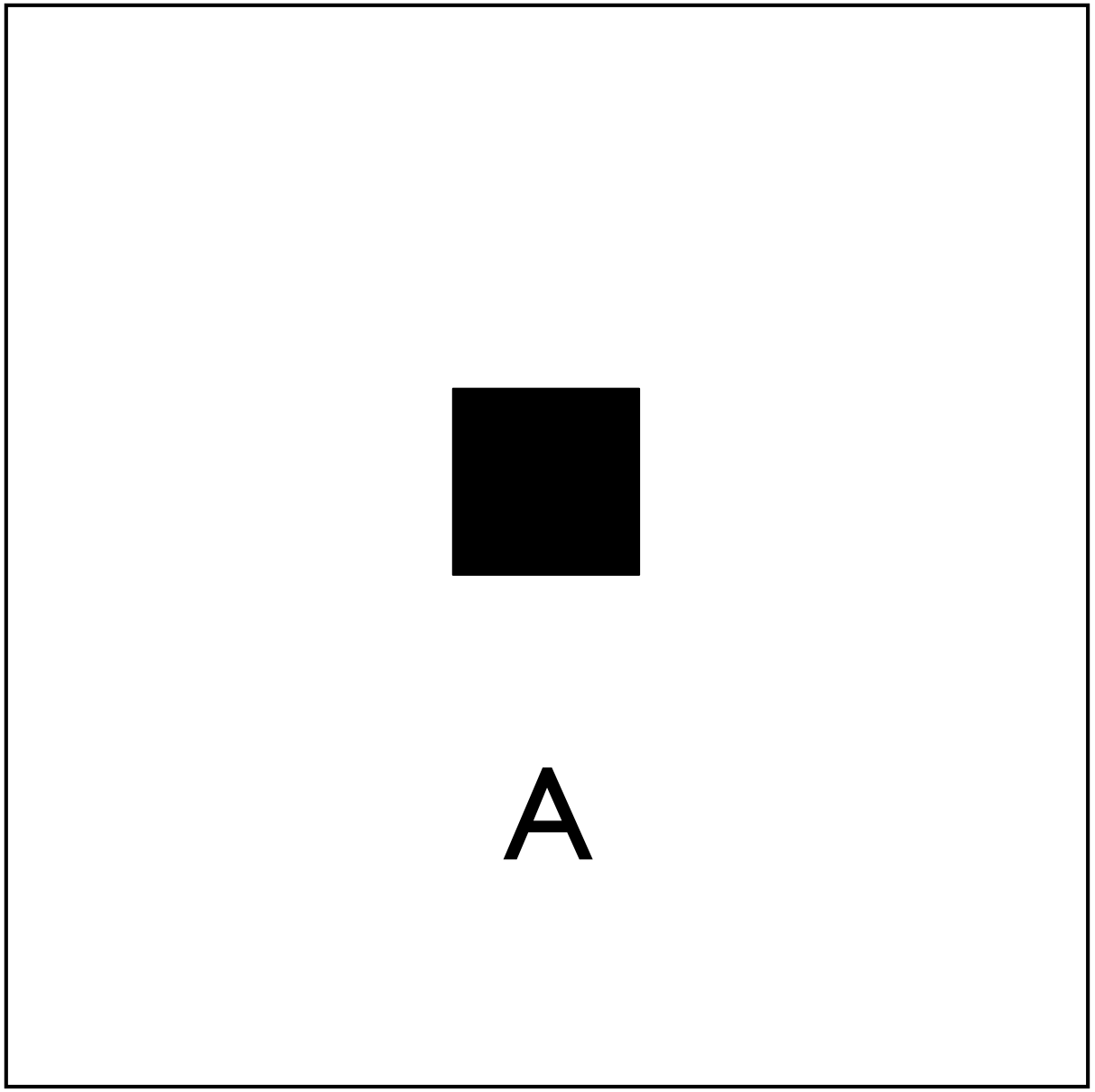



A

Bower and Trabasso (1963)

- Tested between rule and association based accounts of concept learning
- One of the key observations about rules is the idea of "one trial learning". All learning takes place when the correct rule is under consideration and is tested.
- As a result, rule-based theory predicts that changing the rule during learning does not hurt when the correct rule hasn't been discovered yet.
- In contrast, associationist accounts (like ALCOVE) gradually accumulate knowledge about the correct response and right dimensions to attend to. Thus, learning before the switch interferes with learning.

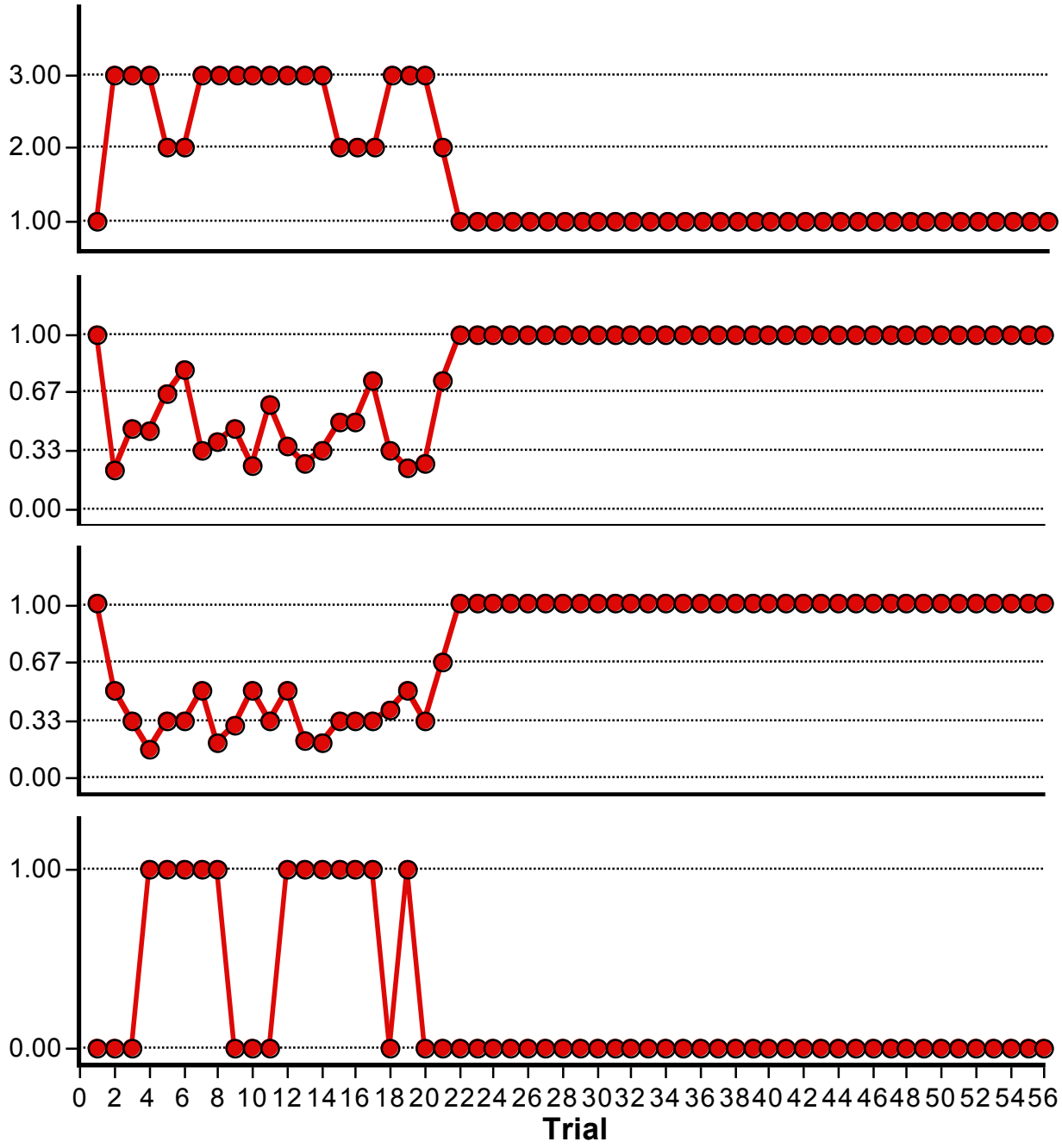
Bower and Trabasso (1963)

- Categories were defined by simple single dimensional rules
- Every time the participant made 2 mistakes in a row, the rule that defined the category switched.
- For example, first category A might be red things, category B, blue things. After two mistakes in a row, the whole category changes so that A is small thing, B is big things.
- RESULT: Little or no cost to learning in this switching environment

The Dangers in AVERAGING

- Group level data supports an ALCOVE-like account of gradual attention learning.
- But, is the appearance of gradual learning just an artifact of averaging over subjects?
- Let's look at one Type I learner, subject 35 in Rehder & Hoffman (2005)

of Dimensions Fixated



Proportion Time (Relevant Dimension)

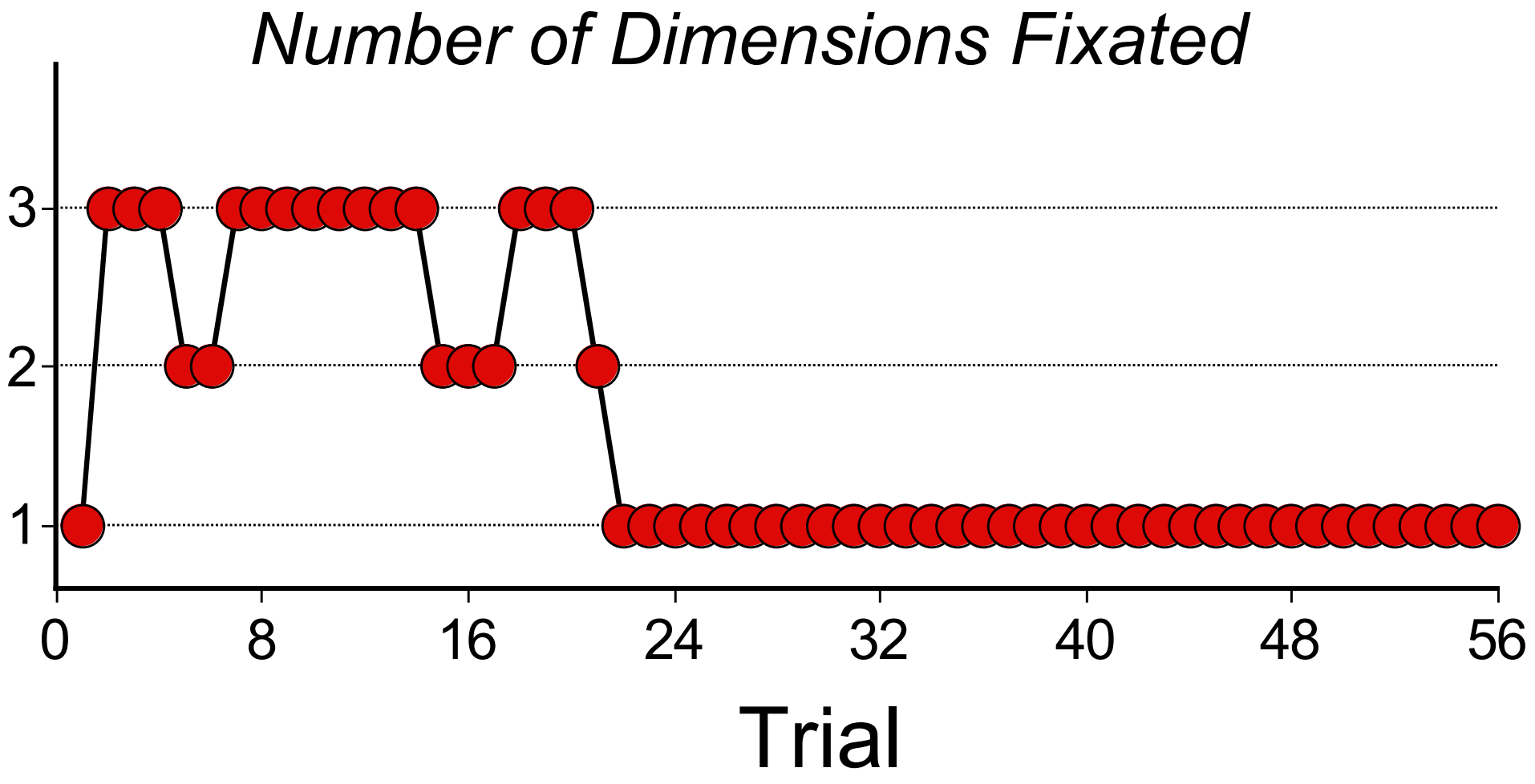
Relative Priority (Relevant Dimension)

Errors

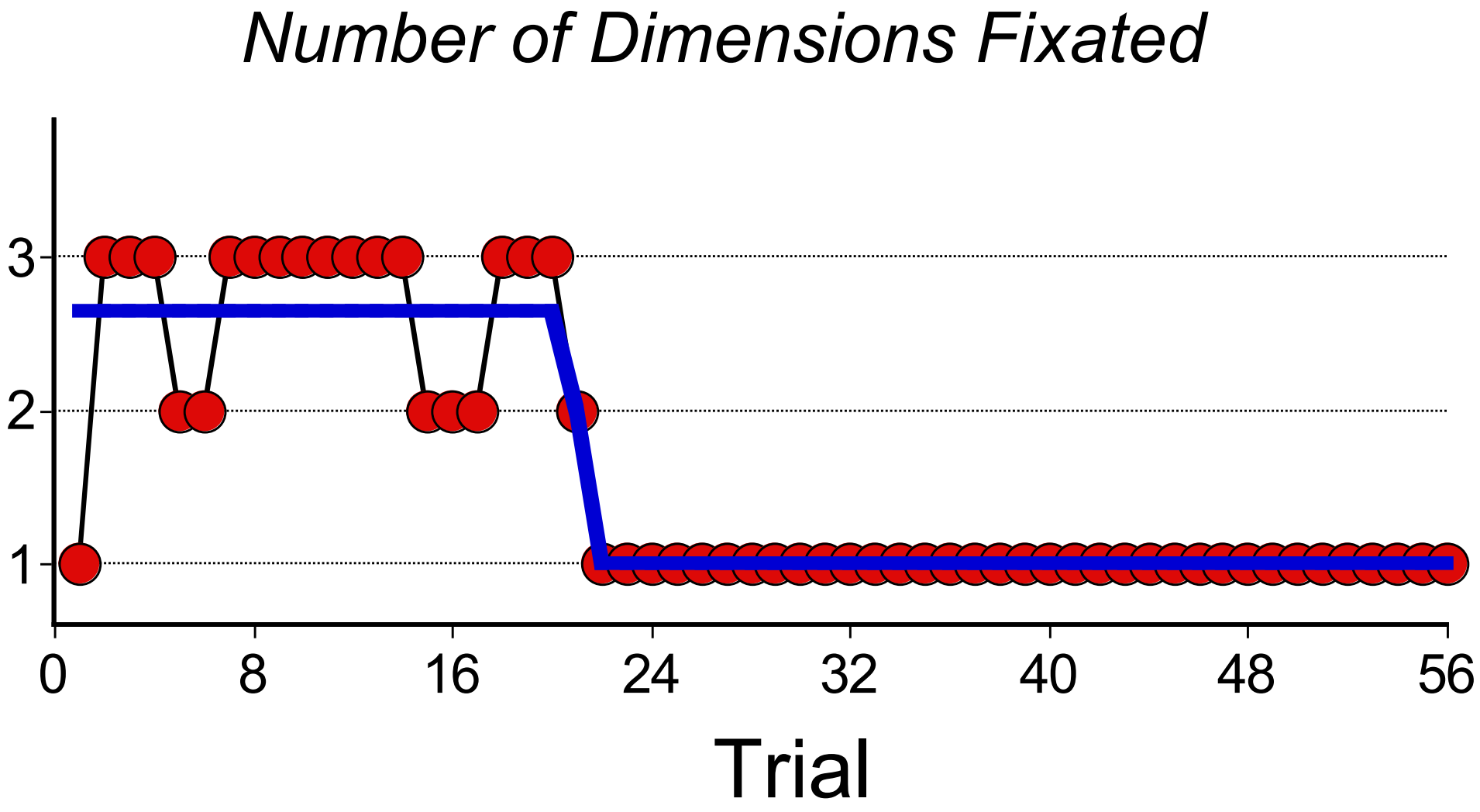
Learning is Sudden, Not Gradual

- Subject 35's results not consistent with Alcove's gradual learning account!
    - Before trial 22:
    - All three dimensions (usually) fixated.
    - No preference for looking at relevant dimension...
        - …more often than other dimensions.
        - …earlier than other dimensions.
    - Performance at chance (many errors).
- After trial 22:
    - Only relevant dimension fixated.
    - No errors.
-

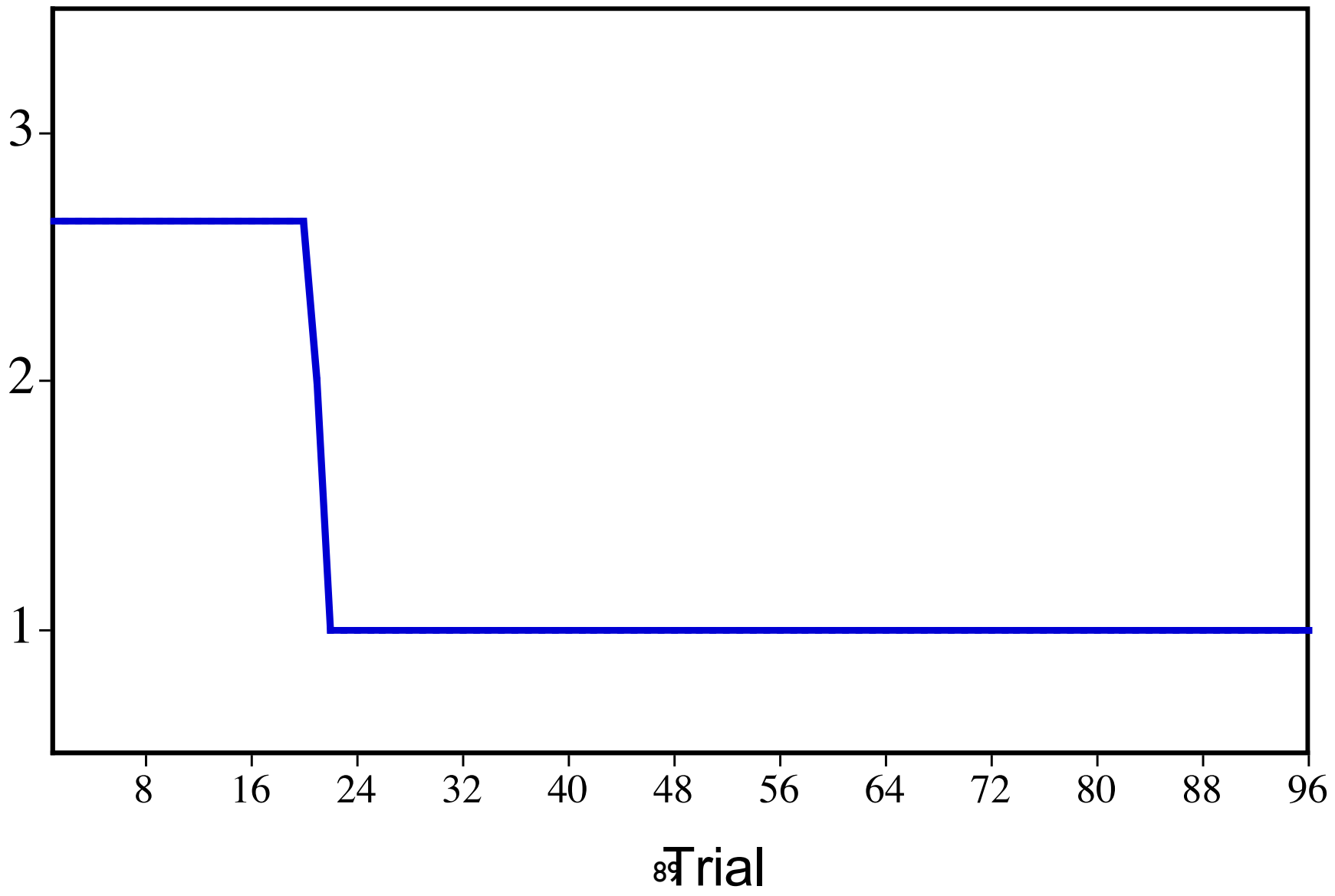
Example Type I subject



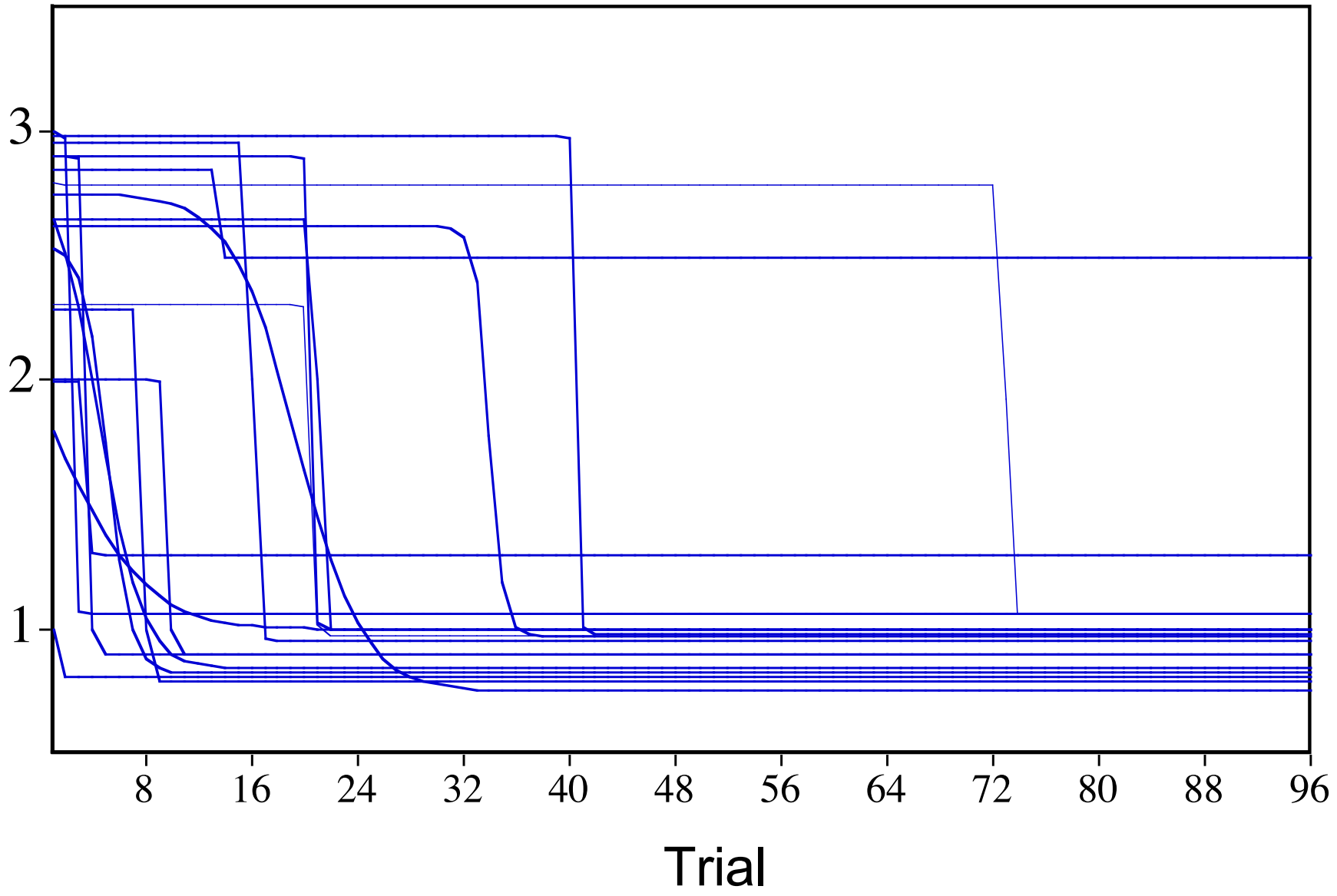
Example Type I subject



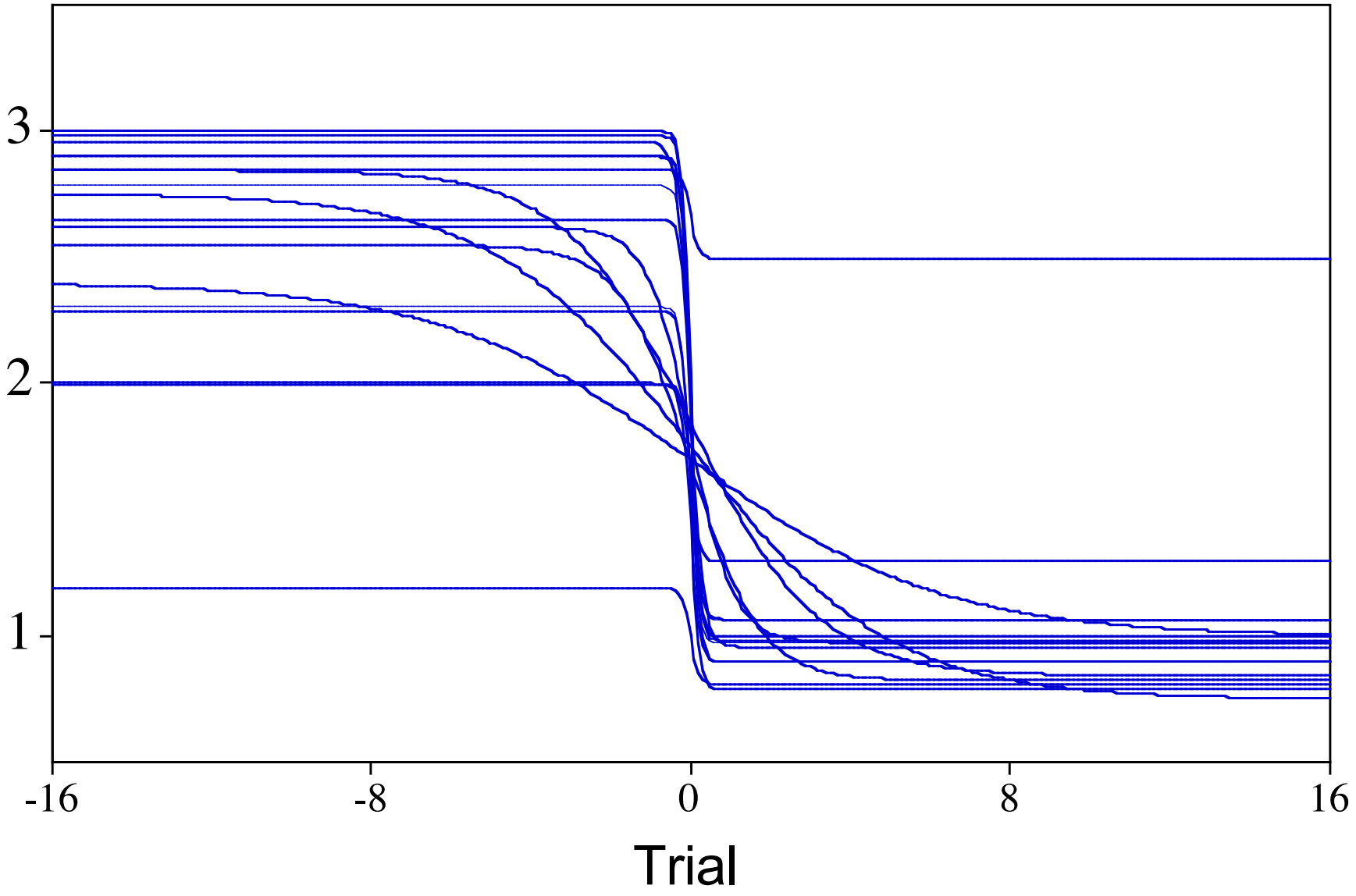
Example Type I subject



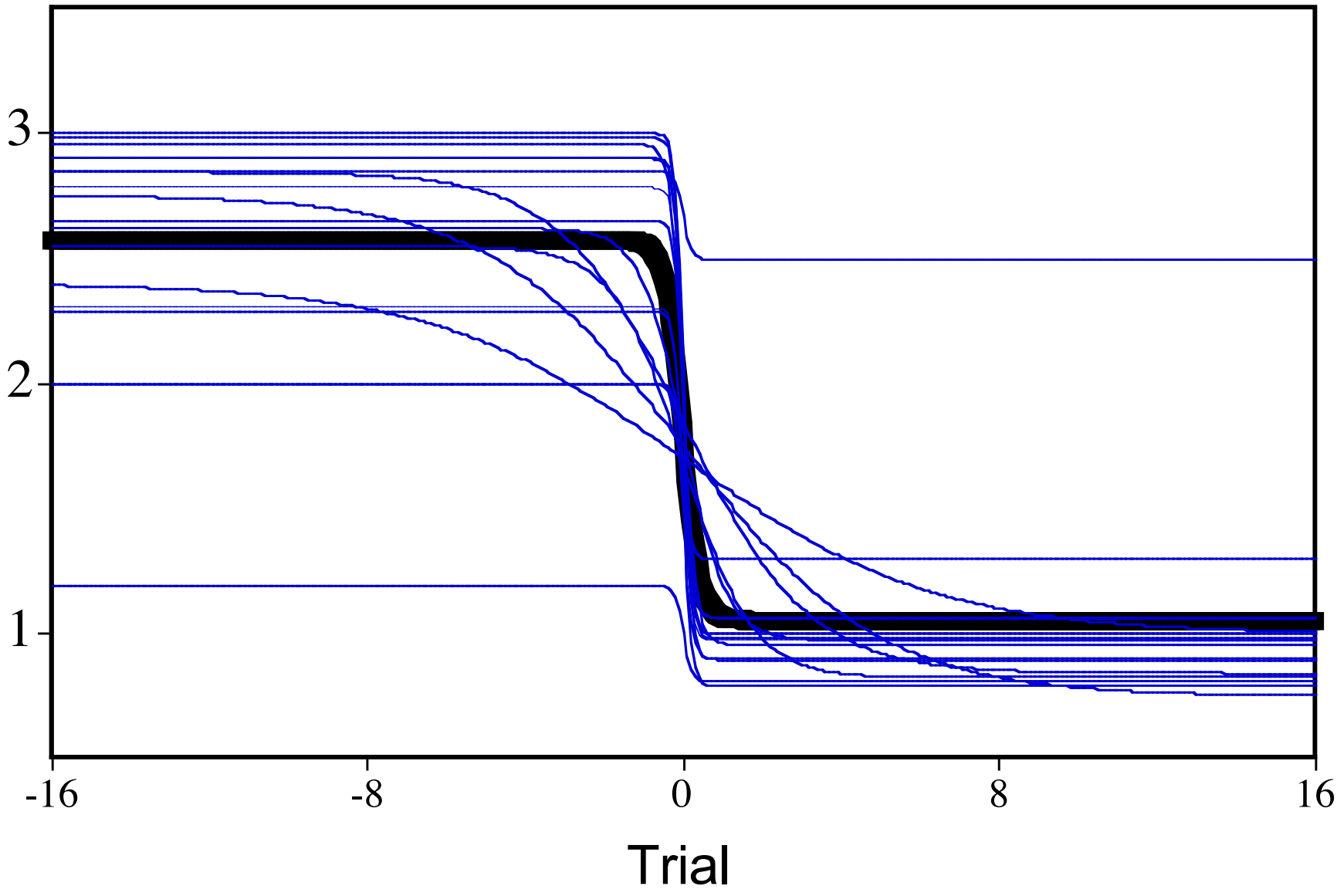
Example Type I subject



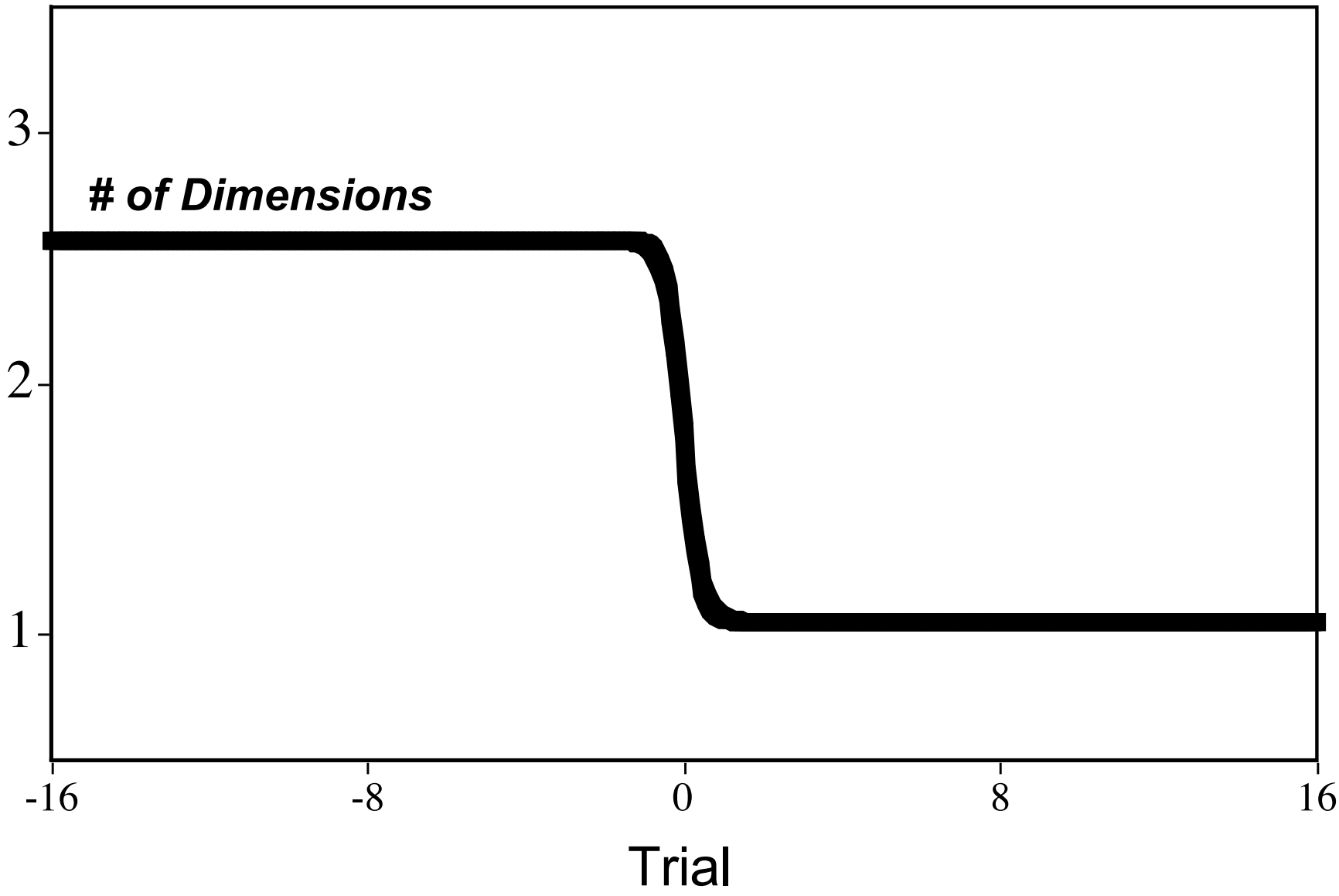
Example Type I subject



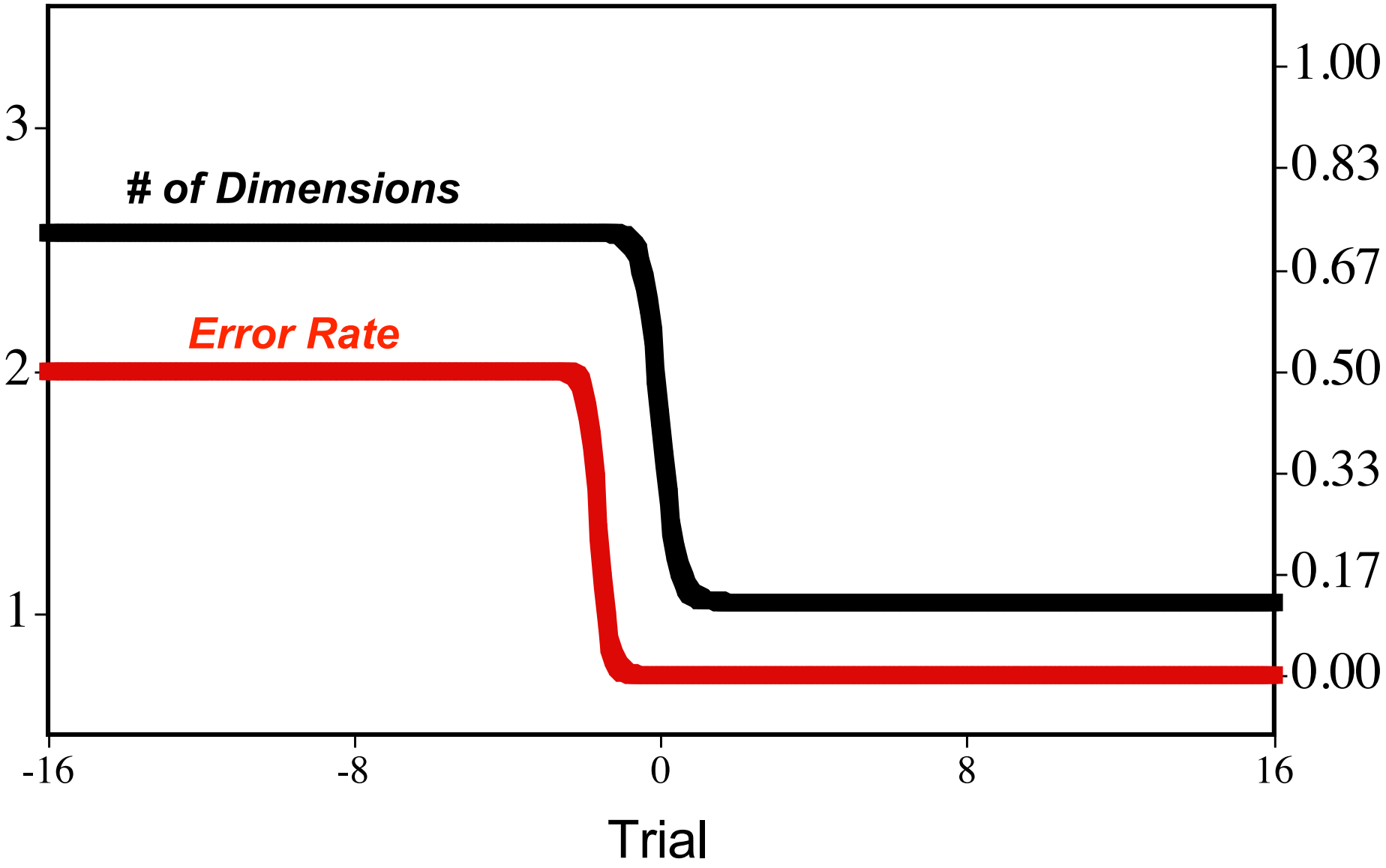
Example Type I subject



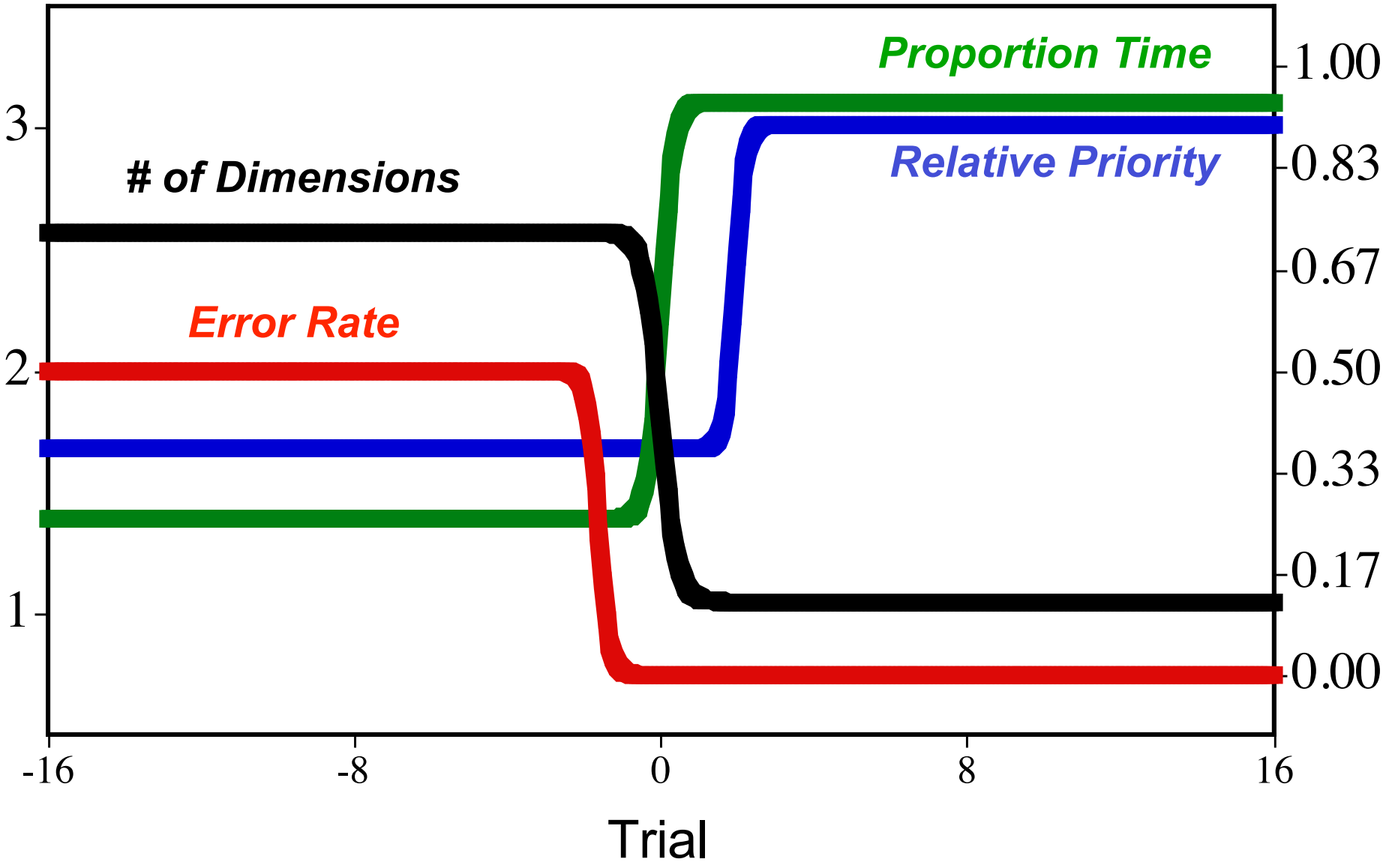
Example Type I subject



Example Type I subject

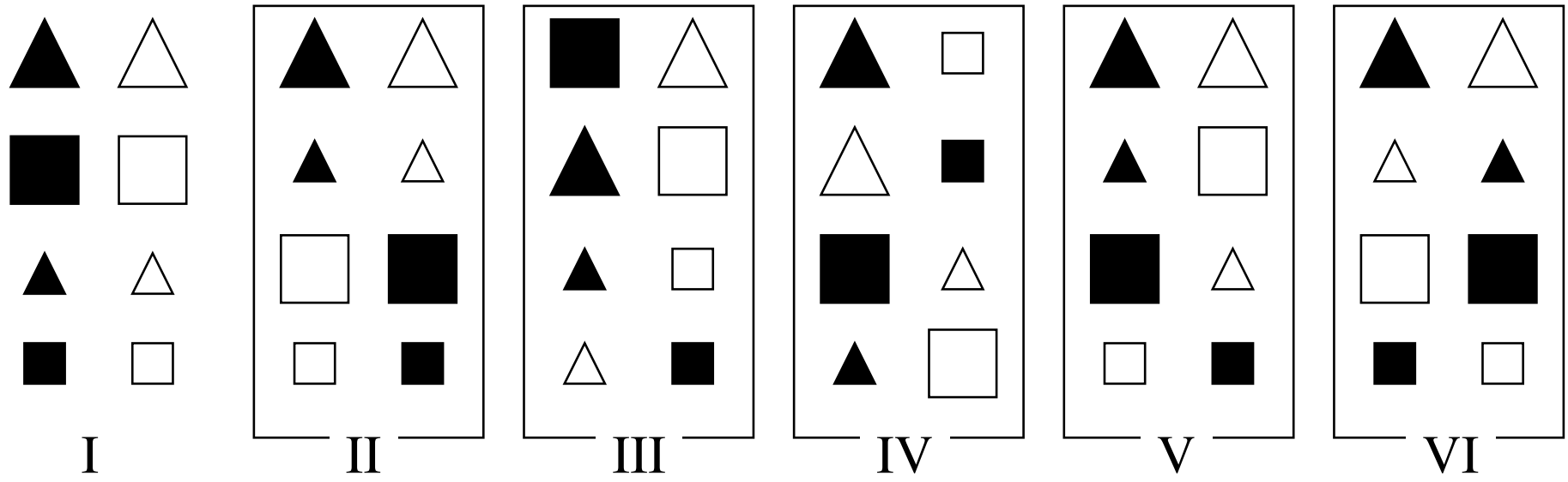


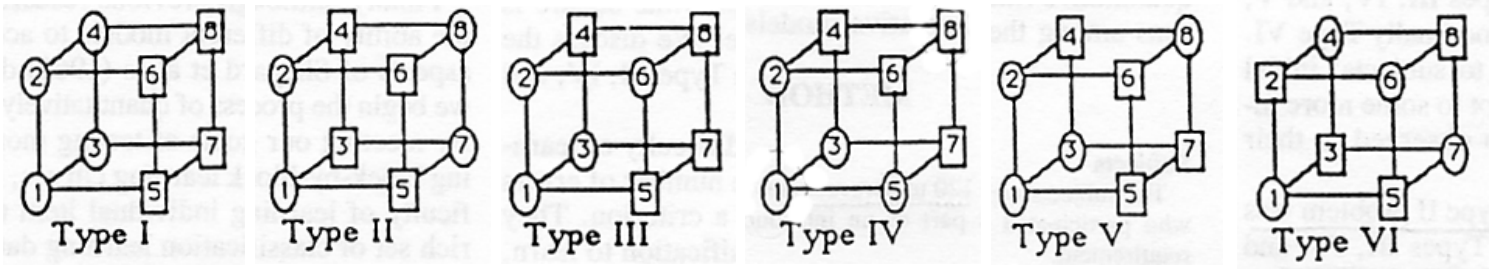
Example Type I subject



Learning via rules/selective attention

Shepard, Hovland, Jenkins (1961)

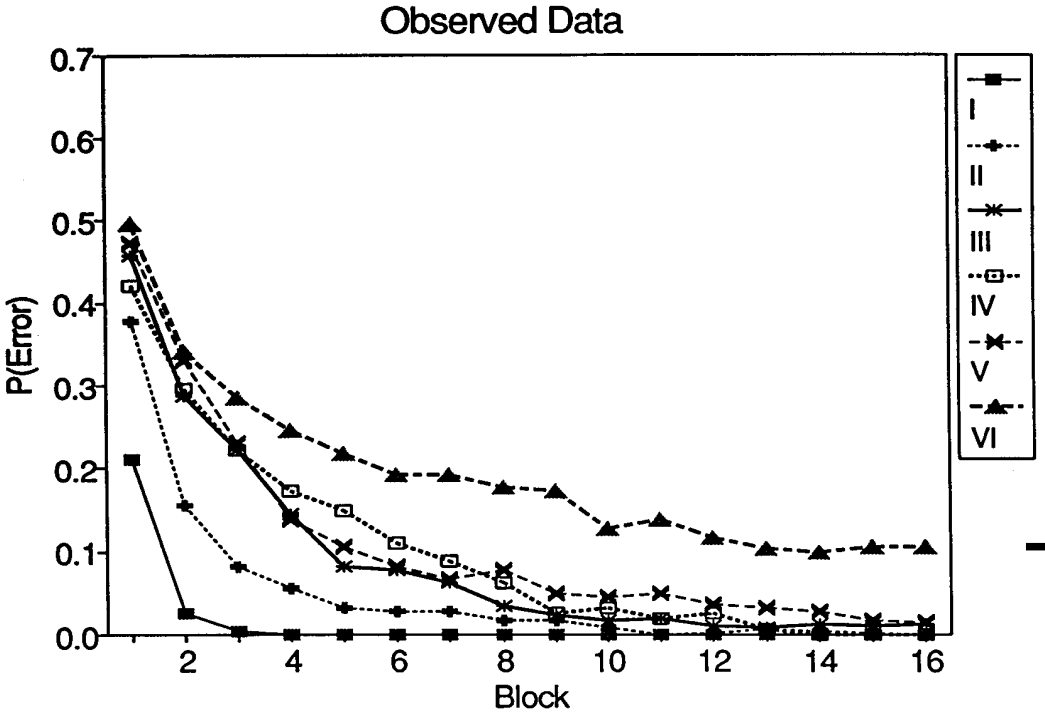




Learning via rules/selective attention

Shepard, Hovland, Jenkins (1961)

Problem Type	Within-Category Similarity	Predicted Learning Difficulty
I	Very high	Very easy
III, IV, V	Moderately high	Moderately easy
II	Moderately low	Moderately hard
VI	Very low	Very hard.



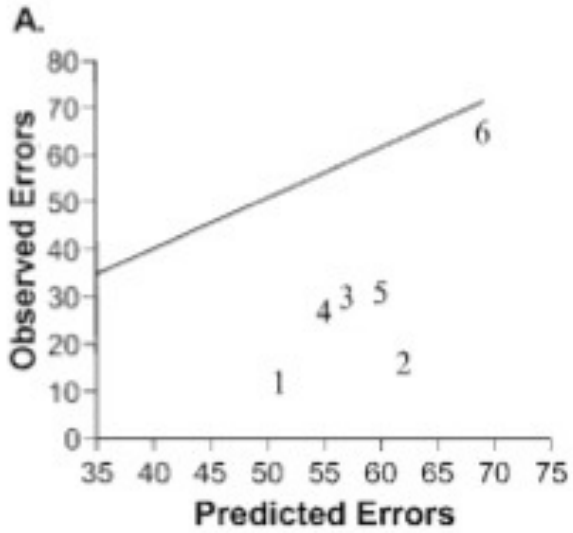
but actually

Type I < II < (III, IV,V) < IV

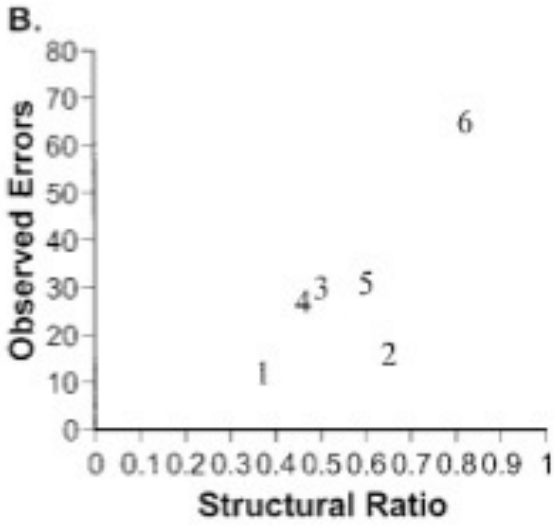
Category Learning and Monkeys

Smith, J.D., Minda, J.P., and Washburn, D.A. (2004)

SHJ's Predictions
for "associative" learner
(based on confusion matrices)



Smith, et al.'s predictions
using
exemplar model's
multiplicative similarity
function



Category Learning and Monkeys

Smith, J.D., Minda, J.P., and Washburn, D.A. (2004)

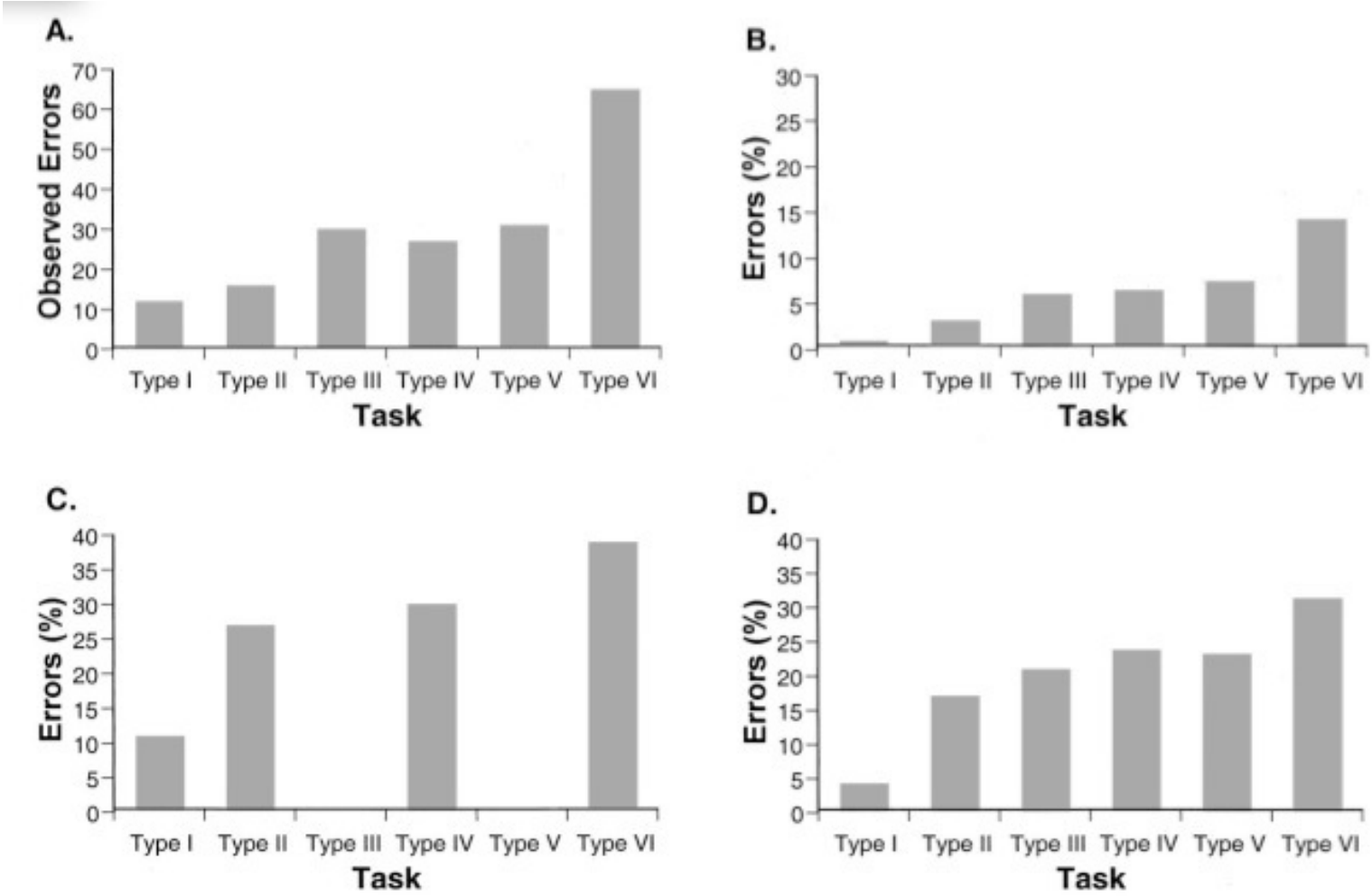


Figure 3. Performance by humans in the Shepard et al. (1961) category tasks in three existing studies and the present study. A: Results from the Shepard et al. study. B: Results from the Nosofsky et al. (1994) study. C: Results from the Love (2002) study. D: Results from the present study.

Category Learning and Monkeys

Smith, J.D., Minda, J.P., and Washburn, D.A. (2004)

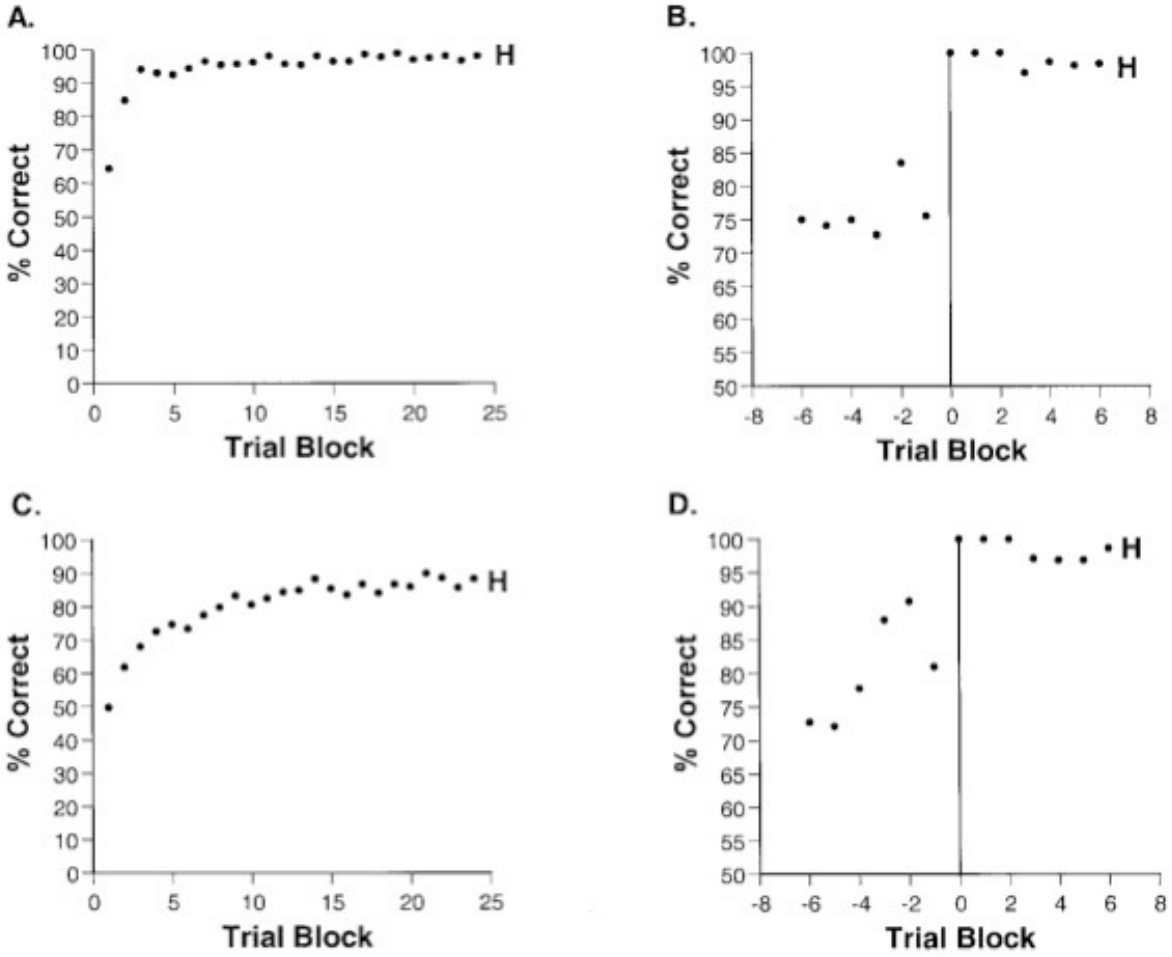


Figure 4. A: Humans' (H) forward learning curve in Type I tasks. Their percentage correct is shown at each eight-trial block. B: Humans' backward learning curve in Type I tasks. Their percentage correct is shown for eight-trial blocks forward and backward from the start of their first run of three consecutive perfect blocks. C: Humans' forward learning curve in Type II tasks. D: Humans' backward learning curve in Type II tasks.

Category Learning and Monkeys

Smith, J.D., Minda, J.P., and Washburn, D.A. (2004)

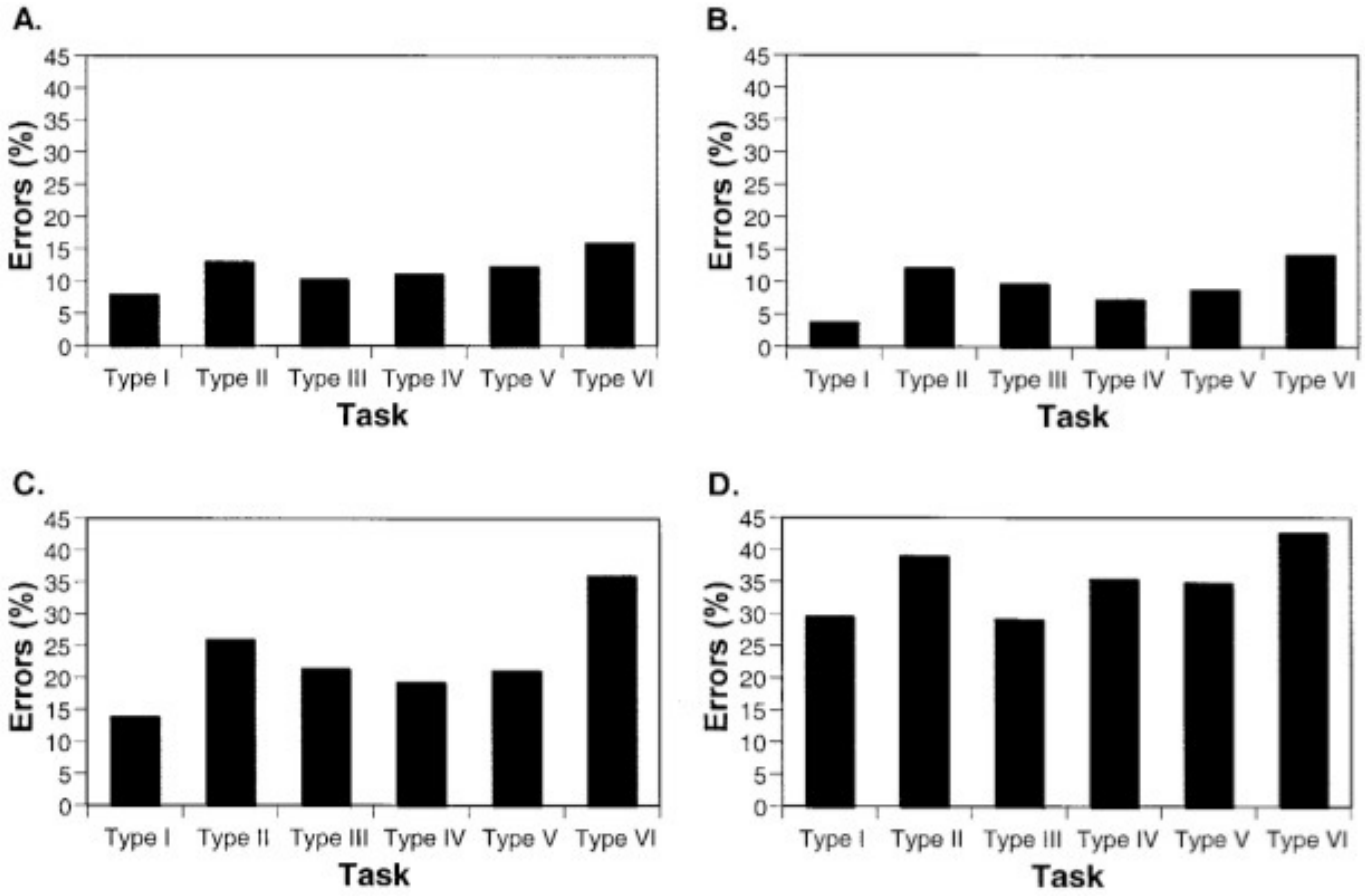


Figure 6. Performance by four individual monkeys in the Shepard et al. (1961) category tasks. A: Performance of Monkey 1. B: Performance of Monkey 2. C: Performance of Monkey 3. D: Performance of Monkey 4.

Category Learning and Monkeys

Smith, J.D., Minda, J.P., and Washburn, D.A. (2004)

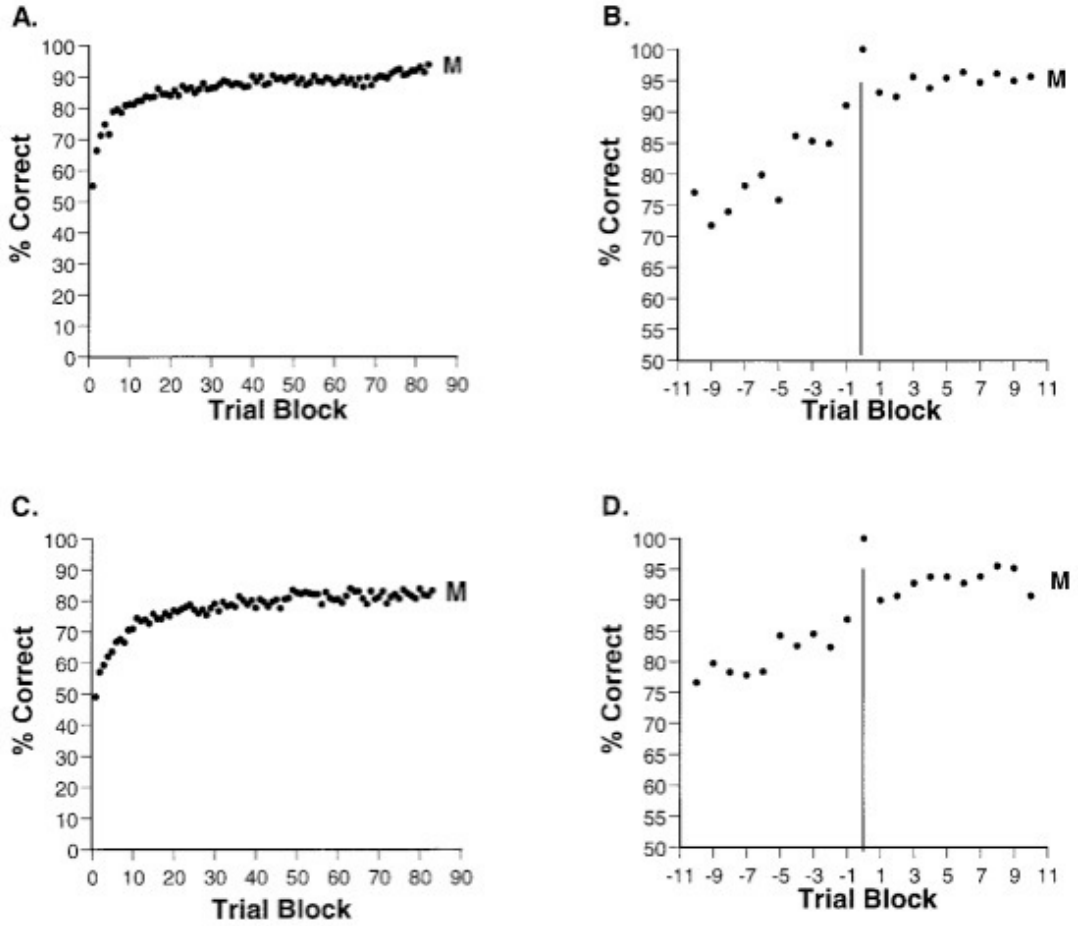


Figure 8. A: Monkeys' (M) forward learning curve in Type I tasks. Their percentage of correct responses is shown at each of eighty-three 24-trial blocks. B: Monkeys' backward learning curve in Type I tasks. Their percentage of correct responses is shown for 24-trial blocks forward and backward from their first perfect 24-trial block. C: Monkeys' forward learning curve in Type II tasks. D: Monkeys' backward learning curve in Type II tasks.

Category Learning and Monkeys

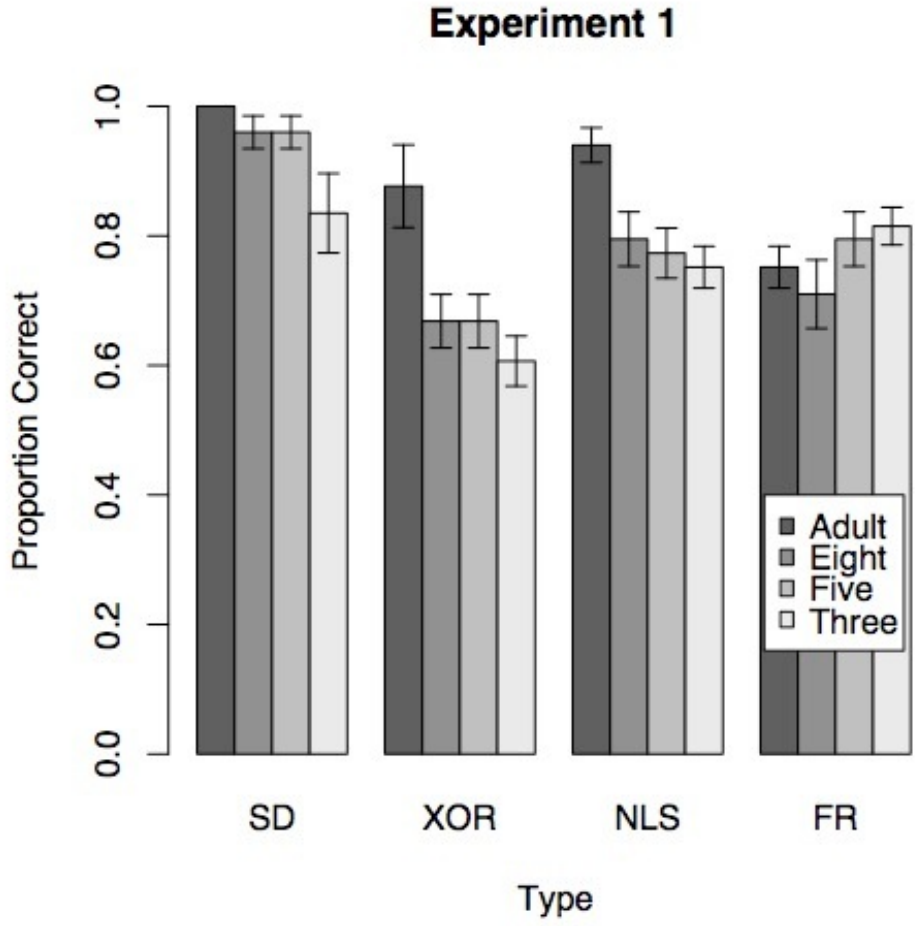
Smith, J.D., Minda, J.P., and Washburn, D.A. (2004)

"It is noteworthy that all the monkeys, even across the six rotations of the six task types, instantiated so well Shepard, et al.'s (1961) idea of a cognitive system that learns categories associatively through cue-conditioning processes or similarity-based generalization processes." - Smith, et al.

Category Learning and Kids

Minda, J.P. and Church (2008)

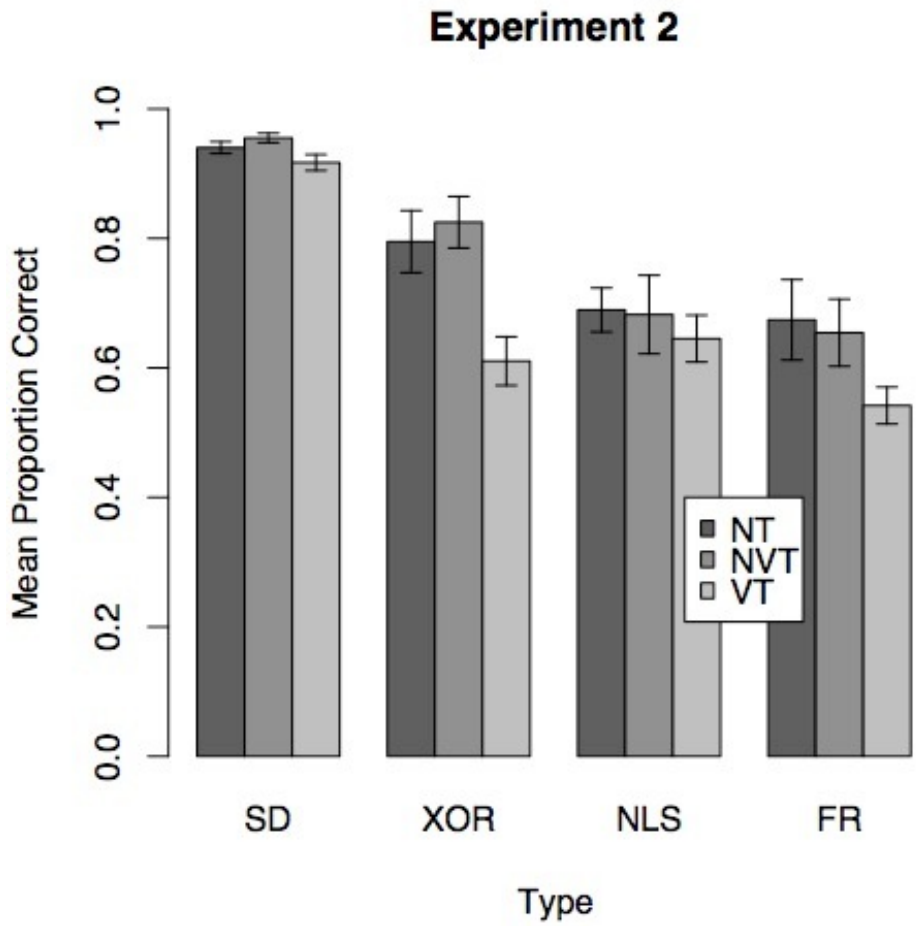
- Compared children (at various ages) and adults on SHJ type task
- Tested Type I, II, III, IV
- III is nonlinearly separable (rule+ex) category
- Hypothesized deficits for Type II and possibly III at early ages due to lack of verbal competence (and continued development of the PFC into adolescence)



Category Learning and Kids

Minda, J.P. and Church (2008)

- Adults under verbal interference look like kids



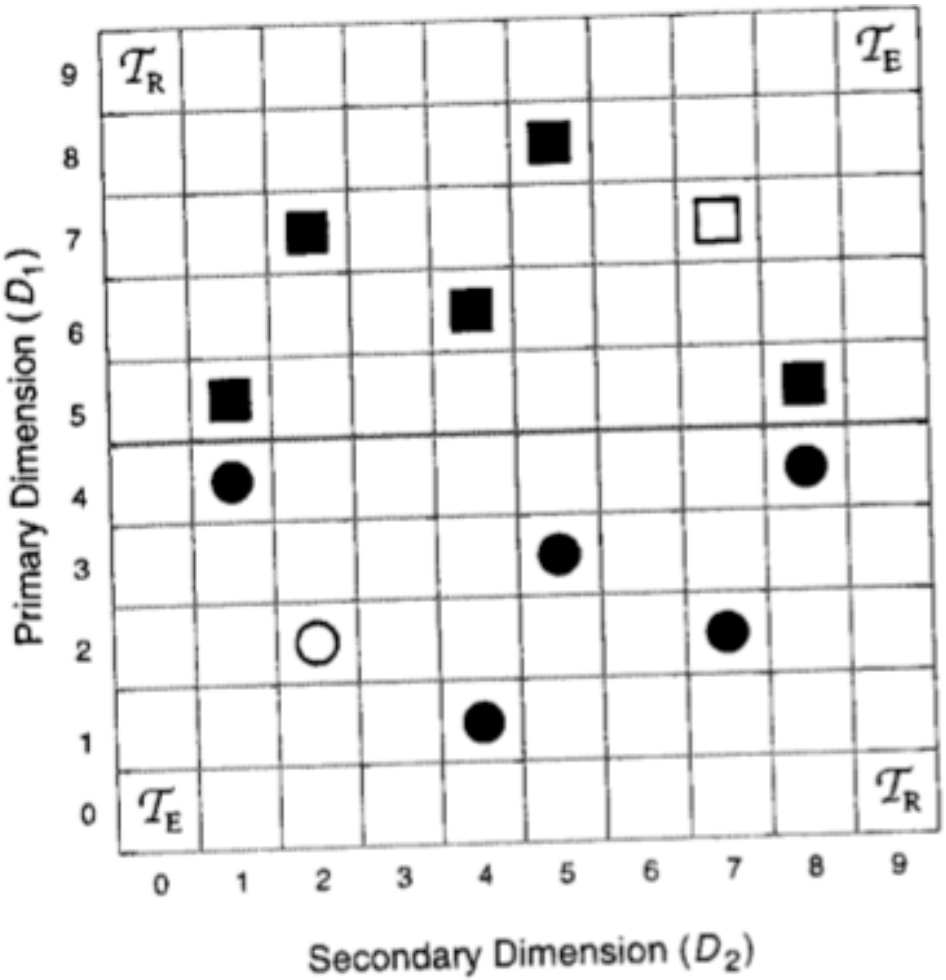
Take home points

- Categorization is the study of how people learn and generalize from examples
- Early theories emphasized definitional rules, while this view was revised in favor of “probabilistic” approaches in the 70s and 80s
- Two major models are prototype and exemplar models. Exemplar models are powerful contenders that subsume many aspects of the prototype account. In addition, exemplar models were developed to bridge Shepard’s work on stimulus generalization into a theory of how people generalize from multiple examples
- A key concept is selective (and adaptive) weighting of stimulus dimensions during learning, and the ability to do so may vary across species and individuals.

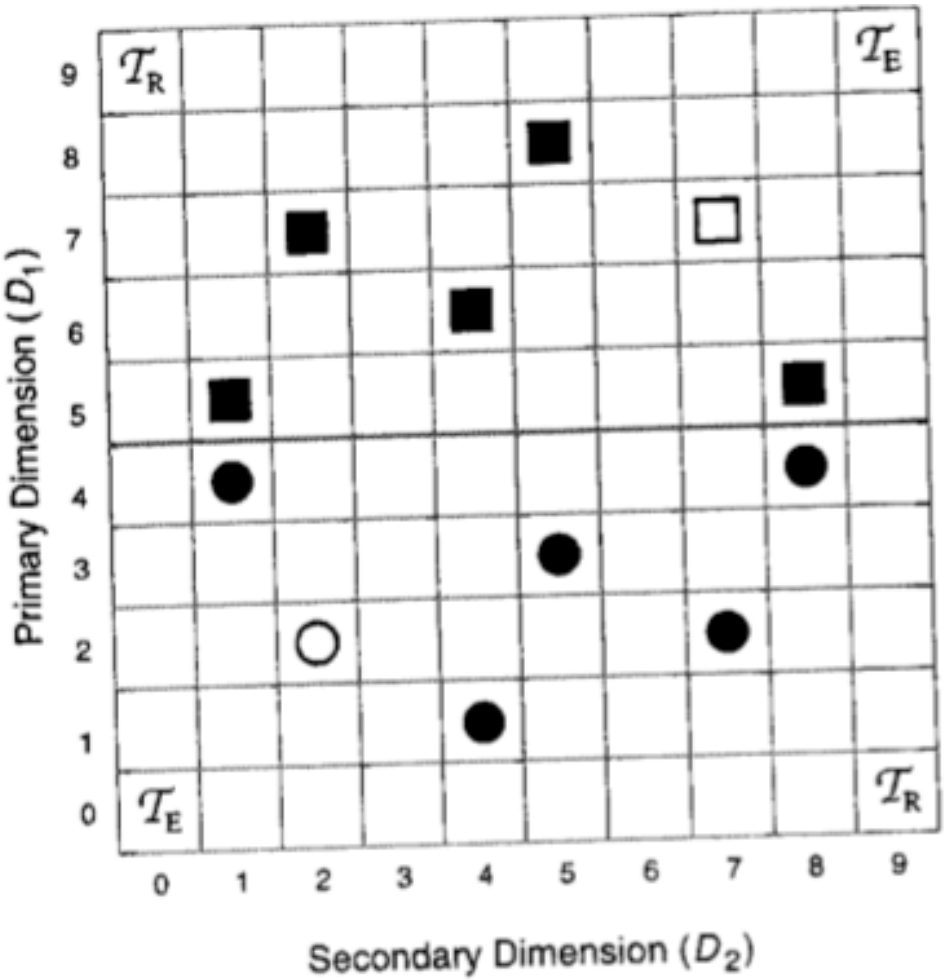
Rules and Generalization

- A couple comments about rules
    - Fast (as in fast/efficient learning, usually slow response times)
    - Resistant to inference from previous learning
    - Discrete - all or none learning
    - *Abstract GENERALIZATION*
- Your experience on the New York Subway system has certain properties (get ticket, refill when empty, insert into turnstile and walk through) that apply to highly dissimilar situations but that follow the same pattern (the DC subway, London Underground).
- Gary Marcus' word learning studies with infants: ABA -> CDC

ATRIUM (Ericsson & Kruschke, 1999)



ATRIUM (Ericsson & Kruschke, 1999)



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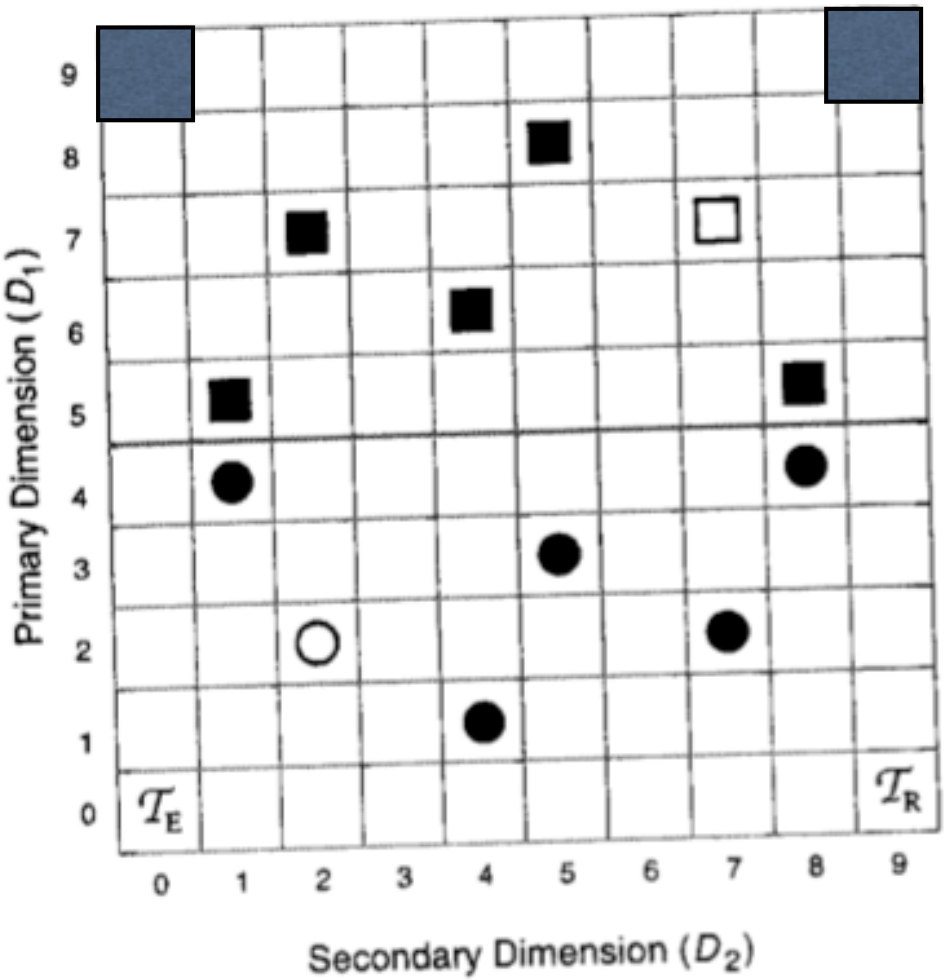

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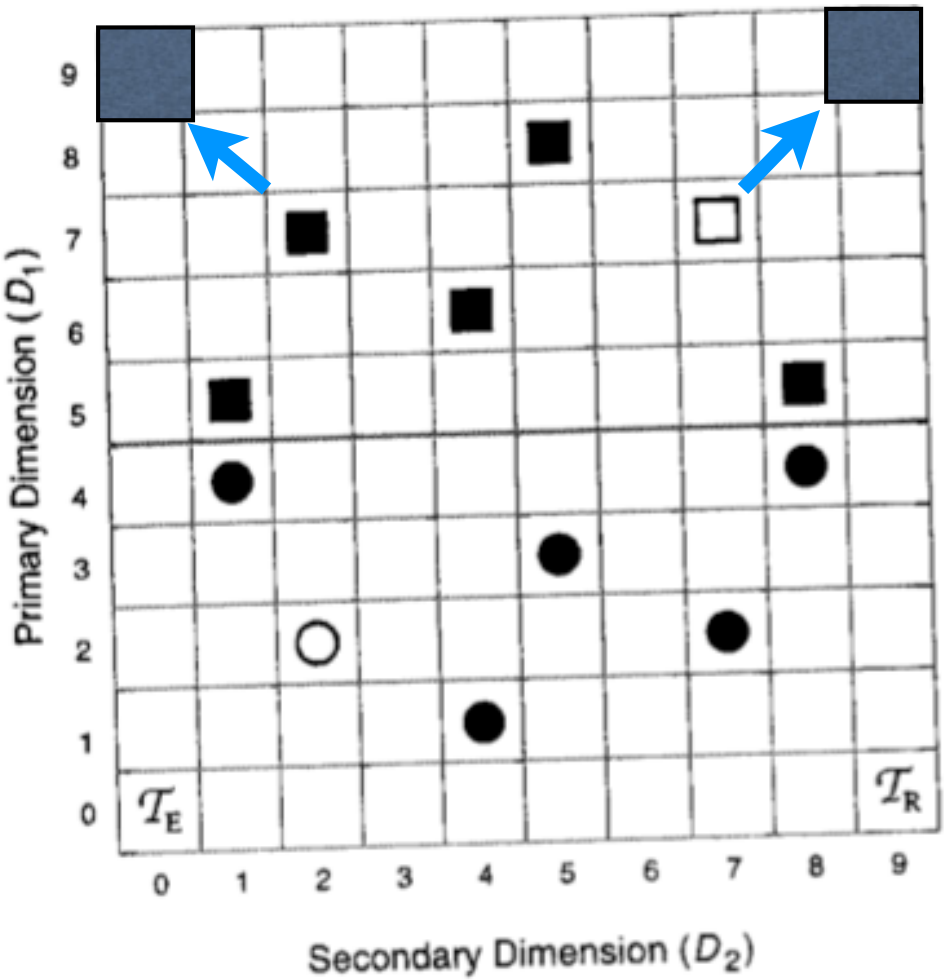

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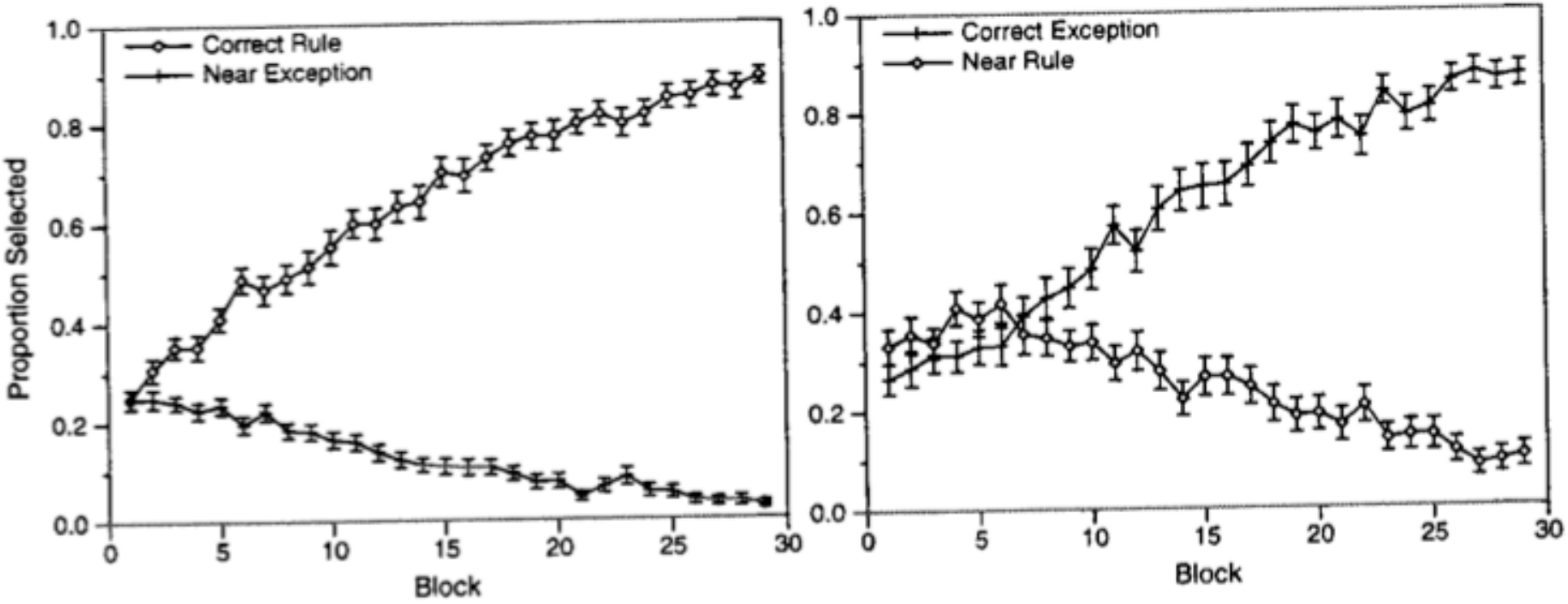
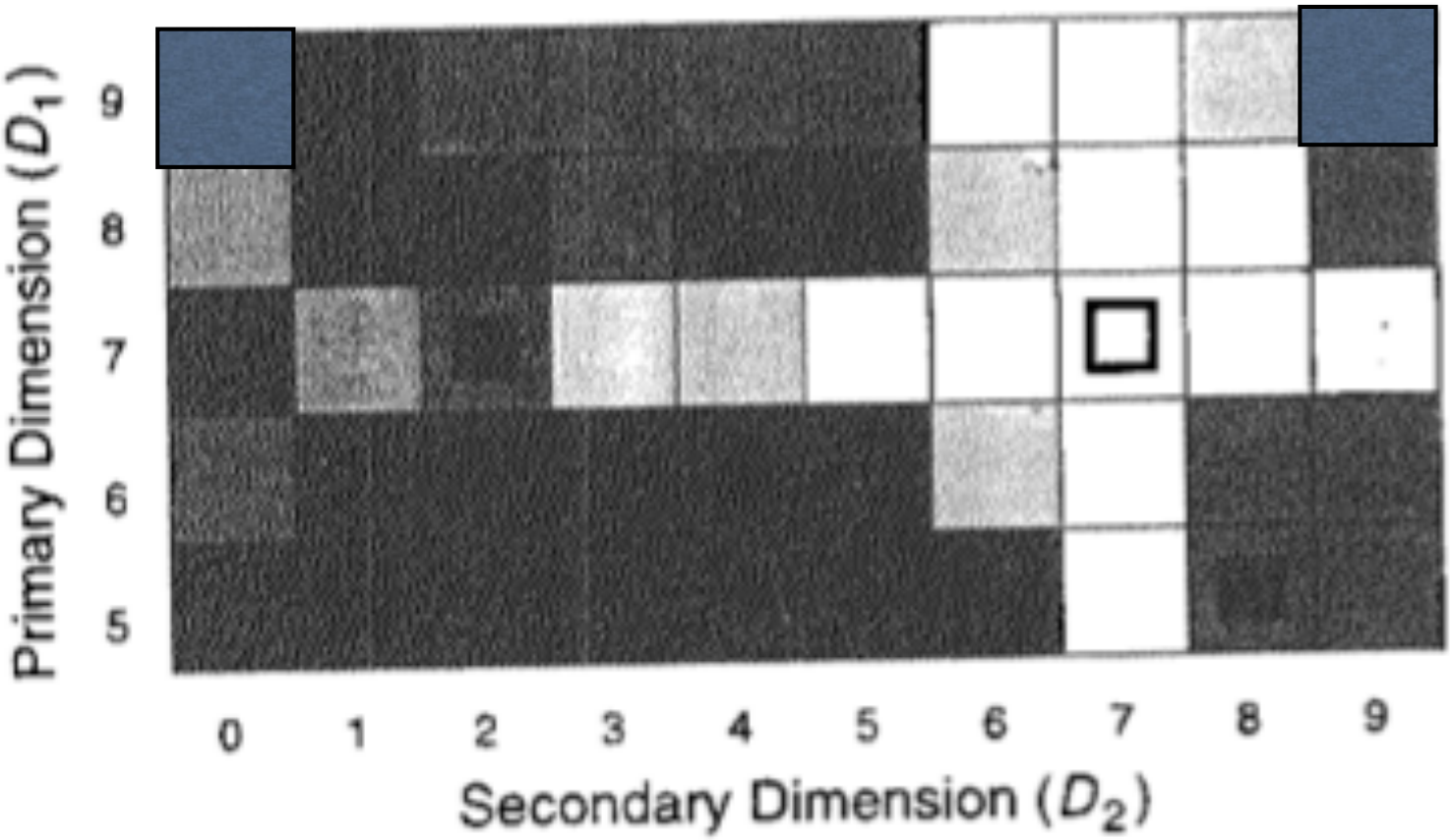
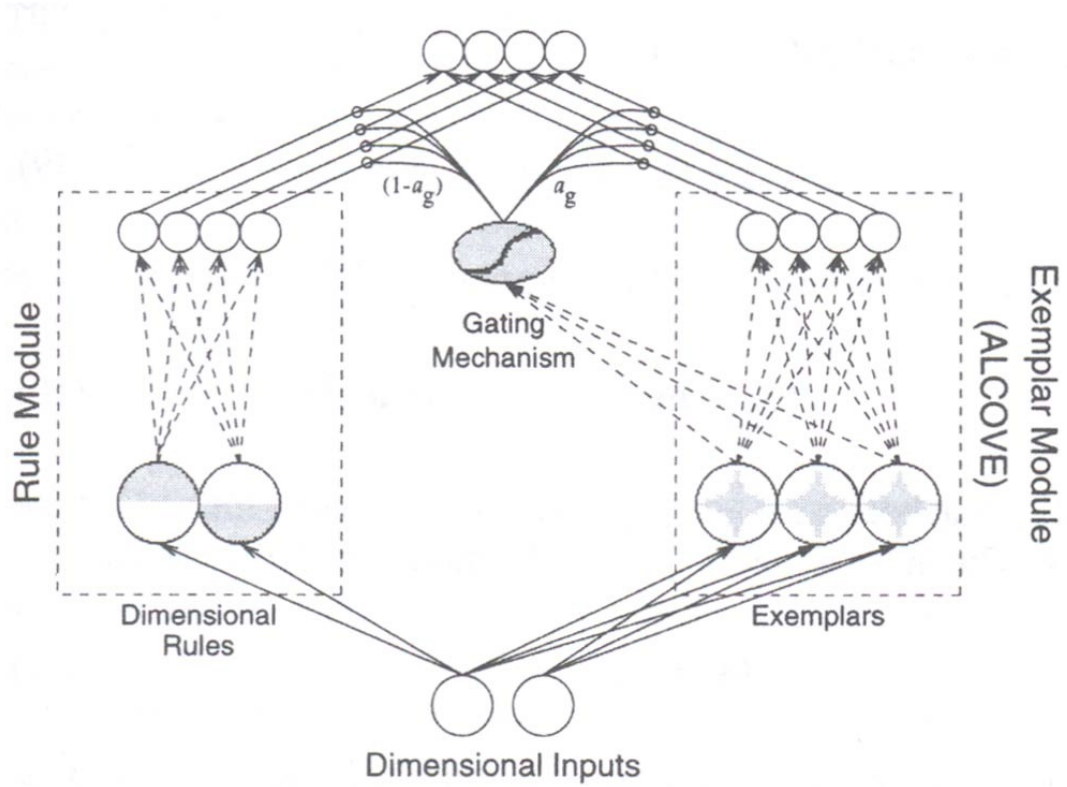


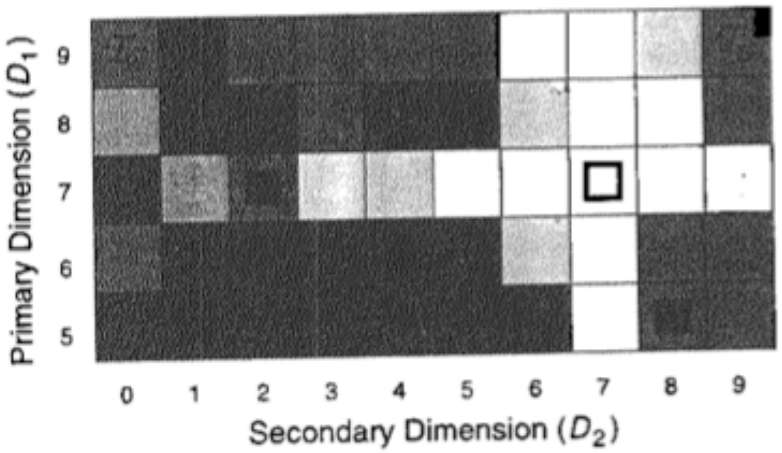
ATRIUM (Ericsson & Kruschke, 1999)

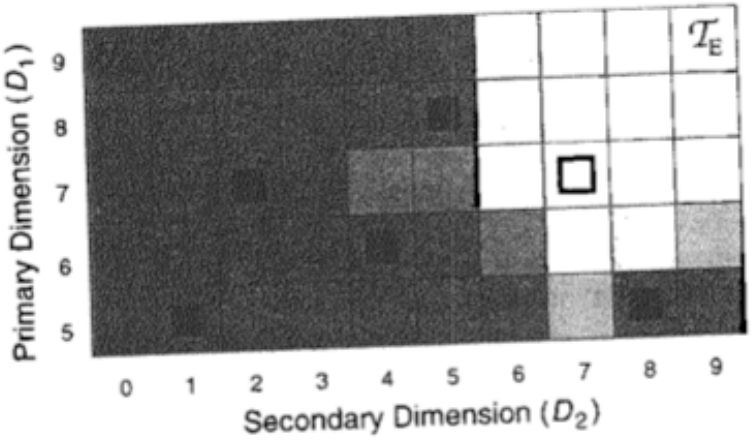


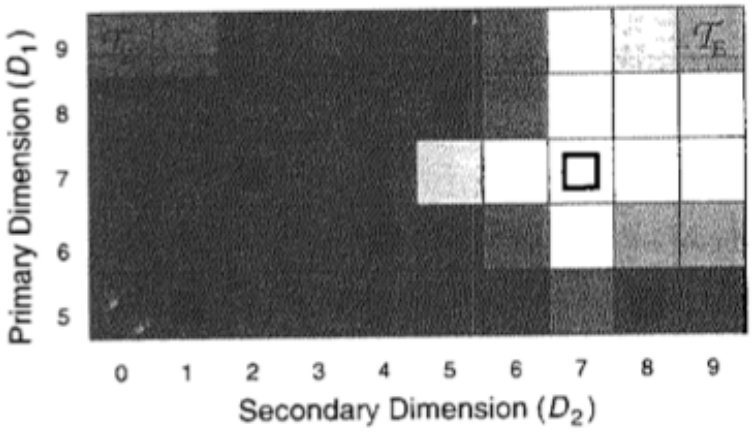
ATRIUM (Ericsson & Kruschke, 1999)



ATRIUM (Ericsson & Kruschke, 1999)







ATRIUM (Ericsson & Kruschke, 1999)

- ATRIUM combines an exemplar and rule based module into a single competitive network
- Each module learns independently and a gating mechanism decides how responses from these two systems should be integrated.
- Critically, the gating system can learn to apply stimulus-specific response strategies (for example, tagging a single exception item as it should be handled by the ALCOVE component while other stimuli should be handled by the rule).

COVIS

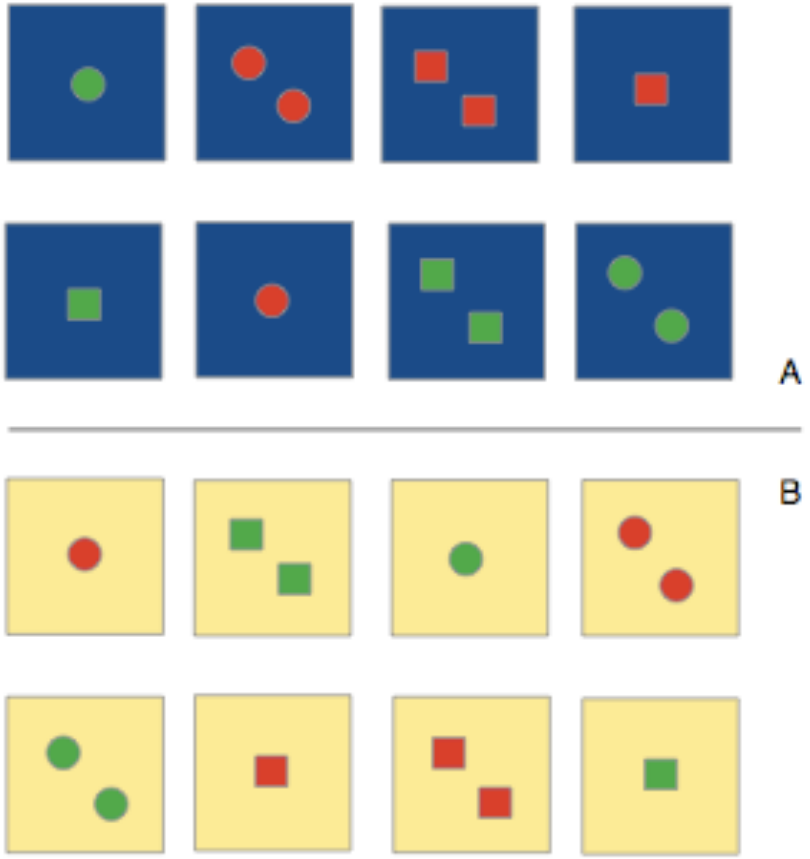
Ashby, Alfonso-Reese, Turken, Waldron (1998) "A neuropsychological theory of multiple system in category learning" *Psychological Review*, 105, 442-481.

- Perhaps the most complete and well-tested multiple-systems theory of categorization that has taken the connections to the biological substrates of behavior seriously
- (At least) two neural systems supporting category learning: An implicit/ **procedural system** and an **explicit/verbally mediated system**

COVIS - The Verbal System

Ashby, Alfonso-Reese, Turken, Waldron (1998) "A neuropsychological theory of multiple system in category learning" *Psychological Review*, 105, 442-481.

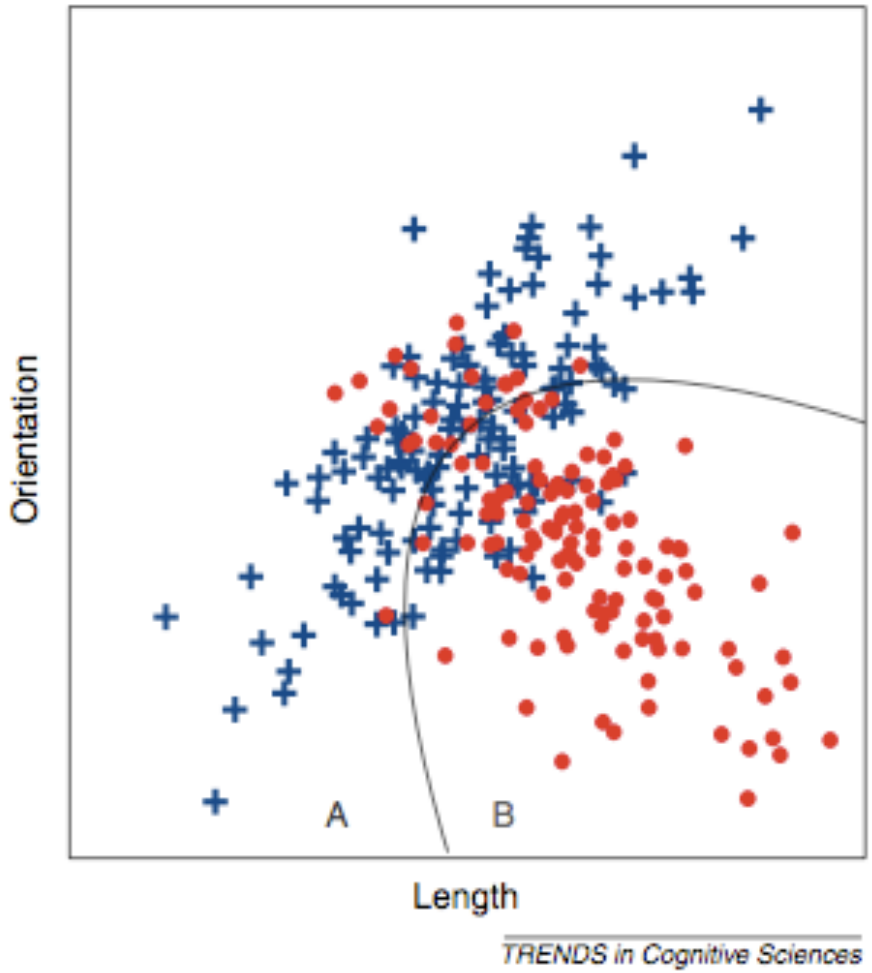
- Rule based tasks: exemplified by the categorization task shown
- Easy to verbalize category boundary
- (As in Sloman) system assumed to relied on verbal processes, logical reasoning, strategic processing, and semantic memory

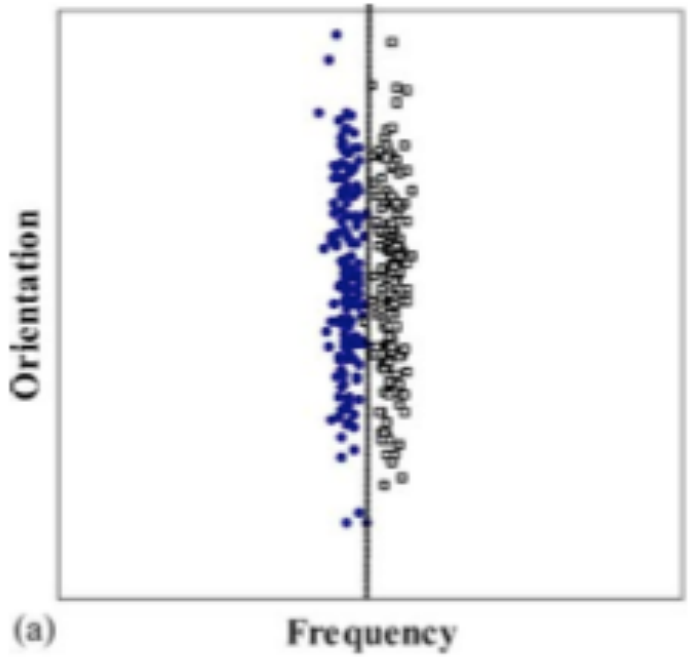


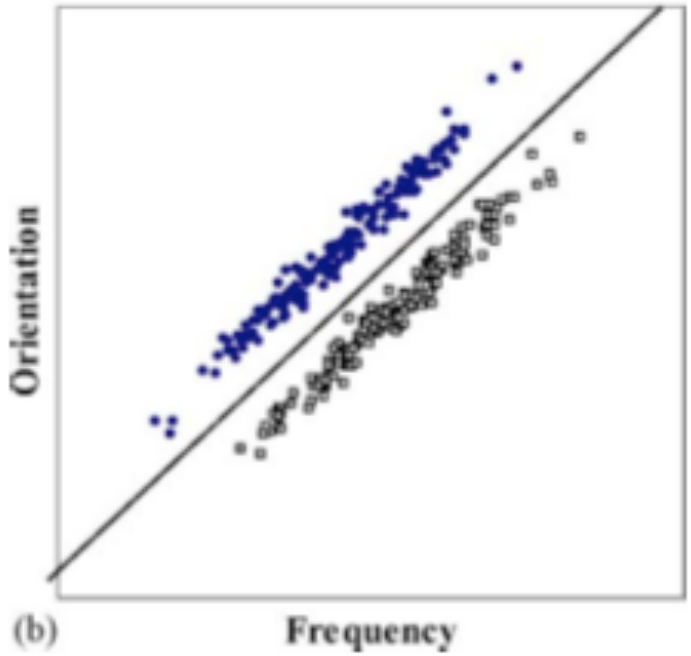
COVIS - The Procedural System

Ashby, Alfonso-Reese, Turken, Waldron (1998) "A neuropsychological theory of multiple system in category learning" *Psychological Review*, 105, 442-481.

- Some debate about if the "implicit" system is supported by an exemplar-like system (Erickson & Kruschke, ATRIUM) or by a procedural learning system
- (COVIS takes the latter view)
- Procedural category learning is associative with an inability to verbally express the "rule" for the category
- Based on a decision-bound system that gradually learns to associate particular regions of stimulus space with a particular response.
- Tied to the perceptual-motor system




Orientation
(a)
Frequency


Orientation
(b)
Frequency

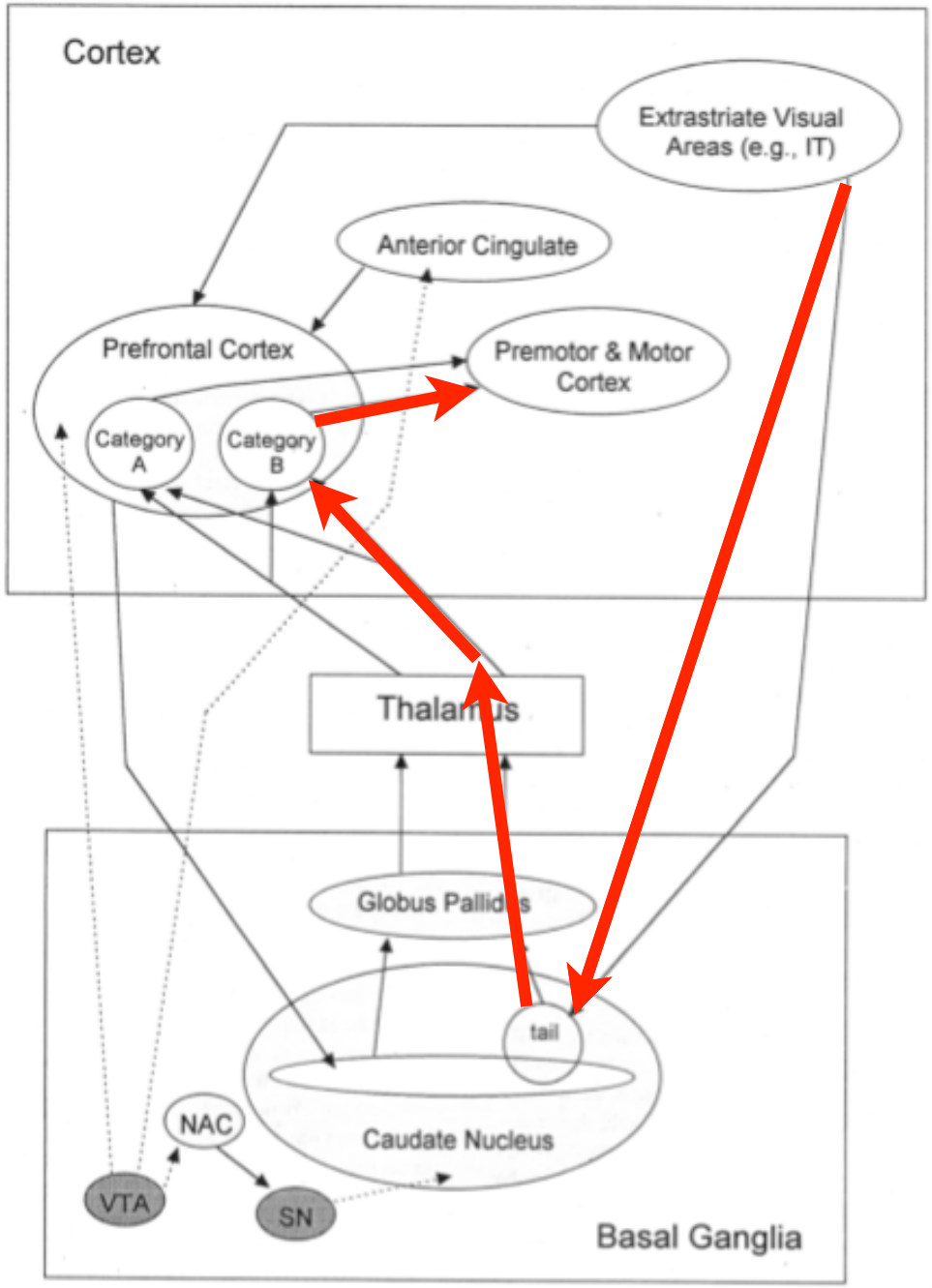
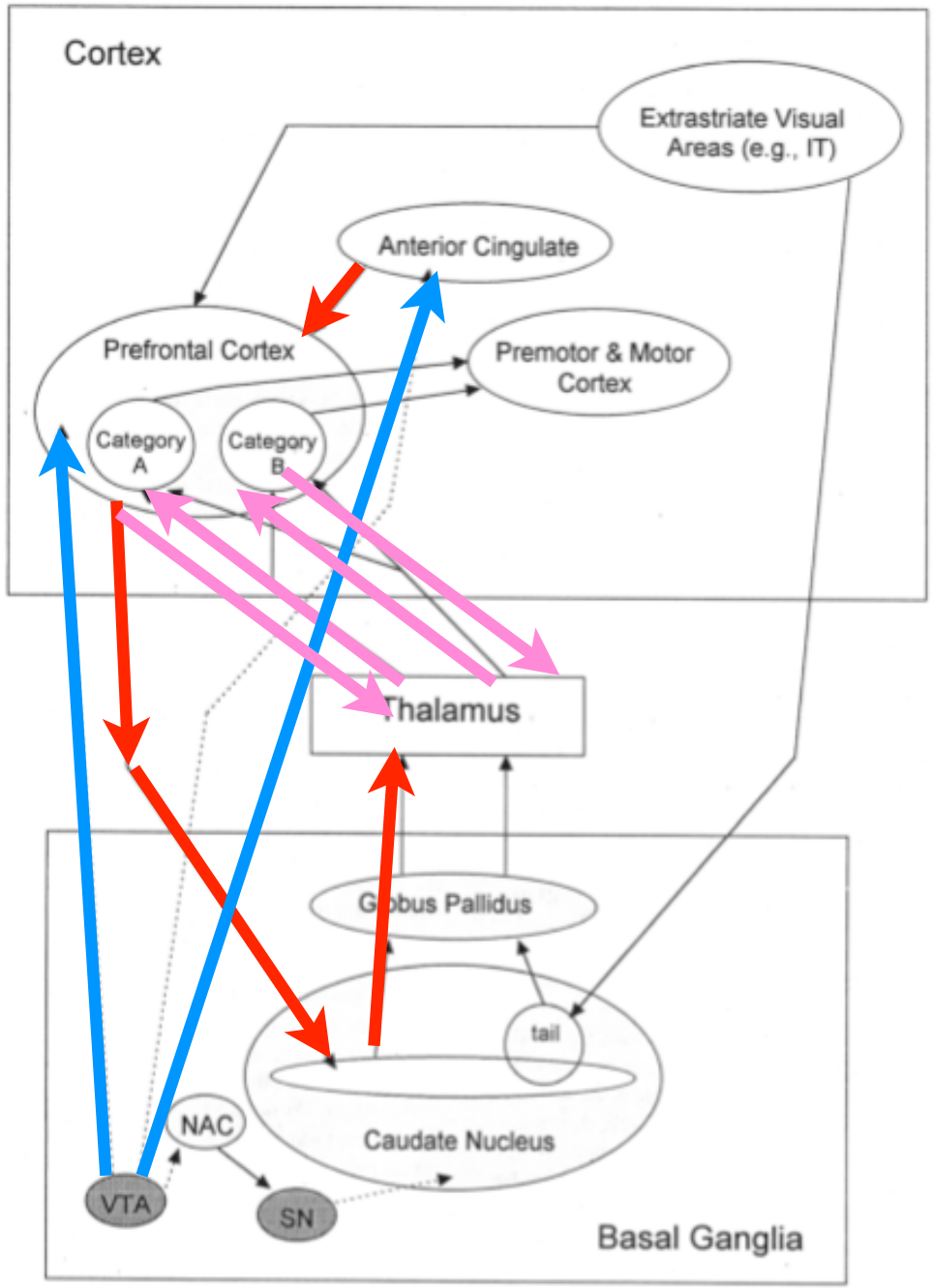


Figure 2. A schematic depicting the neuropsychological underpinnings of COVIS (competition between verbal and implicit systems). The dotted lines denote dopamine projections. VTA = ventral tegmental area; SN = substantia nigra; NAC = nucleus accumbens; IT = inferotemporal cortex.



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Selection

Switching

Working Memory Loops

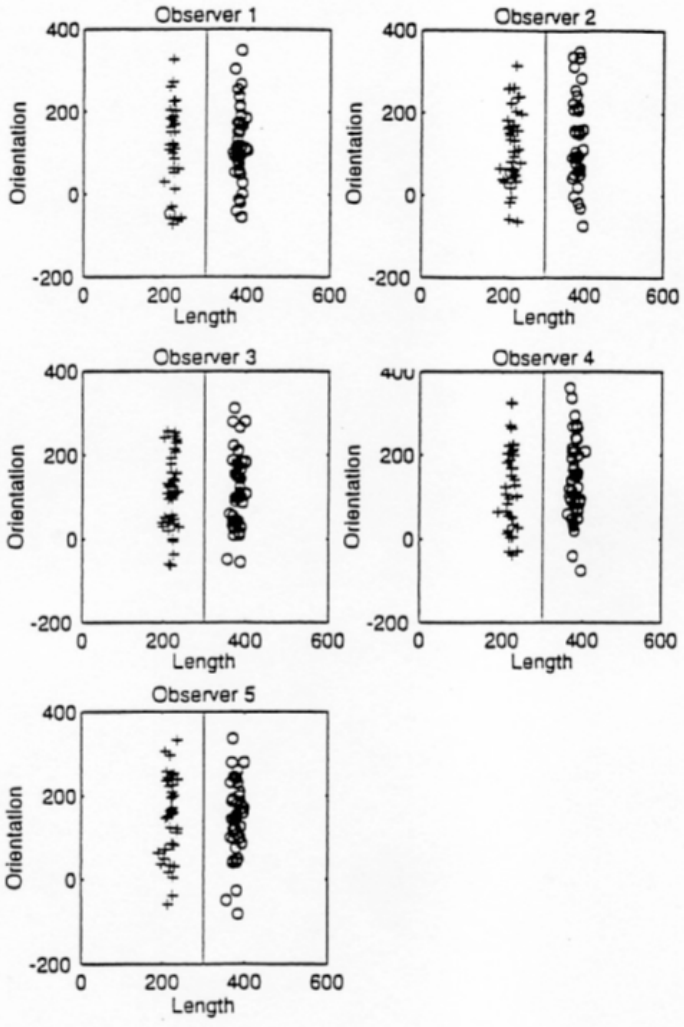
Behavioral Dissociation in support of COVIS

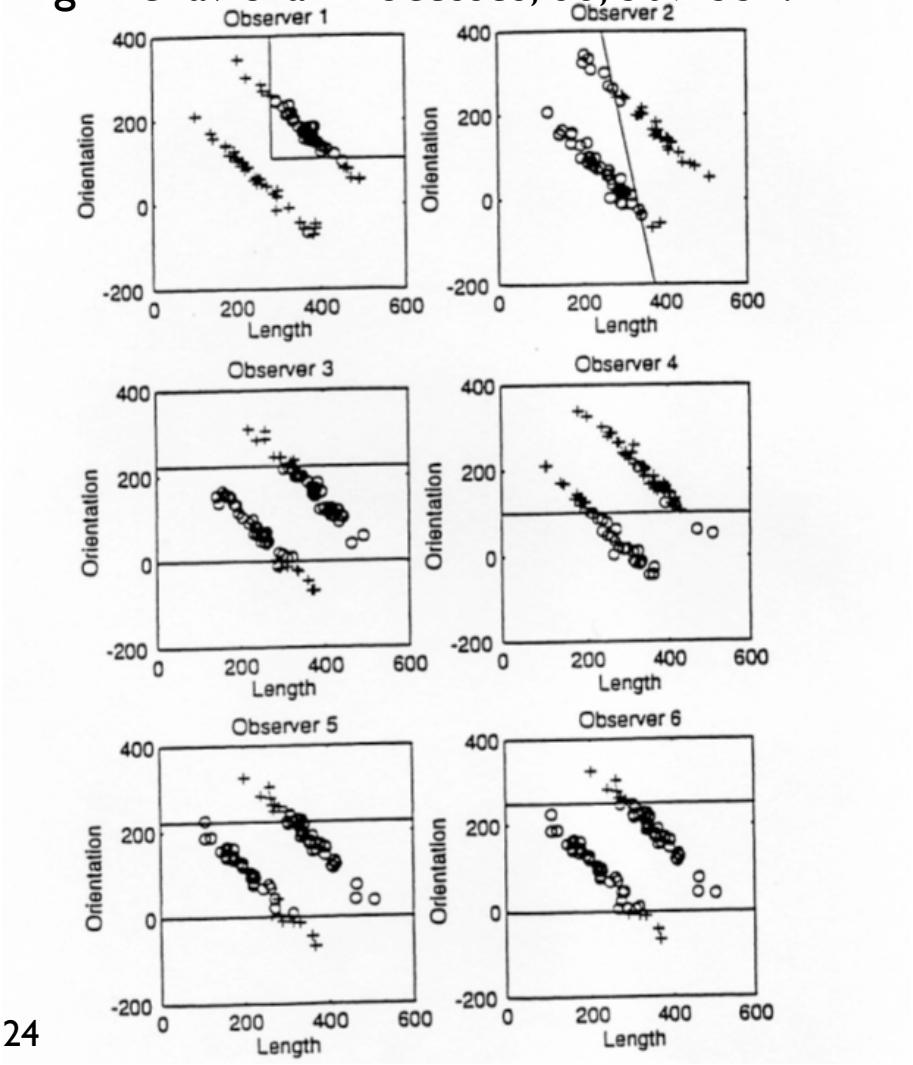
Summarized in Maddox & Ashby (2004) "Dissociating explicit and procedural-learning based systems of perceptual category learning" Behavioral Processes, 66, 309-332.

- Procedural system relies on feedback, thus is impaired in unsupervised learning contexts
- Observational training and delayed feedback negatively impact the procedural system
- Changes in motor response will impact information integration more than rule-based learning

Feedback and Procedural Learning

Summarized in Maddox & Ashby (2004) "Dissociating explicit and procedural-learning based systems of perceptual category learning" Behavioral Processes, 66, 309-332.





Observational Learning

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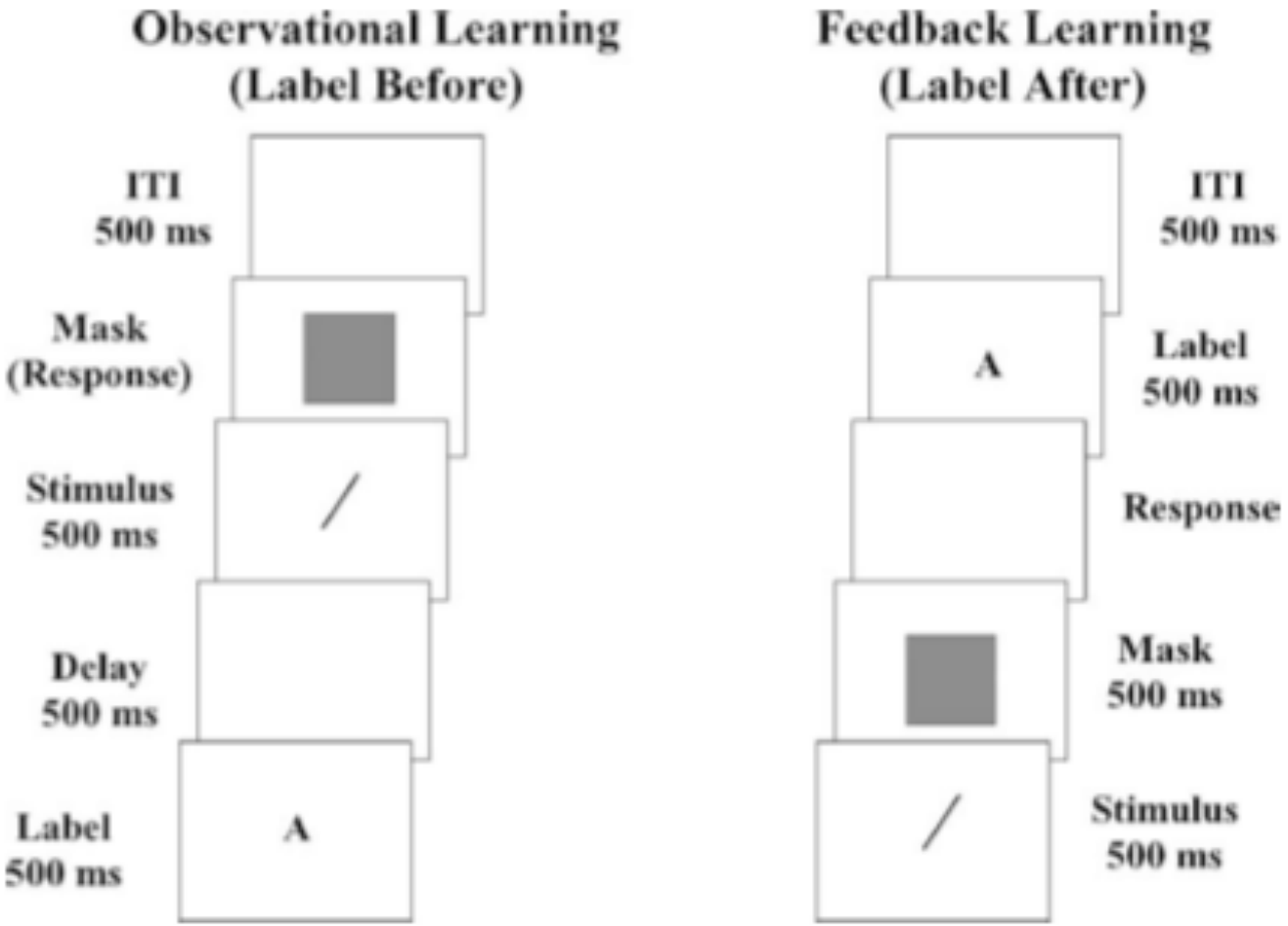

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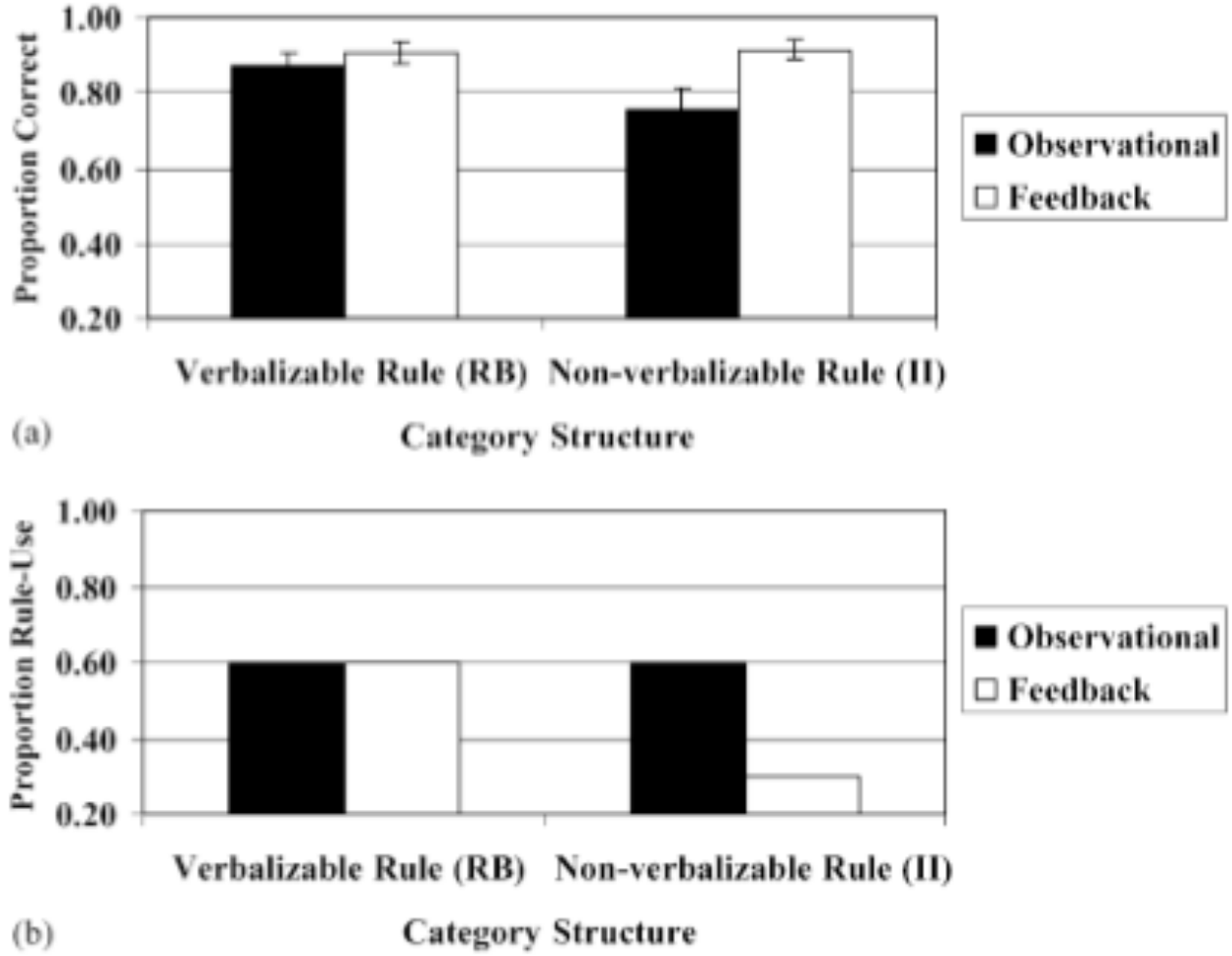

Delayed Feedback

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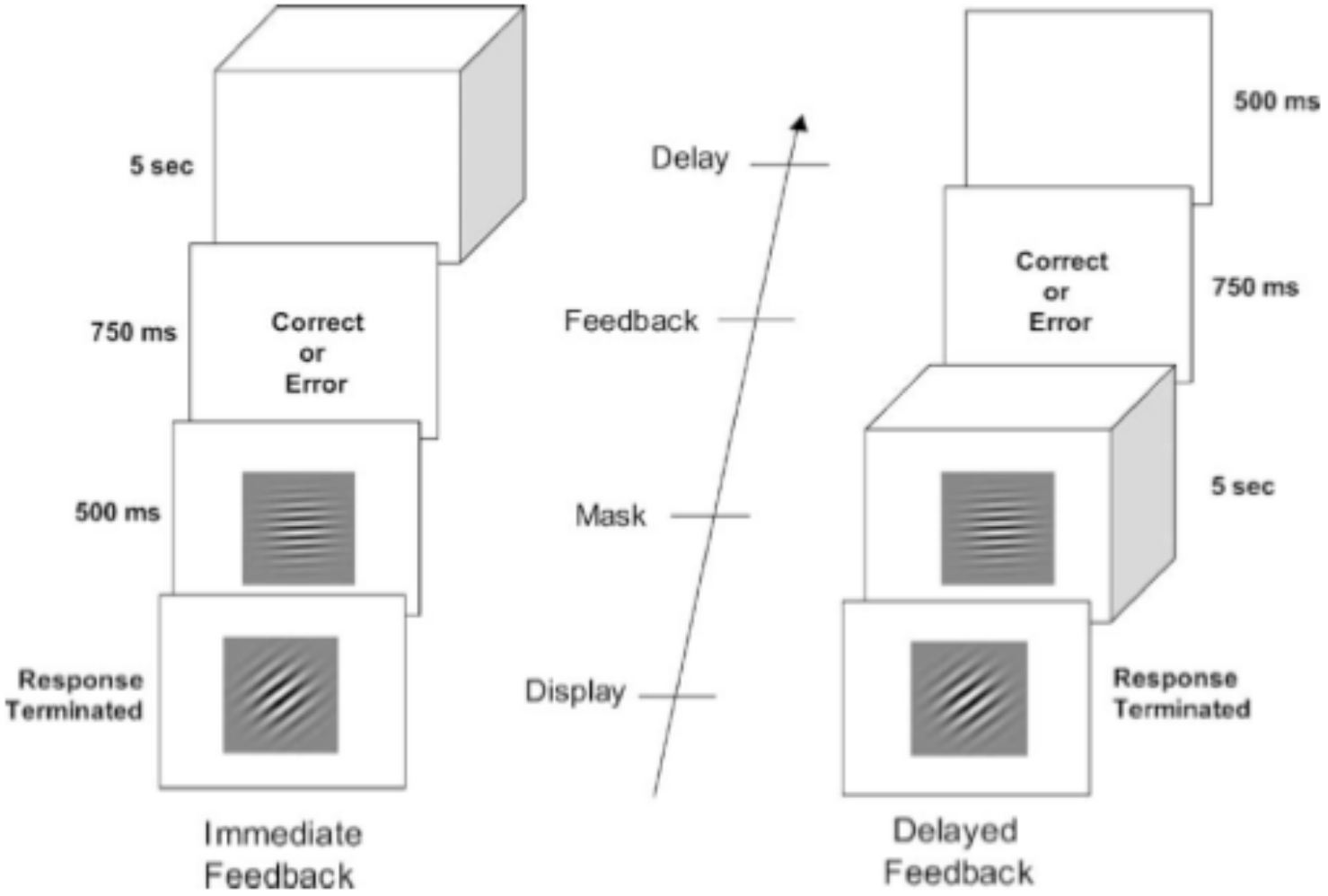

Delayed Feedback

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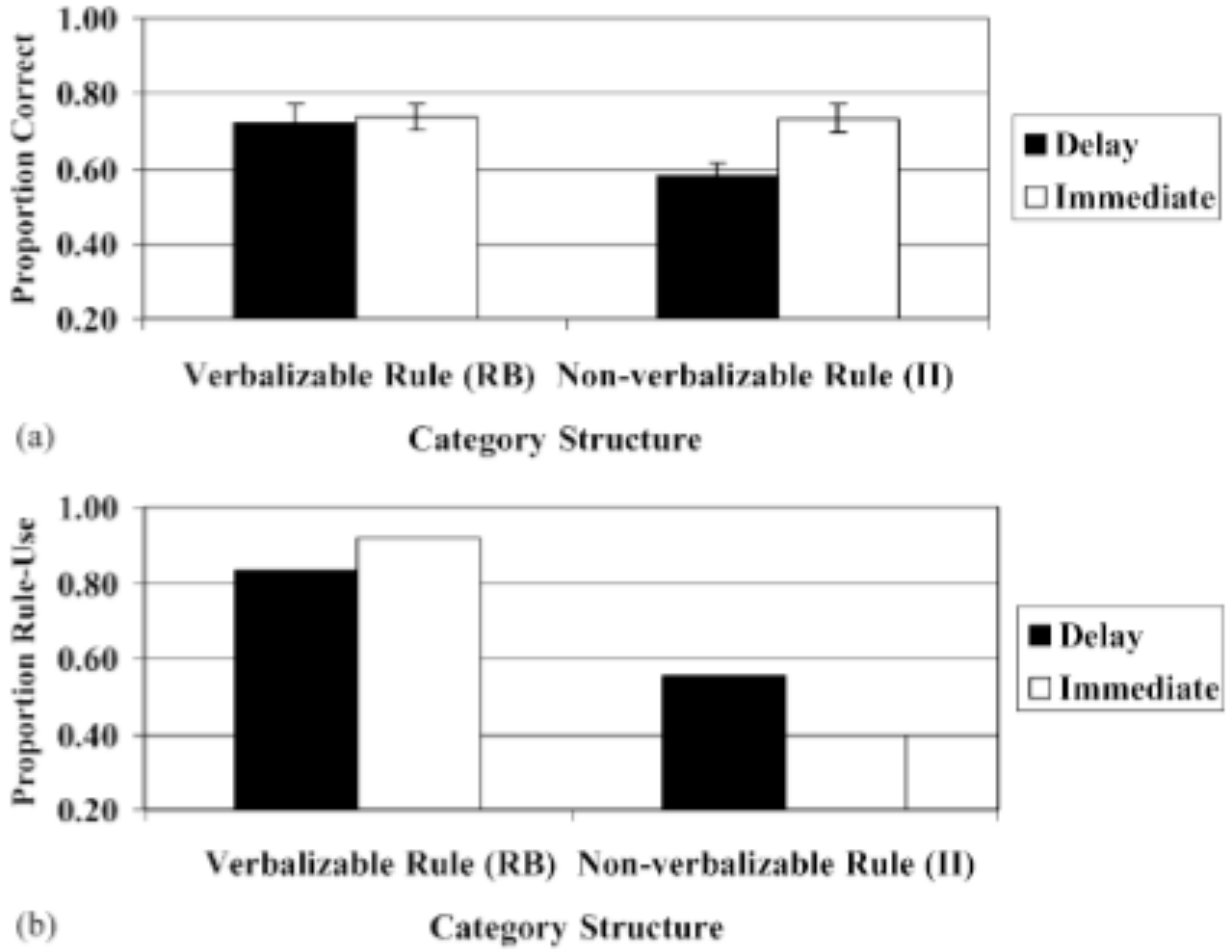
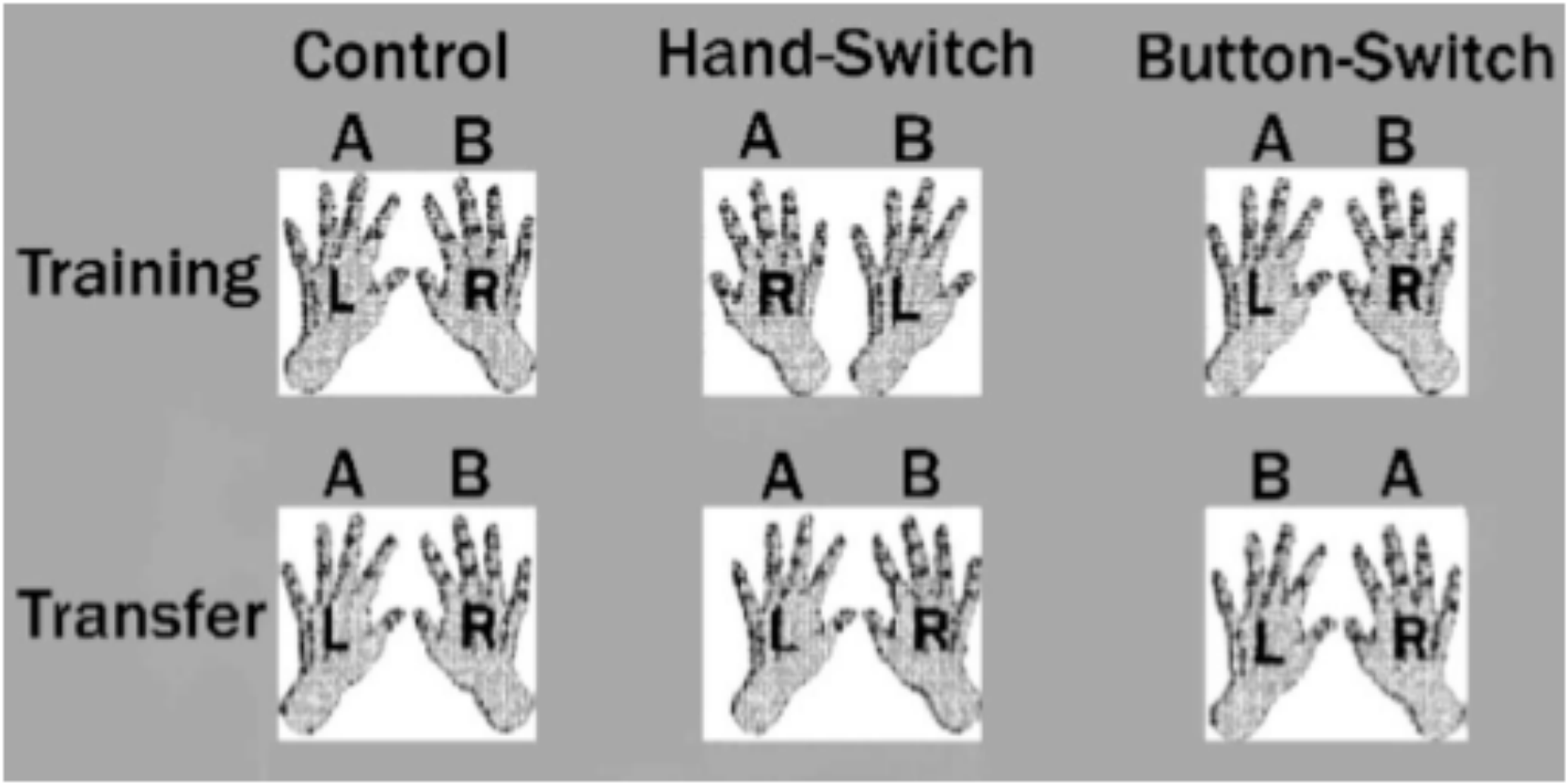


Changing motor response

Summarized in Maddox & Ashby (2004) "Dissociating explicit and procedural-learning based systems of perceptual category learning" Behavioral Processes, 66, 309-332.



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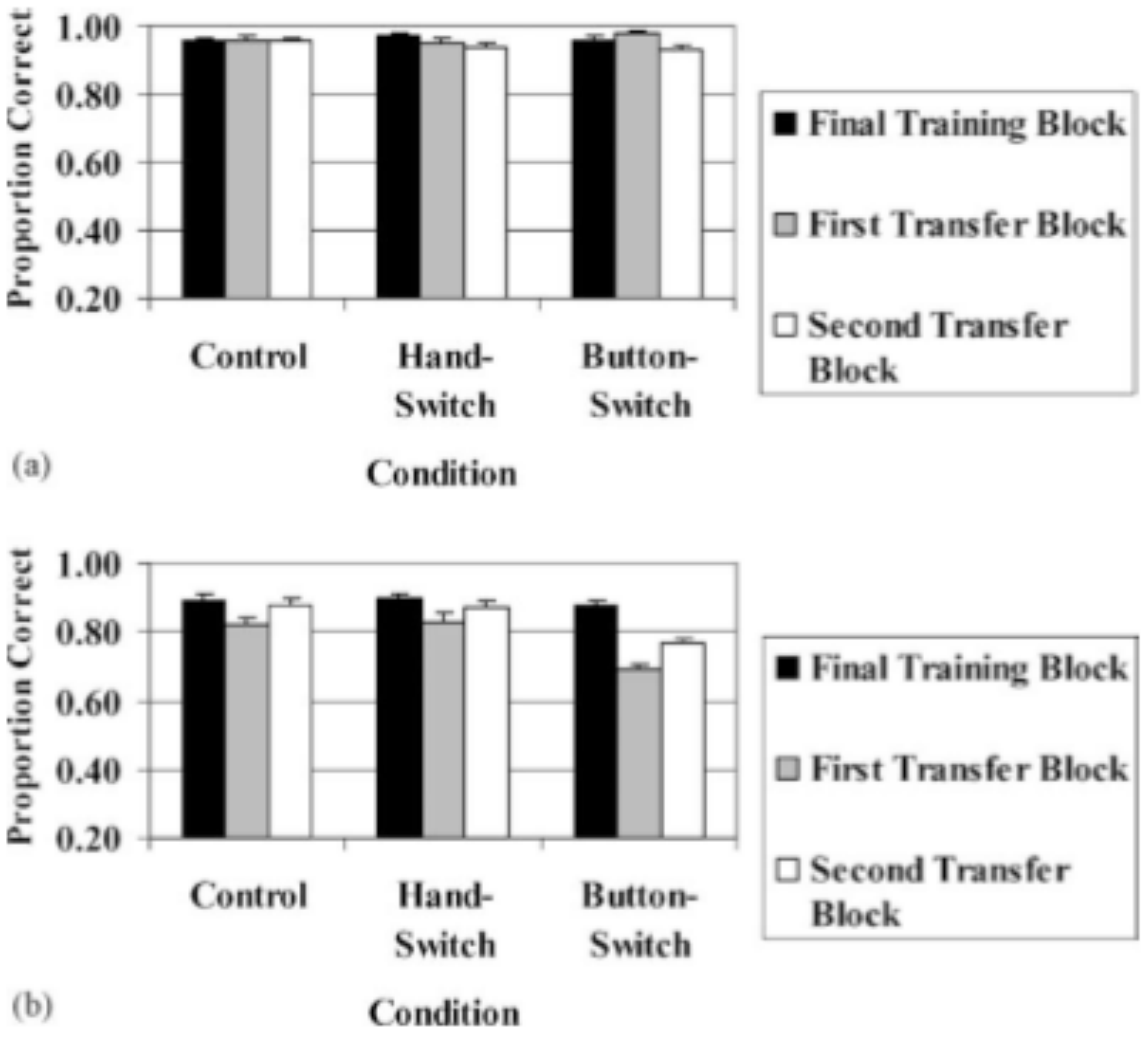

Changing motor response

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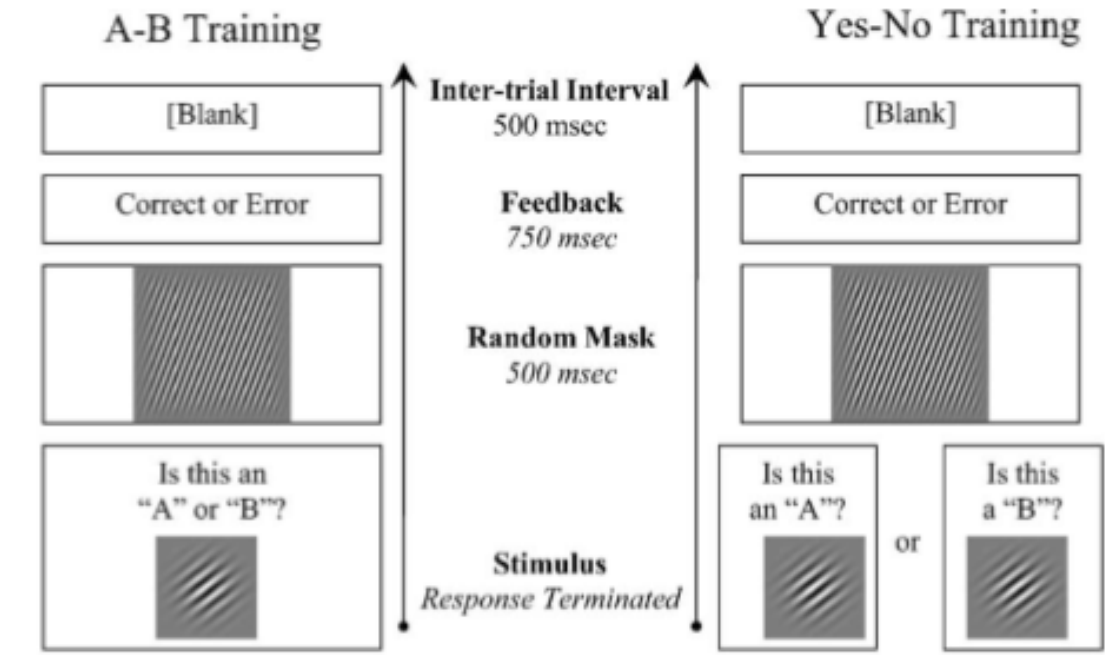
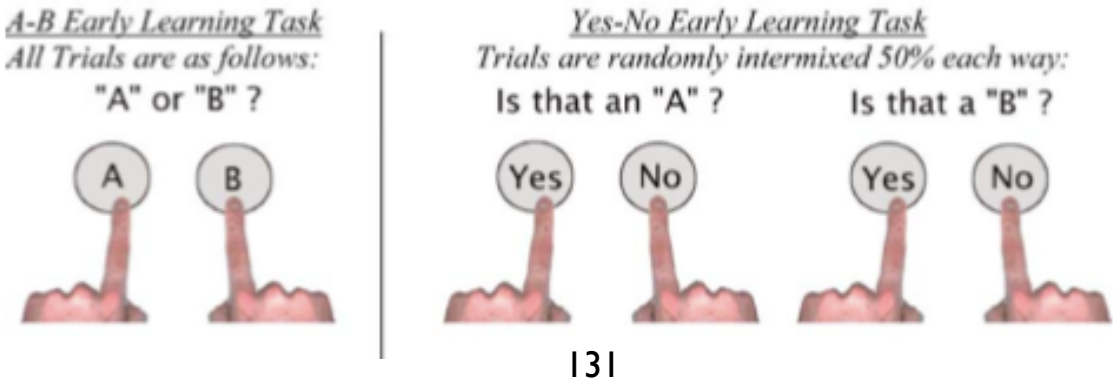
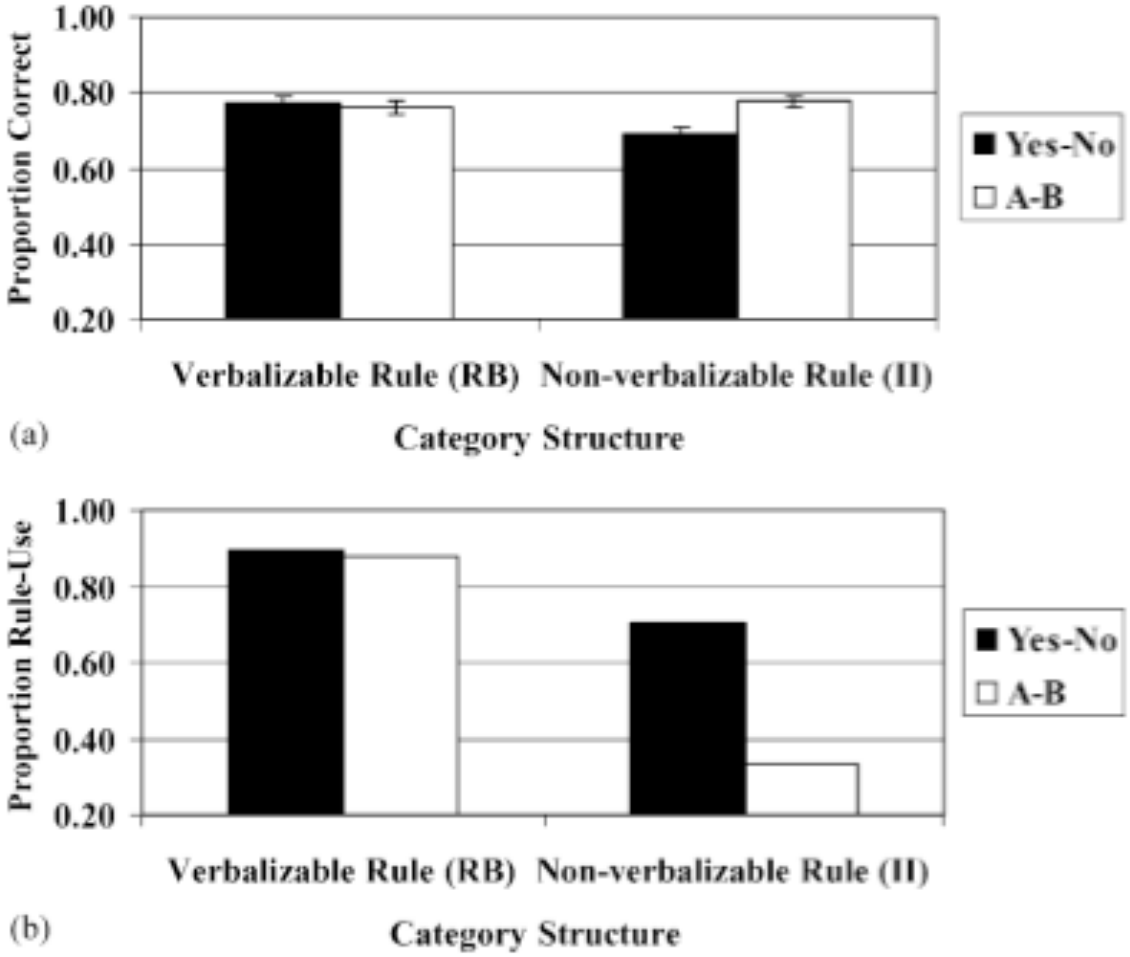




Changing motor response

]Summarized in Maddox & Ashby (2004) "Dissociating explicit and procedural-learning based systems of perceptual category learning" Behavioral Processes, 66, 309-332.



Behavioral Dissociation in support of COVIS

Summarized in Maddox & Ashby (2004) "Dissociating explicit and procedural-learning based systems of perceptual category learning" Behavioral Processes, 66, 309-332.

- Dual task/Distraction impact rule learning more than information integration
- Reduced time to process feedback impacts rule learning more the information integration
- The procedural system is insensitive to the number of categories/ complexity of the category rule (relative to the rule system)

Dual Task

Summarized in Maddox & Ashby (2004) "Dissociating explicit and procedural-learning based systems of perceptual category learning" Behavioral Processes, 66, 309-332.

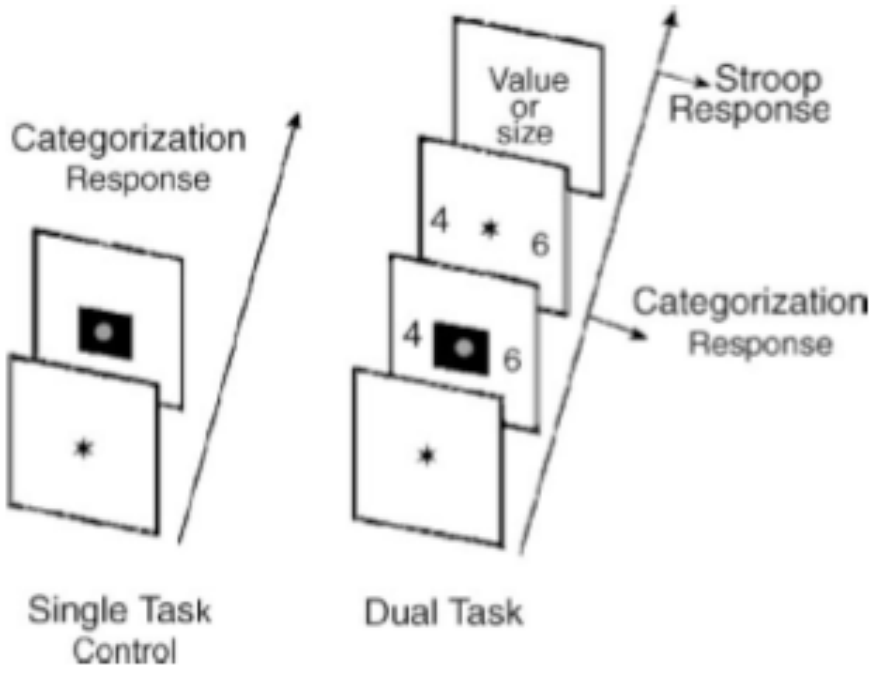
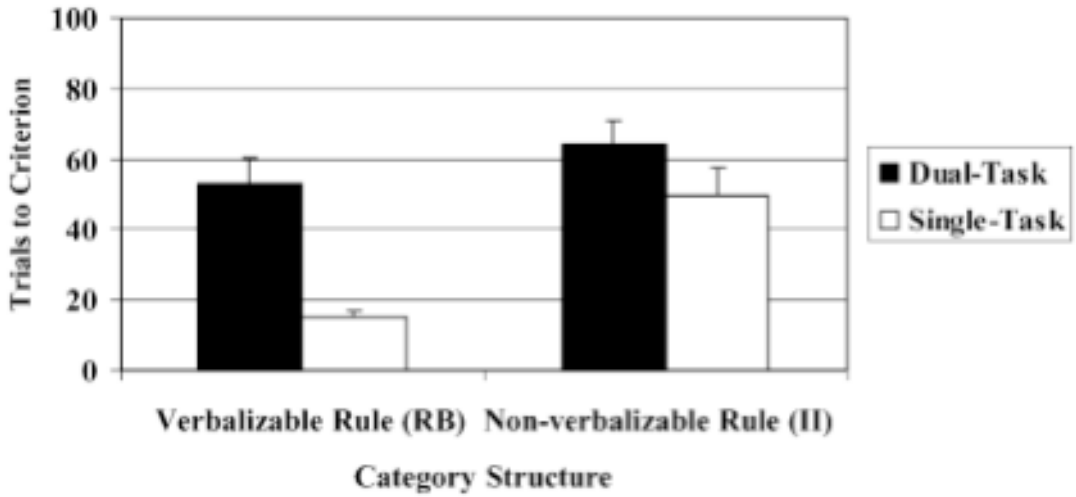
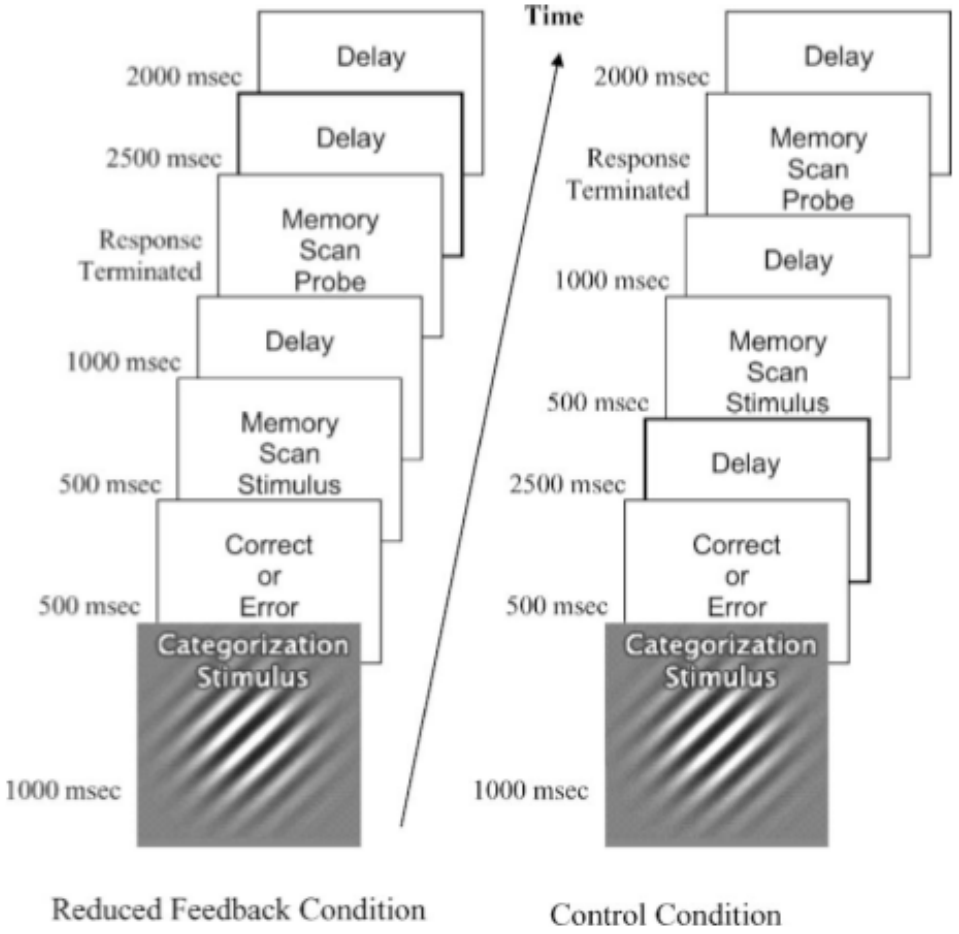


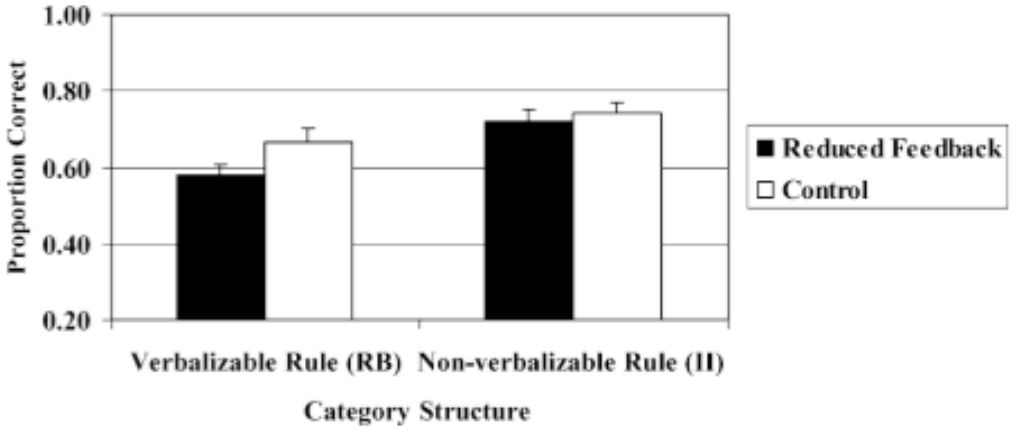
Fig. 15. Basic design for the single and dual task training procedures.



Reduced Time to Process Feedback

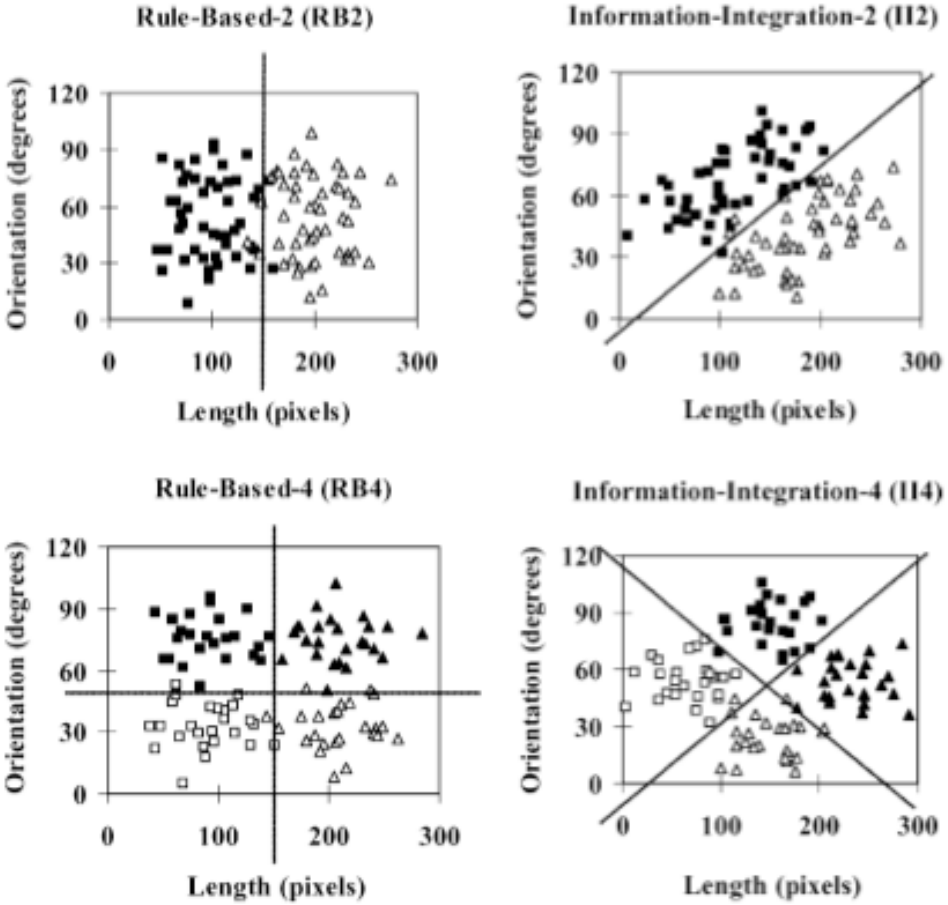
Summarized in Maddox & Ashby (2004) "Dissociating explicit and procedural-learning based systems of perceptual category learning" Behavioral Processes, 66, 309-332.

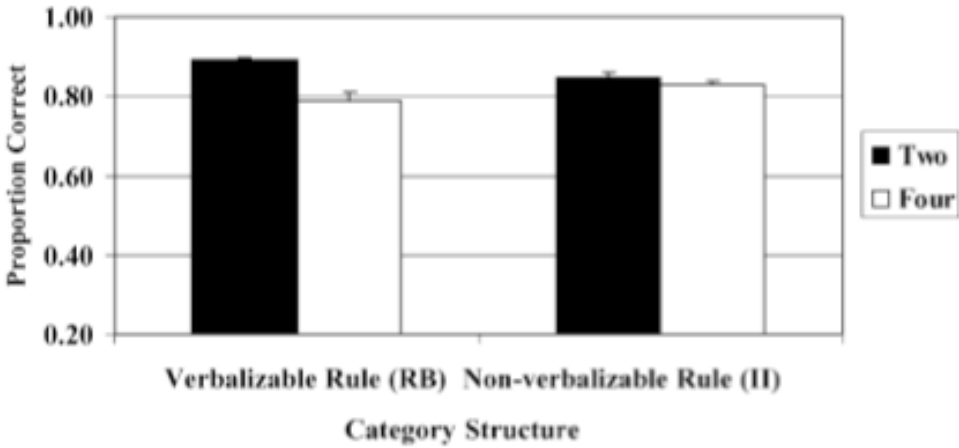




Cluster vs. Categories

Summarized in Maddox & Ashby (2004) "Dissociating explicit and procedural-learning based systems of perceptual category learning" Behavioral Processes, 66, 309-332.

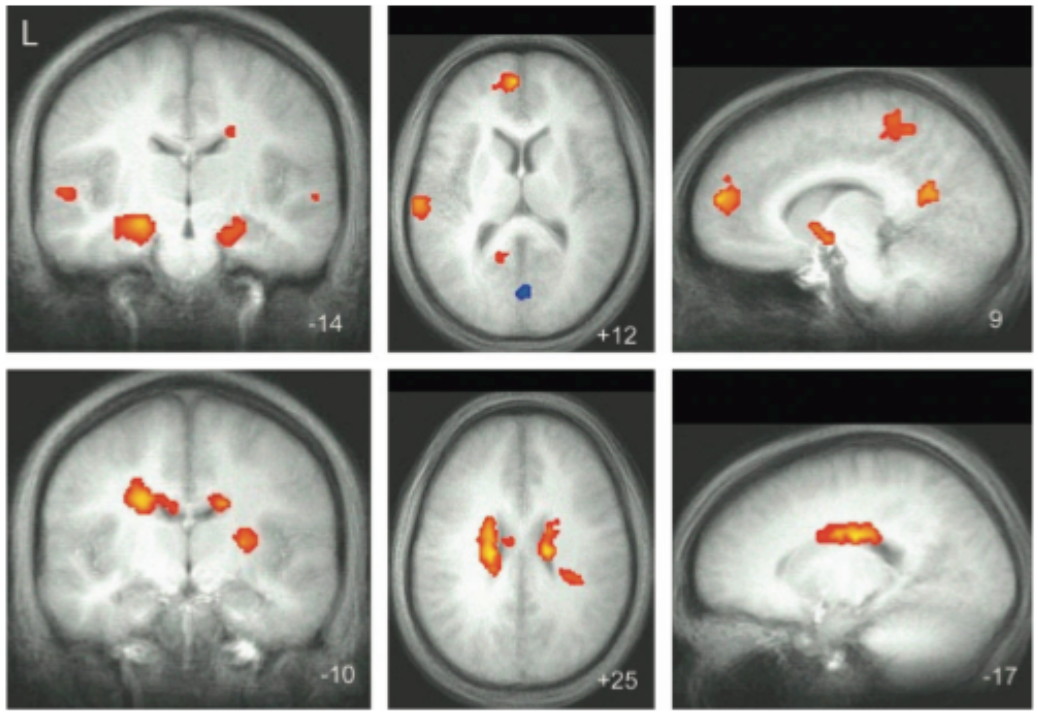




Recent fMRI Evidence

Summarized in Maddox & Ashby (2004) "Dissociating explicit and procedural-learning based systems of perceptual category learning" Behavioral Processes, 66, 309-332.

- Compared II vs. RB categorization (i.e., diagonal versus vertical boundaries)
- Rule-based category learning associated with increased activity in MTL, Right Caudate, Anterior Cingulate, medial frontal gyrus
- II-based category learning associated with increased activities in caudate/striatum



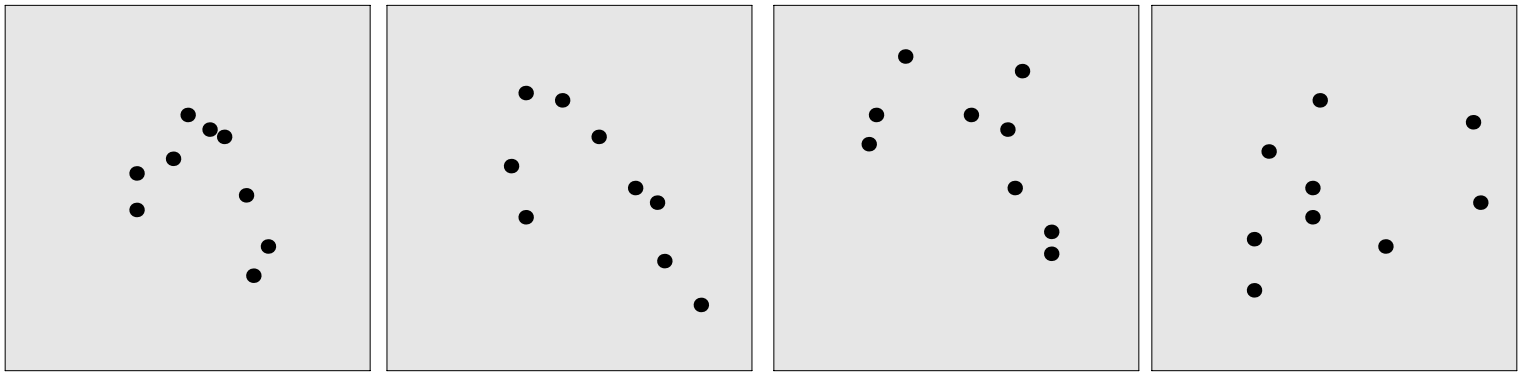
Correct-Incorrect Trials

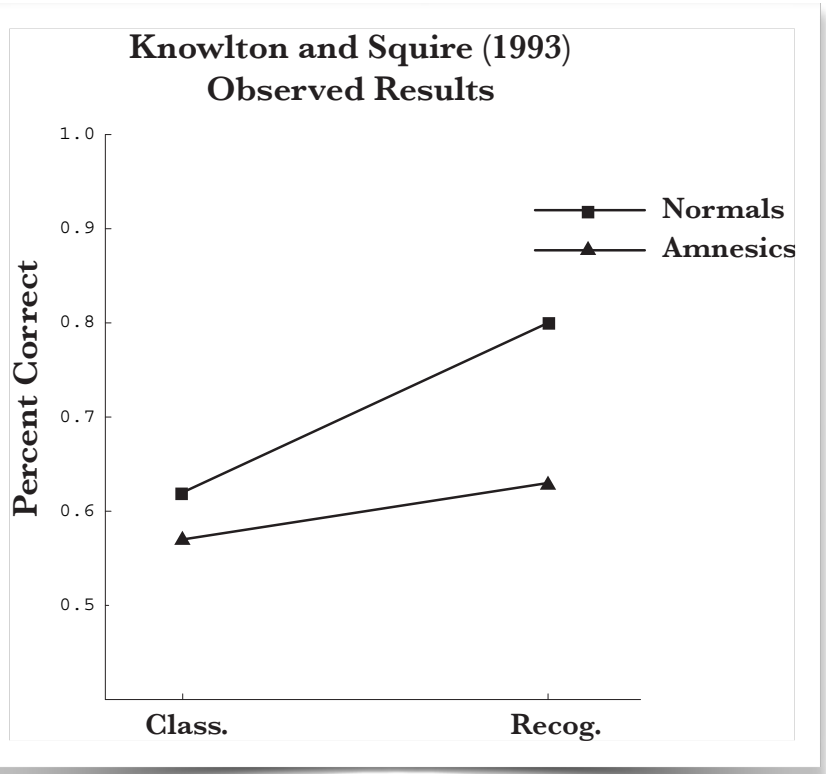
Criticisms of COVIS

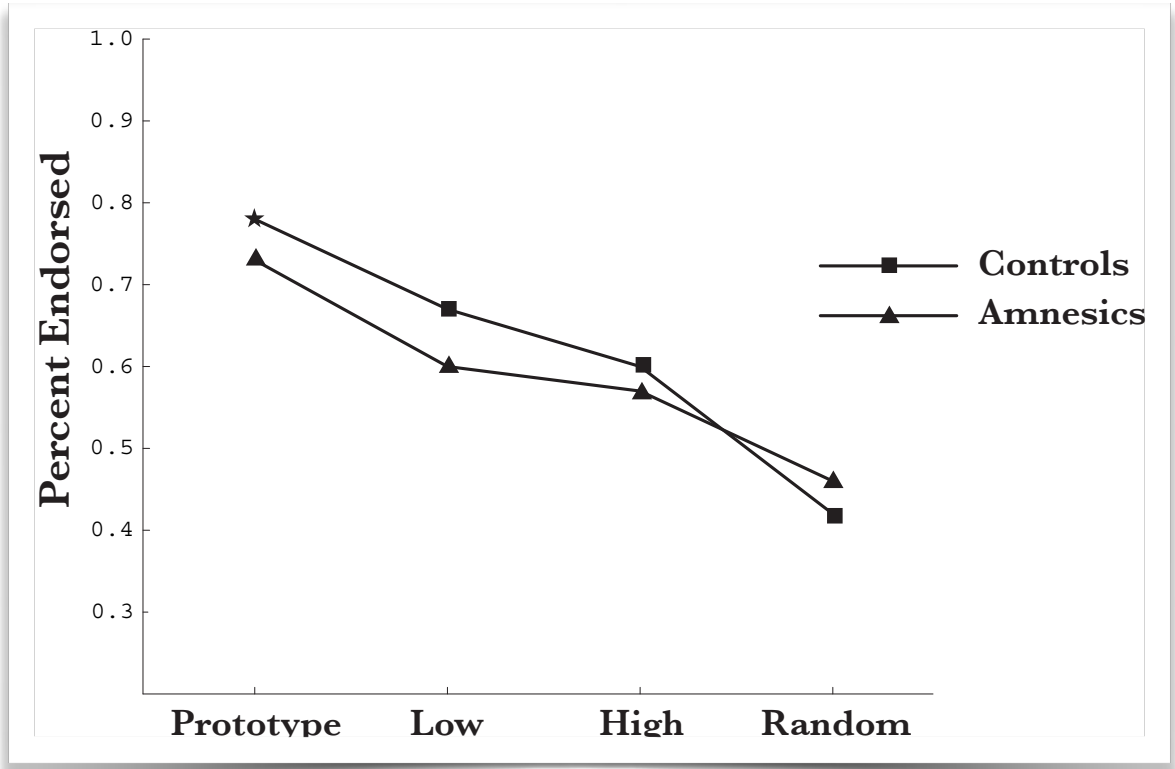
- What are the limits of the verbal system? What says that one rule is harder than the other to learn? In COVIS this is left blank, and in the modeling the complexity of one rule compared to another is set by the experimenter (see Feldman, 2000 for a possible answer to which rules are easier or harder to learn)

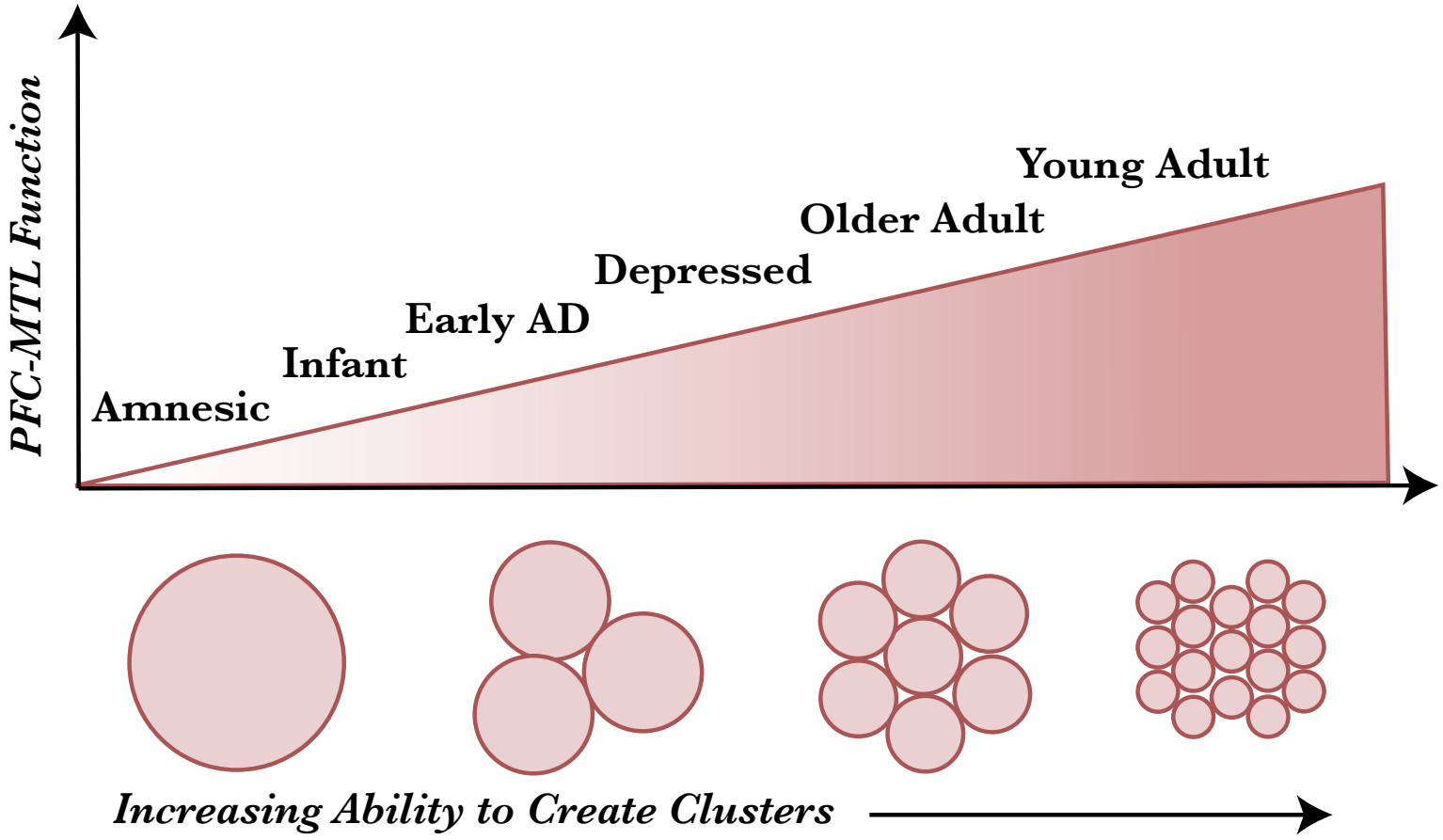
- Can these dissociations be explained other ways? Nosofsky and colleagues have argued that the difference really is one of cognitive complexity. It is hard to control the relative difficulty of the tasks (Nosofsky, Stanton, & Zaki, 2005; Stanton & Nosofsky, 2007, etc...)

- Competition? The competition mechanisms in COVIS is relatively weak. The "model" is never really applied to the data. Instead, two different decision bound models are used: a rule-based one which is limited in the types of decision bounds it can employ, and a procedural one which includes the possibility of "diagonalized" boundaries. Winner is assumed to be "best" model.


Prototype
Low Distortion
High Distortion
Random


Knowlton and Squire (1993)
Observed Results
Percent Correct
1.0
0.9
0.8
0.7
0.6
0.5
Normals
Amnesics
Class.
Recog.


Percent Endorsed
1.0
0.9
0.8
0.7
0.6
0.5
0.4
0.3
Controls
Amnesics
Prototype
Low
High
Random



Continuum of PFC-MTL Function

Various groups are ordered by their ability to individuate events

Is Categorization Intact in Amnesia?

- Nosofsky & Zaki (1998) present an analysis with a single-system exemplar model the accounts of the same pattern of results.
- In exemplar model, similarity is based on exponential function of distance in metric space $s_{ij} = \exp(-c*d_{ij})$
- As c is higher, the exemplar traces in memory are encoded more "sharply"
- If one assumes that amnesic individual acquire the exemplars normally, but have a lower setting of memory sensitivity (c) then they will be ok at categorization (which benefits from "blurred" representations) while impaired at recognition (which require fine-tuned representations)

Does Categorization Require Learning?

- Palmeri & Flannery (2001) presented a innovative study on this
- Normal subject told to look a random pictures of everyday objects
- Then told they were subliminally presented dot patterns (like the K&S stimuli). However they weren't **really** presented
- At test make judgements of items that come from a single category and random patterns.
- **Result:** The do just as well at the task as those that studied the actual patterns!!
- The effect is learning at test (a large number of low distortions and prototypes in the testing phase support learning in the absence of training!)

General Conclusions

- People use a variety of representational strategies to learn categories
- Contemporary formal models have taken the approach of assuming multiple representation systems that learn independently and there is some competition between them for behavioral control
- **THIS IS AN OVERALL MORE COMPLEX STORY BUT GOOD:** This is a more accurate picture of what is going on (and is supported by some of the neuropsychological work as well that we will discuss next time)

Rational Arguments in Favor of this Distinction

- As in Marr's paper, different representations make different kinds of processes more or less accessible: Roman Numerals vs. Base-10 Digits
- The distinction between rule-based and similarity-based/exemplar strategies have a similar flavor:
    - Rules are fast, efficient, and abstract but potentially OVER-regularize the true situation
    - Associations are slow, but in some sense make use of all the information experienced (i.e., statistically optimal)