An Introduction to Learning

Lecture 10

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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
What you see:

Red
Shiny → Apple
In a tree

What you can then infer:

Has seeds
Sweet
Edible
Healthy
A little history....

Progress (hopefully)
A little history....
A little history....

The Classical View

The Prototype View

Progress (hopefully)
A little history....

The Classical View

The Prototype View

Progress (hopefully)
A little history....
A little history....
A little history....

The Classical View

The Prototype View

The Exemplar View

The Theory View

The Cultural View

The (neo) Prototype View

The Clustering View

The Rational View

Hybrid: Rules-Examples View

Rules

...

Progress (hopefully)
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

<table>
<thead>
<tr>
<th>Name</th>
<th>Concept</th>
<th>Pack I</th>
<th>Pack II</th>
<th>Pack III</th>
<th>Pack IV</th>
<th>Pack V</th>
<th>Pack VI</th>
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Hull, 1920 - phd thesis

Studied learning concepts defined by simple features
According to the classical view, category learning usually involves hypothesis testing or rule discovery:

A search for the defining features

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.

<table>
<thead>
<tr>
<th>Item</th>
<th>Percent</th>
</tr>
</thead>
<tbody>
<tr>
<td>A shelf</td>
<td>76%</td>
</tr>
<tr>
<td>A rug</td>
<td>52%</td>
</tr>
<tr>
<td>A lampshade</td>
<td>63%</td>
</tr>
<tr>
<td>Bookends</td>
<td>57%</td>
</tr>
<tr>
<td>Candlestick</td>
<td>28%</td>
</tr>
</tbody>
</table>

Many borderline cases
One prediction

2: Category membership should be unambiguous

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

<table>
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</tbody>
</table>

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)

<p>| | |</p>
<table>
<thead>
<tr>
<th></th>
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<tbody>
<tr>
<td>Robin</td>
<td>1.4</td>
</tr>
<tr>
<td>Eagle</td>
<td>1.8</td>
</tr>
<tr>
<td>Wren</td>
<td>2.4</td>
</tr>
<tr>
<td>Chicken</td>
<td>2.8</td>
</tr>
<tr>
<td>Ostrich</td>
<td>3.2</td>
</tr>
</tbody>
</table>

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 subjects list features of instances 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.

<table>
<thead>
<tr>
<th>Properties</th>
<th>Examples</th>
<th>Feature Score (a.k.a. “Weight”)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Robin</td>
<td>Cardinal</td>
</tr>
<tr>
<td>Has wings</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Flies</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Has feathers</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Sings</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Builds nests in trees</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Eats worms/insects</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Family Resemblance</td>
<td>5+4+4+2+3+3=</td>
<td>5+4+4+2+3+3=</td>
</tr>
<tr>
<td>Score</td>
<td>21</td>
<td>21</td>
</tr>
</tbody>
</table>
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 seen so far.
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 seen so far.
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.
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)  \Rightarrow Builder
2 of (short legs, curved body, not spots)  \Rightarrow Digger

Example of Builder

Example of Digger
Environmental context
Forest scene => \textit{Builder}
Arctic scene  => \textit{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)

Percent Errors (Non-Rule Answers)

- Memory
- Rule

- Rule/Environment Match
- Rule/Environment Mismatch
Brooks and Allen (1991)

Percent Errors (Non-Rule Answers)

- Rule/Environment Match
- Rule/Environment Mismatch

Group

Memory

Rule
Brooks and Allen (1991)

Response Time (ms)

Rule/Environment Match
Rule/Environment Mismatch
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
Exemplar Theory

Birds
You’ve Seen

Bird?
X is a bird because it is similar to many other birds.
Exemplar Theory

Y is an insect because it is similar to many other insects.
<table>
<thead>
<tr>
<th>Empirical Effect</th>
<th>Classical View</th>
<th>Prototype Model</th>
<th>Exemplar Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>No defining features</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Borderline cases</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
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<tr>
<td>Graded typicality</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
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<tr>
<td>Prototype effect</td>
<td>✓</td>
<td>✓</td>
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<tr>
<td>Exemplar effects</td>
<td></td>
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<td>✓</td>
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</table>
Exemplar Theory

A is equally close to all birds and all insects
Exemplar Theory

Ostriches are not close to most other birds.
Exemplar Theory

Prototype is very similar to many 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
  - $m_i = s_i$ if values on that dimension mismatch
- Overall similarity 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

$$p(C_j | S_i) = \frac{sum(C_j, S_i)}{\sum_k sim(C_k, S_i)}$$
Pearce (1987): Many learning results arise from the similarity of cue-combinations at training versus test

Overshadowing
External inhibition
Overexpectation
Blocking

etc...

Response drops off (quickly) if any cues or contextual elements are missing ("context model"). Compare to Gershman, Blei, & Niv latent cause model!!
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!!).

\[ d_{ij} = c \left( \sum_{k=1}^{N} w_k |x_{ik} - x_{jk}|^r \right)^{1/r} \]

\[ d_{ij} = \left( \sum_{k=1}^{K} |x_{ik} - x_{jk}|^r \right)^{1/r} \]
The Generalized Context Model
Nosofsky (1984; 1986)

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

\[ \eta_{ij} = e^{-d_{ij}} \]

- Response rule

\[
p(R_j | S_i) = \frac{b_j \sum_{j \in C_j} n_{ij}}{\sum_{k=1}^{m} (b_k \sum_{j \in C_k} n_{ik})}
\]
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
Selective Attention
Nosofsky (1986)

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

<table>
<thead>
<tr>
<th></th>
<th>DIMENSIONAL</th>
<th>CRISS-CROSS</th>
<th>INTERIOR-EXTERIOR</th>
<th>DIAGONAL</th>
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w1 0   .58   .64   .60
w2 1   .42   .36   .40

w1 0.09 .66 .66 .56
w2 0.91 .34 .34 .44
Selective Attention
Shepard, Hovland, Jenkins (1961)
Selective Attention
Shepard, Hovland, Jenkins (1961)

<table>
<thead>
<tr>
<th>Problem Type</th>
<th>Within-Category Similarity</th>
<th>Predicted Learning Difficulty</th>
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<tbody>
<tr>
<td>I</td>
<td>Very high</td>
<td>Very easy</td>
</tr>
<tr>
<td>III, IV, V</td>
<td>Moderately high</td>
<td>Moderately easy</td>
</tr>
<tr>
<td>II</td>
<td>Moderately low</td>
<td>Moderately hard</td>
</tr>
<tr>
<td>VI</td>
<td>Very low</td>
<td>Very hard</td>
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</table>

but actually
Type I < II < (III, IV, V) < IV
# Selective Attention

Shepard, Hovland, Jenkins (1961)

<table>
<thead>
<tr>
<th>Problem Type</th>
<th>Within-Category Similarity</th>
<th>Predicted Learning Difficulty</th>
<th># of Dimensions</th>
</tr>
</thead>
<tbody>
<tr>
<td>I</td>
<td>Very high</td>
<td>Very easy</td>
<td>1</td>
</tr>
<tr>
<td>III, IV, V</td>
<td>Moderately high</td>
<td>Moderately easy</td>
<td>3</td>
</tr>
<tr>
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<td>2</td>
</tr>
<tr>
<td>VI</td>
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<td>3</td>
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</table>

- For Type II, attention resources can be concentrated on two dimensions, making it easier.

- Types III, IV, and V require attention to be diluted over three dimensions.
Eye Movement Data
Rehder & Hoffman (2005)
Category Learning and Monkeys

SHJ’s Predictions
for “associative” learner
(based on confusion matrices)

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

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


Category Learning and Monkeys

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.
“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.
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.
2 Categorization

Multiple systems framework
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

Number of Dimensions Fixated

Trial
Example Type I subject

Number of Dimensions Fixated

Trial
Example Type I subject
Example Type I subject
Example Type I subject
Example Type I subject
Example Type I subject

# of Dimensions

Trial
Example Type I subject

![Graph showing # of Dimensions and Error Rate over trials]

- **# of Dimensions**
- **Error Rate**

- **Trial**
- **# of Dimensions**
  - 1
  - 2
  - 3

- **Error Rate**
  - 0.00
  - 0.17
  - 0.33
  - 0.50
  - 0.67
  - 0.83
  - 1.00
Example Type I subject
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)
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- 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).
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)
3 Categorization
Cognitive Neuroscience of Category Learning
Multiple Systems in Categorization

- The bird’s eye view is that:
  - Distinct neural pathways may be tapped for different forms of learning
  - Different patient population have a specific (and somewhat predictable) pattern of deficits
  - Critically, the pattern of deficits varies as a function of the information structure of the category itself and the study conditions
Smith, Palatino, Jonides (1998)

- “Alternative Strategies of Categorization”: In contrast to unitary view, people use multiple strategies, often at the same time.

- Built off Allen & Brooks (1991) “Builders”/”Diggers” study
Smith, et al. (1998) PET results

• Subtractions compared to a control phase where just made responses (to subtract non-specific motor components)
• Large number of areas unique to rule based categorization including: parietal lobes, dorsolateral PFC, supplementary motor cortex, cerebellum, right thalamus
• Common areas included visual cortex, cerebellum
• Only memory: visual cortex/cerebellum
Smith, et al. (1998) PET results

- **Parietal lobes** used in Rule condition are associated with controlled, effortful attention (i.e., selective attention)
- **Right Dosolateral PFC** -> implicated on rule-based task switching like WCST
- **Supplementary Motor Cortex** = speech, motor preparation
Smith, et al. (1998)

PET results

- **Visual cortex** activated in all groups consistent with perceptual categorization, exemplar retrieval?
Executive Function and the Wisconsin Card Sorting Task (Milner, 1964)

- Sort a set of cards on a basis of a single dimension.

- Correct dimension switches after a certain number of correct responses (compare to the Bower and Trabasso study... here it is switch when correct, not when make mistakes)

- Generally, patients with impaired frontal lobe function show deficits in the task which presumably requires representation and maintenance of a rule in working memory.
General Conclusion

• The strategy used to learn the category not only influenced the pattern of behavioral results (consistent with Allen and Brooks original study) but also influenced the neural systems engaged.

• Overall a strong effect of the Rule condition (network of regions involved in executive function, working memory, and attention)

• Pure effect of memory task was less pronounced as was the overlap

• Additional support for models like RULEX or ATRIUM that posit separate rule and similarity-based (i.e., exemplar) processing
COVIS


- 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


- 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


- 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
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.
Selection
Switching
Working
Memory
Loops

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.
Behavioral Dissociation in support of COVIS


- 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

Observational Learning

Observational Learning

Delayed Feedback

Delayed Feedback

Changing motor response


Changing motor response

Changing motor response

Changing motor response

Behavioral Dissociation in support of COVIS


- 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


![Graph showing dual task and single task comparison](image)

Fig. 15. Basic design for the single and dual task training procedures.
Reduced Time to Process Feedback

Cluster vs. Categories

Recent fMRI Evidence


- 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.
Knowlton and Squire (1993) Observed Results

- Class.: Normals and Amnesics
- Recog.: Prototypes, 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 \( s_{ij} = \exp(-c \cdot d_{ij}) \)

- 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 an innovative study on this

- Normal subject told to look at 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!)