# Cognitive Psychology

Lecture 9: Knowledge

# How do we make sense of the world?

- What is this?
- What do you know about it?

- Two general topics for today:
    1. How do people decide on a category?
    2. What is the representation of knowledge in the mind?

# What do radiologists do?

- Categorization!
- Broken?
- Not Broken?

# What does TSA do?

- Categorization!
- Threat?
- No threat?

Fig. 1. Example of a target-present stimulus image. The target (the blade and shaft show up in dark blue, and the handle in orange) is a little above the center of the image, to the left of the toy airplane.

# What do birdwatchers do?

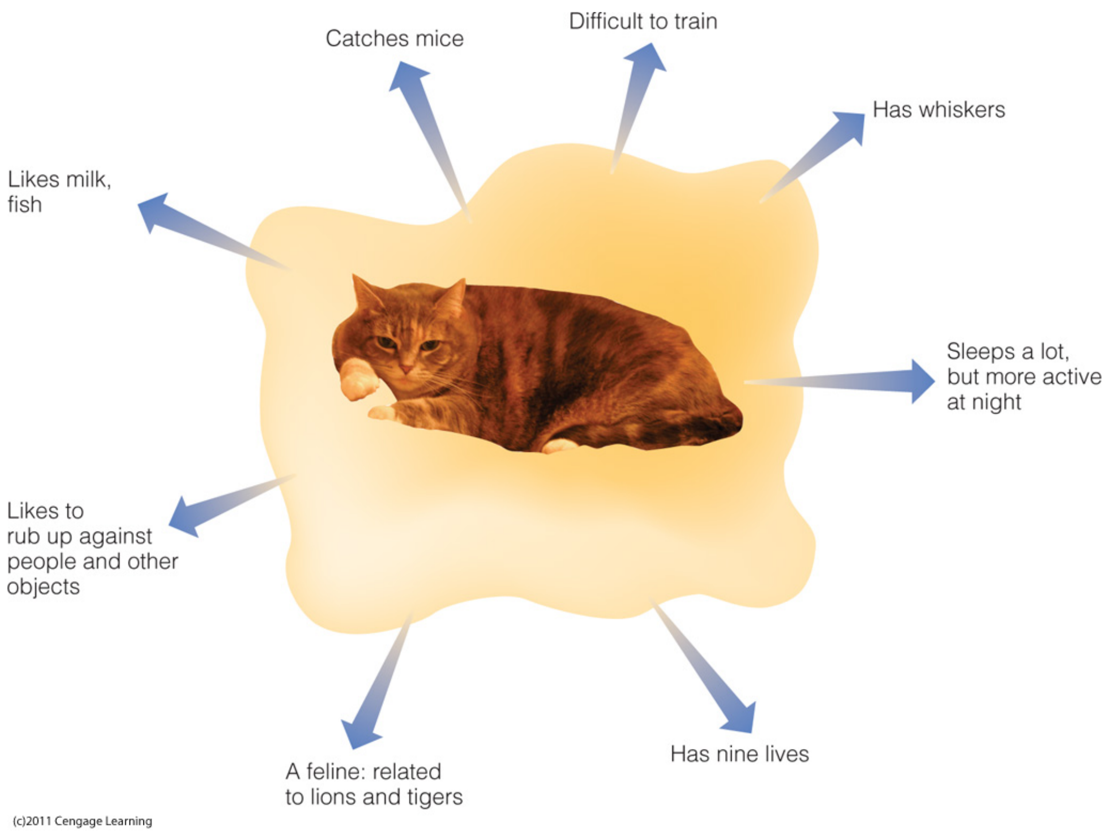
- Categorization!
- Rare bird?
- Common bird?

# Knowledge

- **Categories:** group of objects, events, or ideas which share attributes or features in common
  - Categorization is the process by which things are placed into groups called categories
- **Concept**: mental representation of categories used for a variety of cognitive functions

# Why categories are useful

- Help to understand individual cases not previously encountered
- **“Pointers to knowledge”**
  - Categories provide a wealth of general information about an item
  - Allow us to identify the special characteristics of a particular item

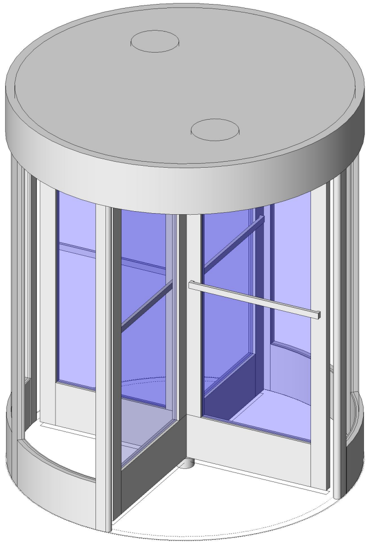


# How do we decide on a category?

- Hypothesized ways that we decide if an item belongs to a category
  - Definitional approach
  - Prototype approach
  - Exemplar approach

# Definitional Approach

- Determine category membership based on whether the object meets the definition of the category
- Try to create a definition of the "doors" or "games" category
  - It should be able to include everything we consider a game, and exclude everything that is not a game



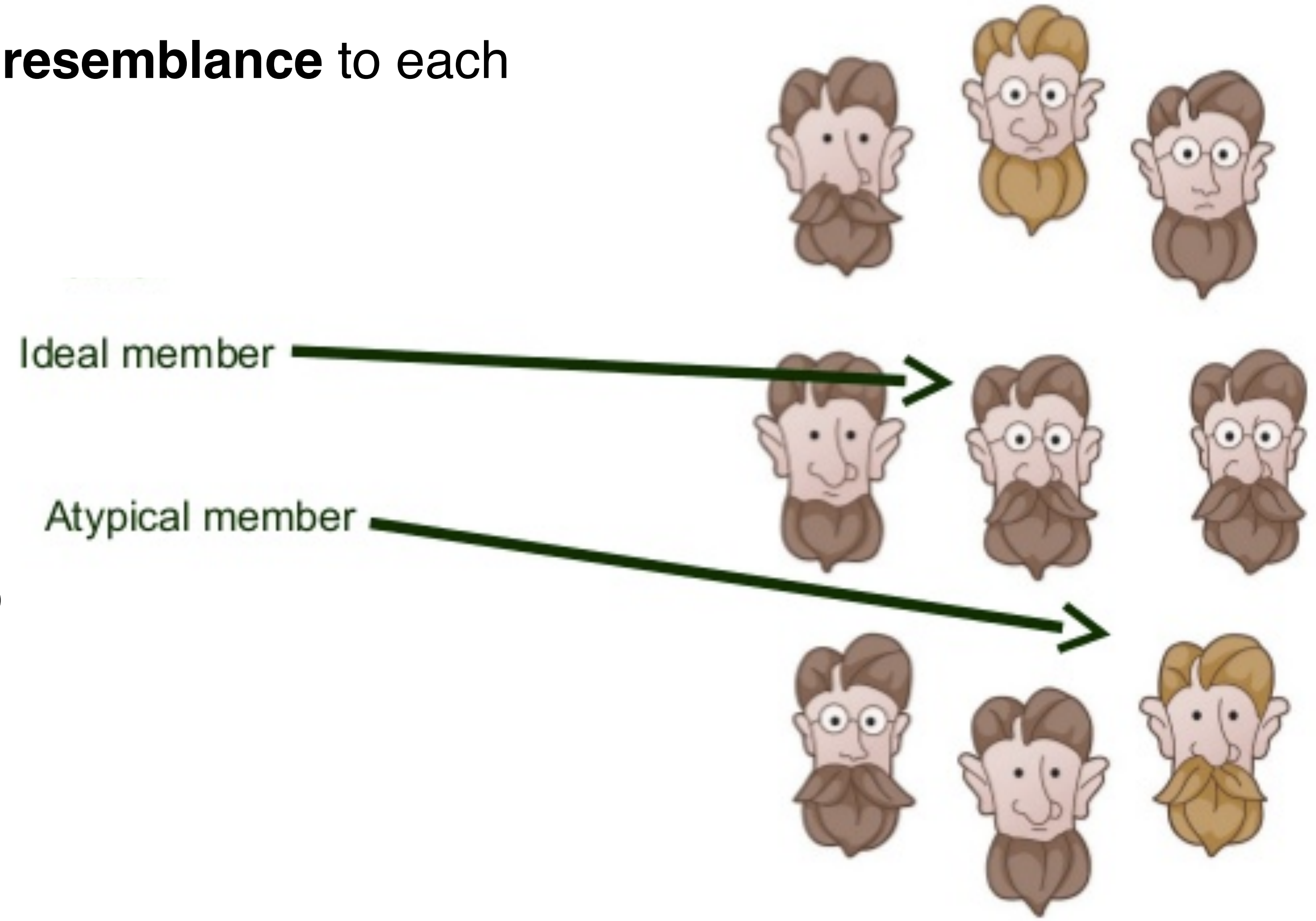
# Definitional Approach

- Does not work well
- Not all members of everyday categories have the same defining features
- Update: Family resemblance
  - Things in a category resemble one another in a number of ways
  - Precursor to prototype theories


Figure 9.2 Different objects, all possible "chairs."

# Family Resemblance

- Members of a category have a **family resemblance** to each other
- Common features like dark hair, glasses, moustache, and a big nose
- However, the features do not strictly **define** the family category
  - That is, a member does not need to have all the common features to be a member
- Lead to the idea that we may compare new items to a “standard representation”



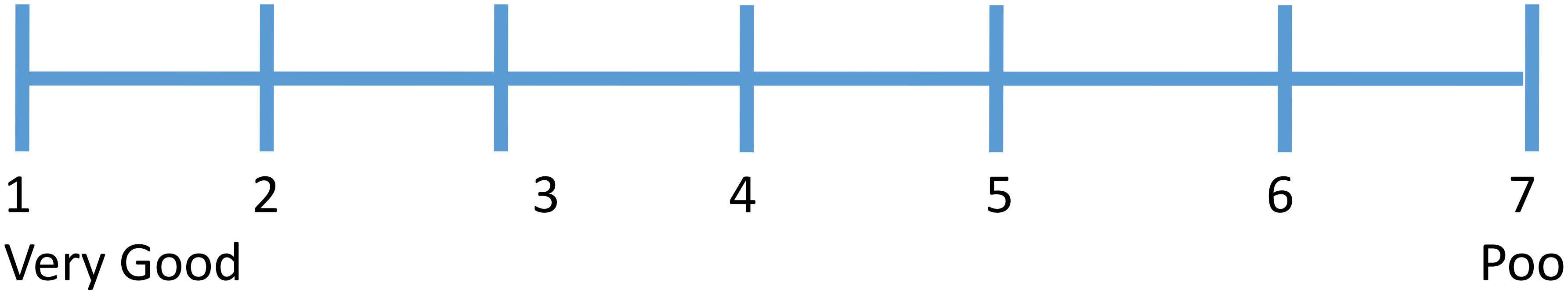
# The Prototype Approach

- Prototype = “typical”
- An average representation of the “typical” member of a category
- Characteristic features that describe what members of that concept are like
- **Prototype:** An average of category members encountered in the past

Figure 9.3 Three real birds—a sparrow, a robin, and a blue jay—and a “prototype” bird that is the average representation of the category “birds.”

# The Prototype Approach

How good of an example of a bird is ____________________?




Penguin
Sparrow
Bat
Owl

# The Prototype Approach

- **High-prototypicality**: category member closely resembles category prototype
  - “Typical” member
  - For category “bird” = robin
- **Low-prototypicality**: category member does not closely resemble category prototype
  - For category “bird” = penguin

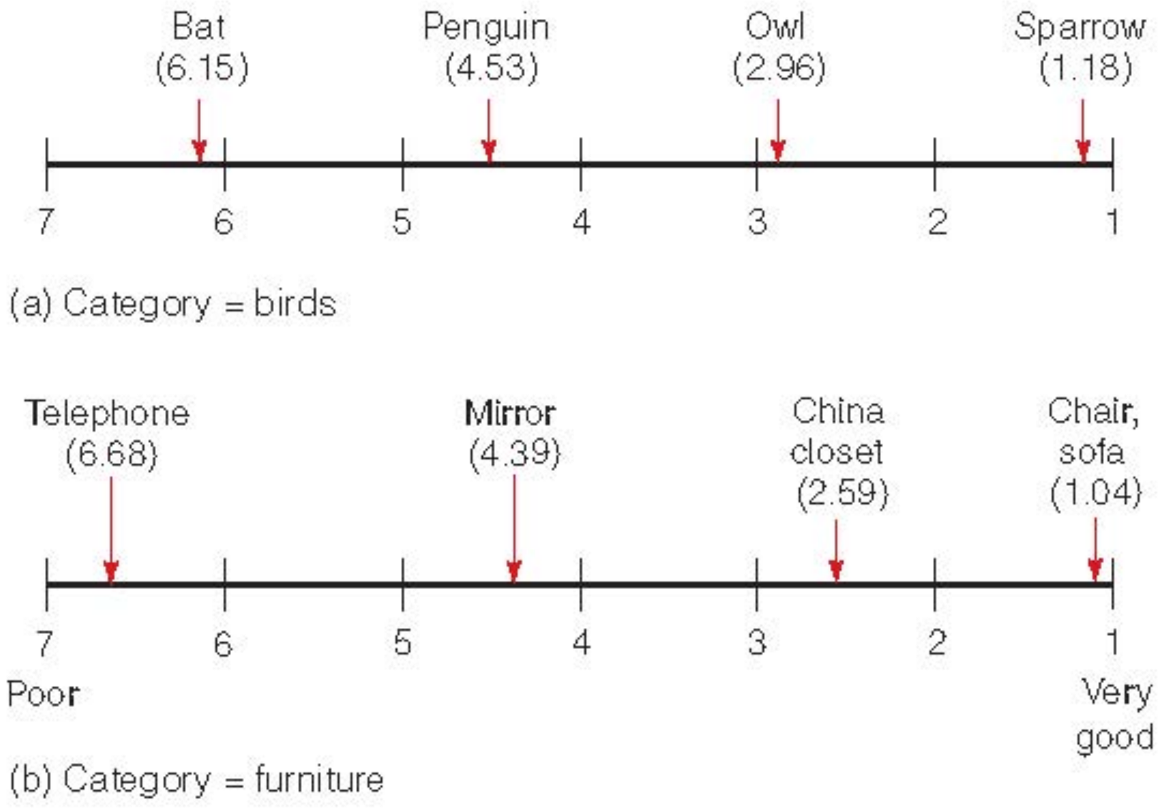



**Figure 9.4** Results of Rosch’s (1975a) experiment, in which participants judged objects on a scale of 1 (good example of a category) to 7 (poor example): (a) ratings for birds; (b) ratings for furniture. 

# The Prototype Approach

- Strong positive relationship between prototypicality and family resemblance
- When items have a large amount of overlap with characteristics of other items in the category, the family resemblance of these items is high
- Low overlap = low family resemblance

# The Prototype Approach: Evidence

**The Typicality effect**

- prototypical objects are processed preferentially

# The Prototype Approach: Evidence

**The Typicality Effect**

- Sentence Verification Technique
  - “An apple is a fruit”
  - ”A pomegranate is a fruit”

- Highly prototypical objects judged more rapidly

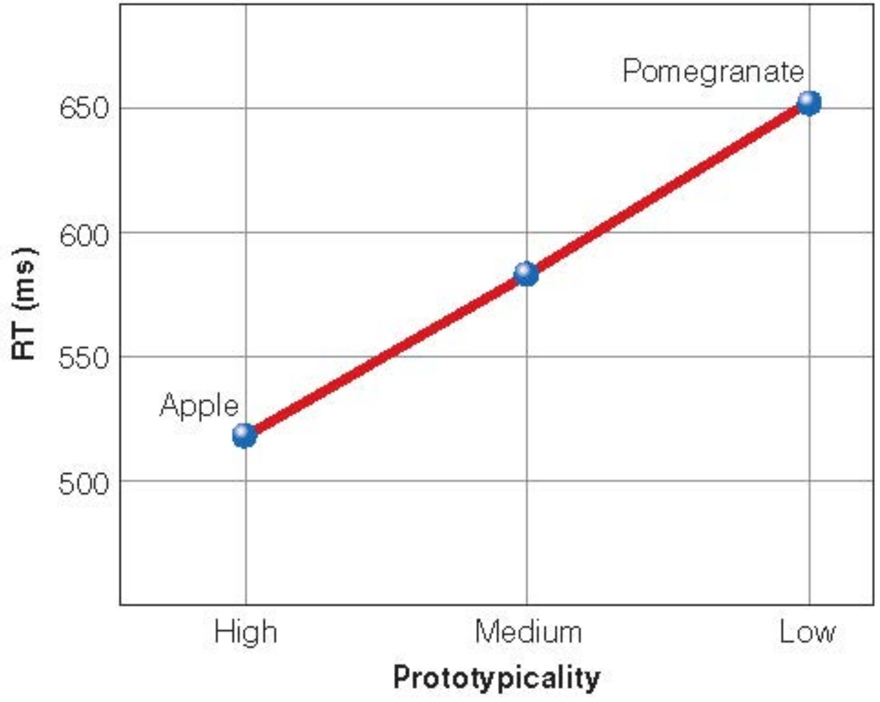



Figure 9.5 Results of E. E. Smith et al.’s (1974) sentence verification experiment. Reaction time (RT) was faster for objects rated higher in prototypicality. 

# The Prototype Approach: Evidence

**The Typicality Effect**

- Prototypical category members are more affected by a priming stimulus
- Rosch (1975b)
  - Task: Indicate whether two colors are the same/different
  - Hearing “green” primes a highly prototypical “green”
    - Hearing “green” is irrelevant to task

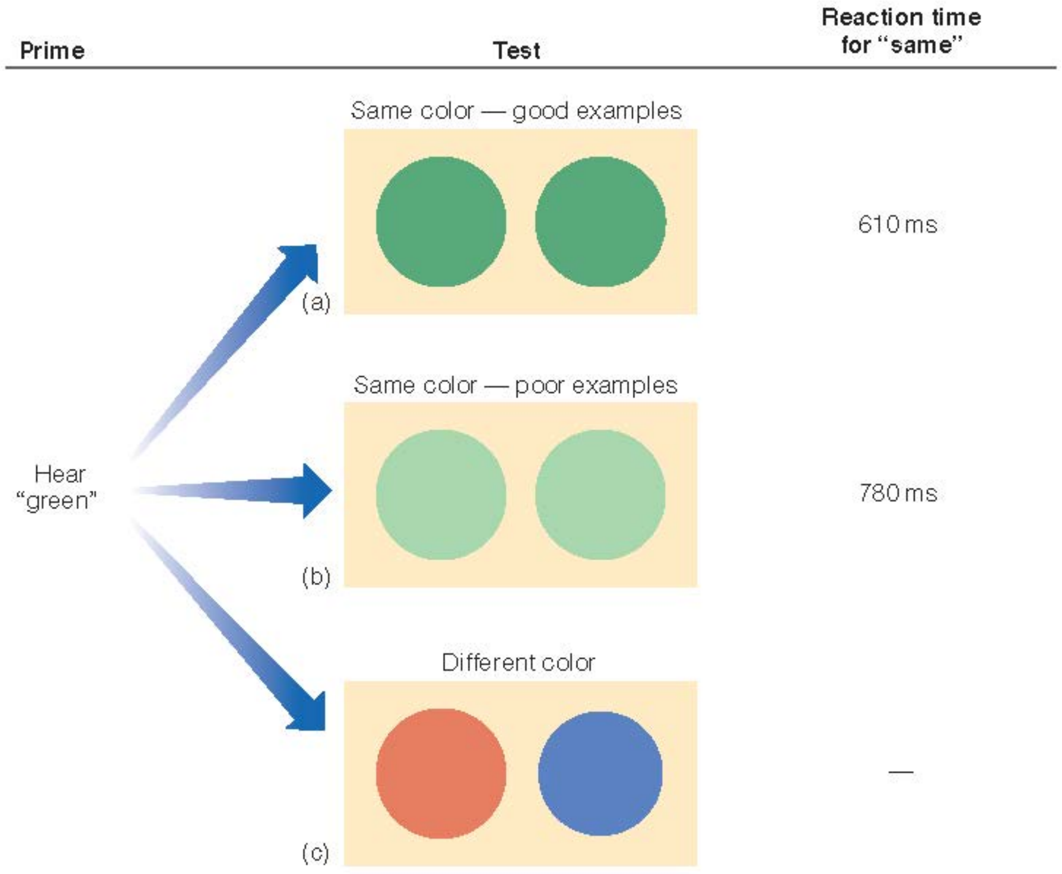
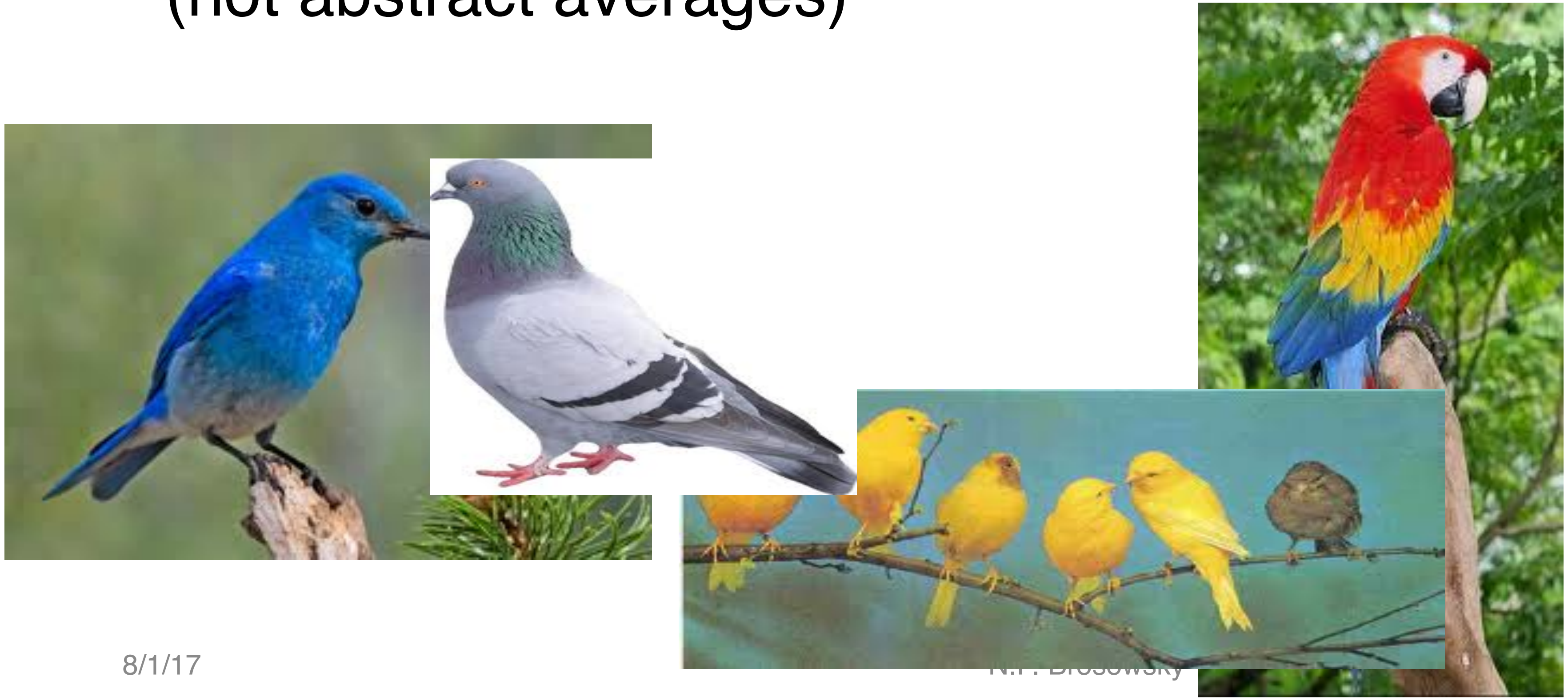



Figure 9.6 Procedure for Rosch’s (1975b) priming experiment. Results for the conditions when the test colors were the same are shown on the right. (a) The person’s “green” prototype matches the good green but (b) is a poor match for the light green; (c) shows the condition in which colors were different. 

# The Exemplar Approach

- Concept is represented by multiple examples
- Examples are actual category members (not abstract averages)



# The Exemplar Approach

- Similar to prototype view
  - Representing a category is not defining it
- Different: representation is not abstract
  - Descriptions of specific examples
- The more similar a specific exemplar is to a known category member, the faster it will be categorized (family resemblance effect)

# The Exemplar Approach

- Explains typicality effect
  - Sparrow is similar to many “bird” exemplars = classified quickly
  - Penguin is similar to few “bird” exemplars = classified slowly
- Easily takes into account atypical cases
  - Can have exemplars for atypical cases like penguins
- Easily deals with variable categories
  - Difficult to imagine a prototype for “games” that includes solitaire, golf, football, etc.

# Prototypes or Exemplars

- May use both
- May change over learning
  - Initial = prototype
  - With expertise, exemplars become stronger
- Exemplars may work best for small categories
- Prototypes may work best for larger categories

# A Hierarchical Organization

**How is knowledge organized in the mind?**

- To fully understand how people categorize objects, one must consider
  - Properties of objects
  - Learning and experience of perceivers

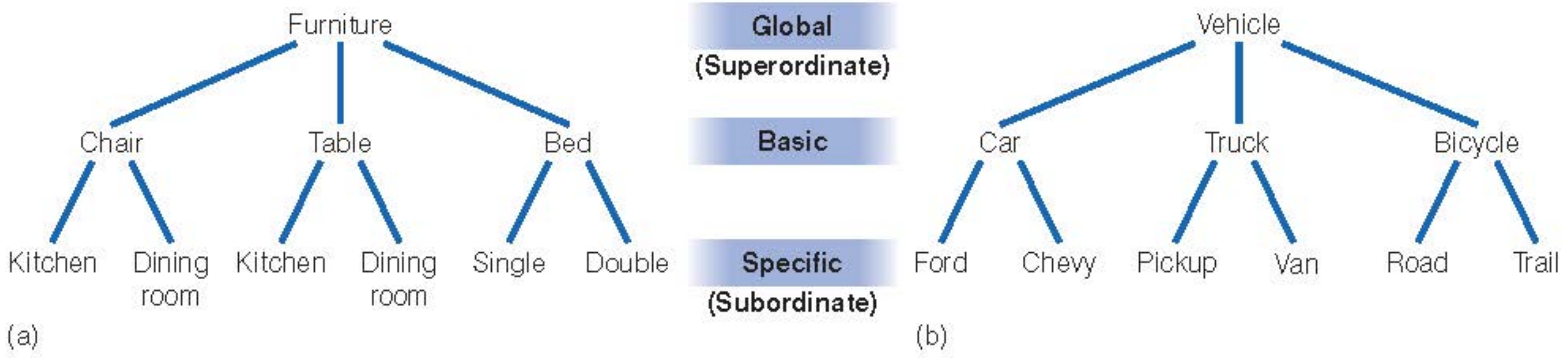



Figure 9.8 Levels of categories for (a) furniture and (b) vehicle. Rosch provided evidence for the idea that the basic level is "psychologically privileged." © Cengage Learning

# Is the "basic-level" special?

- The just-right amount of information (left)?
- People tend to land on the basic-level (right)

| LEVEL | EXAMPLE | NUMBER OF COMMON FEATURES |
|---|---|---|
| Global | Furniture | 3 |
| | | *Lose a lot of information.* |
| Basic | Table | 9 |
| | | *Gain just a little information.* |
| Specific | Kitchen table | 10.3 |

Figure 9.9 Category levels, examples of each level, and average number of common features listed by participants in Rosch et al.'s (1976) experiment. 

FIGURE 9.10 Stimuli for the Naming Things demonstration.

# Is the ”basic-level” special?

**Some evidence says yes:**

- People almost exclusively use basic-level names in free-naming tasks
- Quicker to identify basic-level category member as a member of a category
- Children learn basic-level concepts sooner than other levels
- Basic-level is much more common in adult discourse than names for superordinate categories
- Different cultures tend to use the same basic-level categories, at least for living things

# Is the “basic-level” special?

- **However,** knowledge can impact categorization
- Experts use more specific categories than novices
- The “special” level might be different for everyone depending on their experience

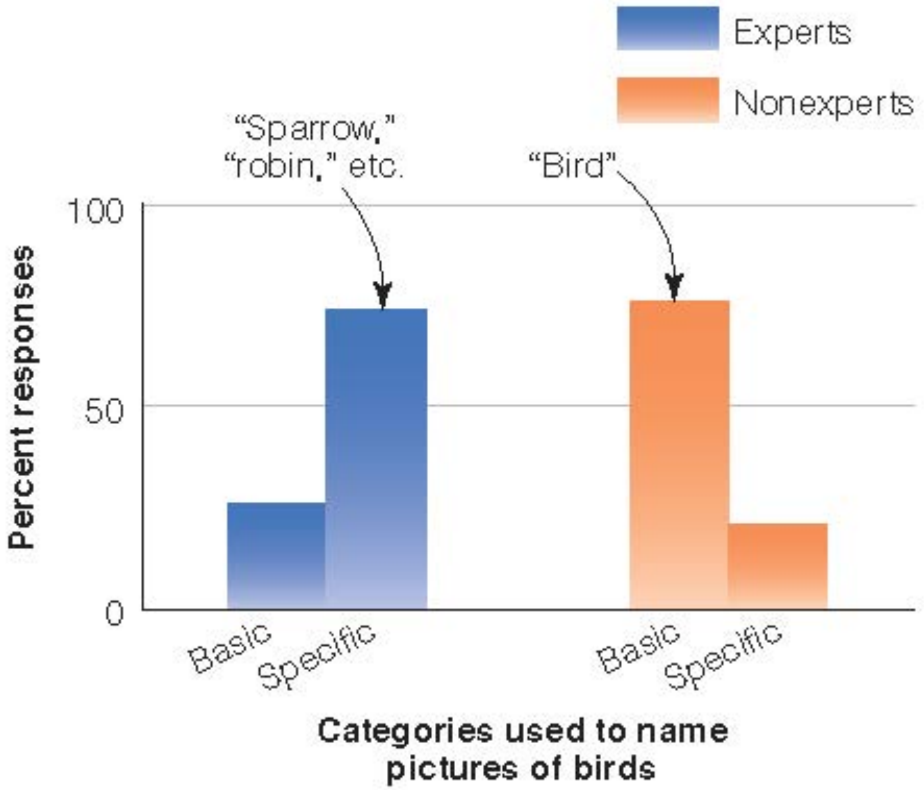
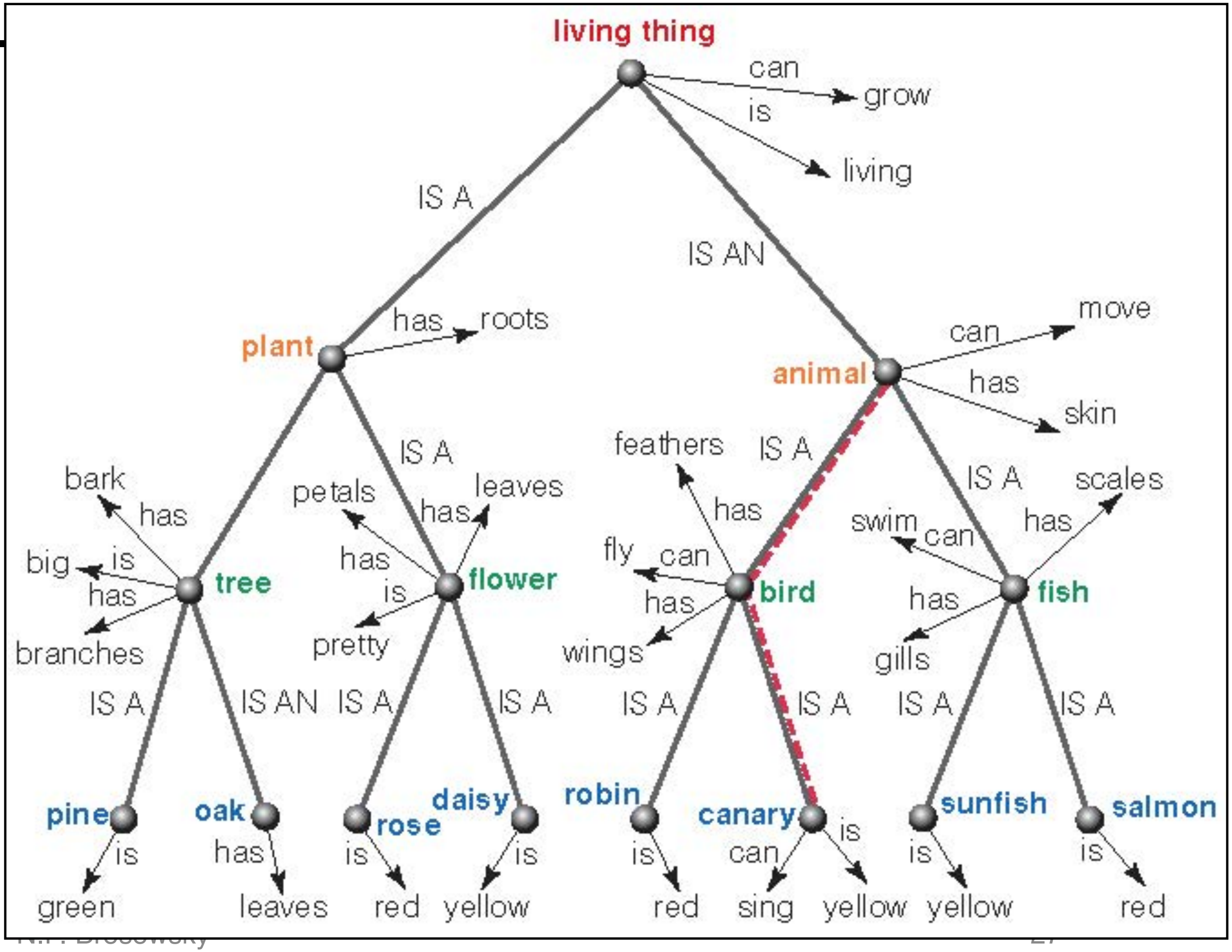



Figure 9.11 Results of Tanaka and Taylor’s (1991) “expert” experiment. Experts (left pair of bars) used more specific categories to name birds, whereas nonexperts (right pair of bars) used more basic categories. 

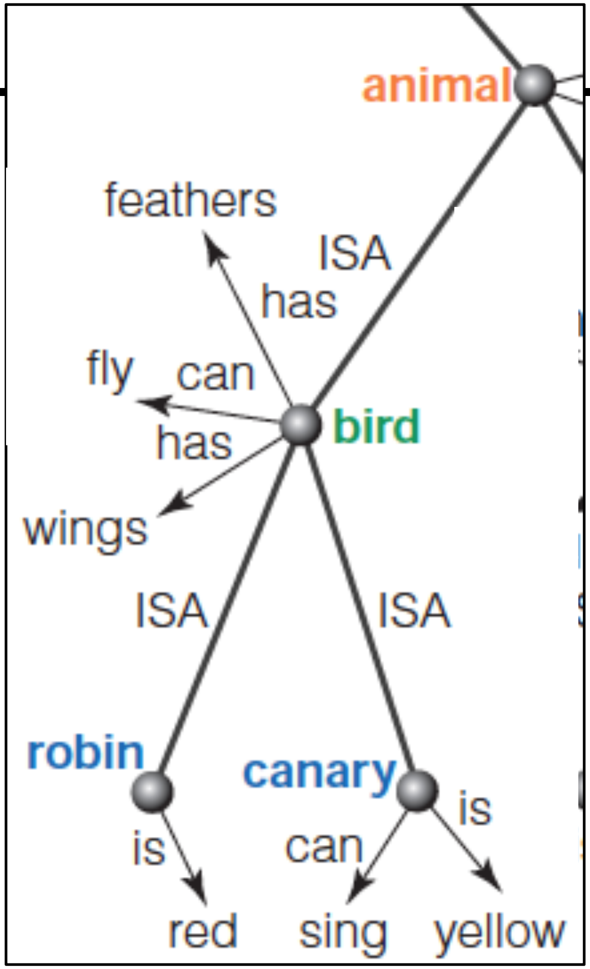
# Semantic Networks

- How are categories organized in the mind?
- Collins and Quillian (1969)
- Concepts are arranged in networks that represent the way concepts are organized in the mind



# Semantic Networks

- Collins and Quillian (1969)
- General principles of the model:
  - **Cognitive economy**: shared properties are only stored at higher-level nodes
  - Inheritance
    - Lower-level items share properties of higher-level items
  - Exceptions are stored at lower nodes



# Semantic Networks

- Collins and Quillian (1969)
- **Model of organization**
  - Does not need to be a physiological model
  - How concepts are *associated* in the mind
  - Testable predictions
    - Shorter connection = closer association and easier accessibility

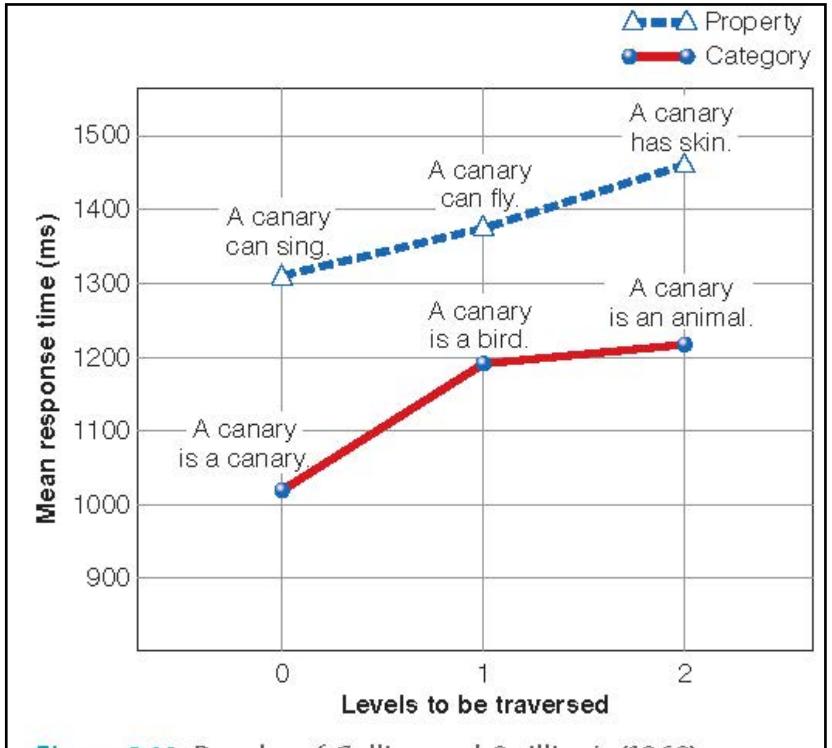
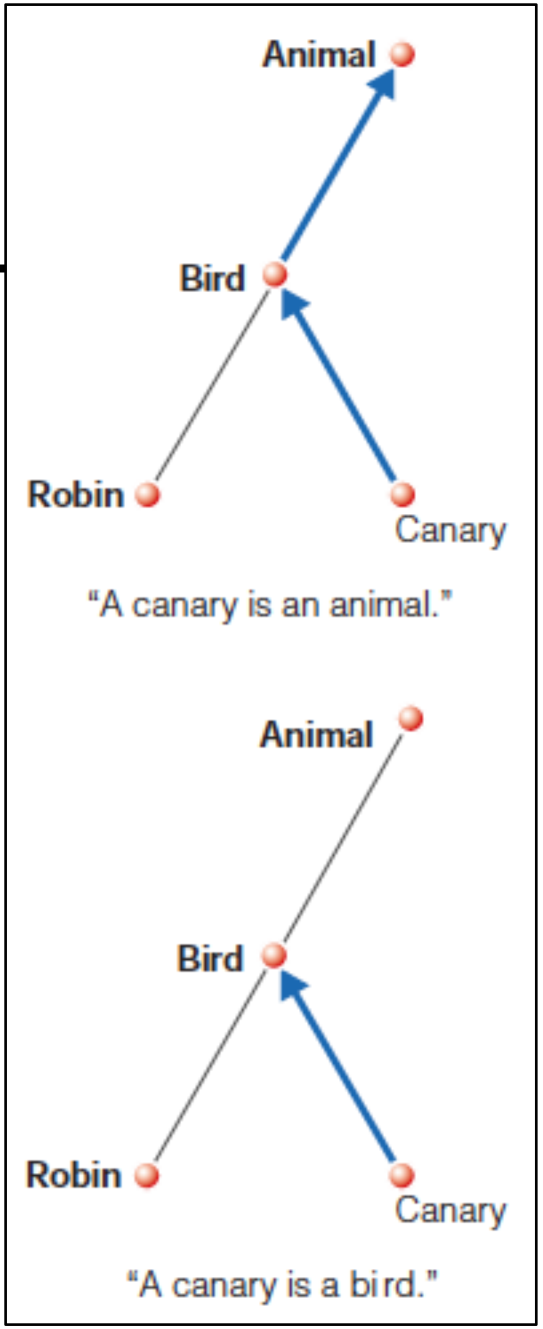


Figure 9.13 Results of Collins and Quillian's (1969)



# Semantic Networks

- Spreading activation
  - Activation is the arousal level of a node
  - When a node is activated, activity spreads out along all connected links
  - Concepts that receive activation are primed and more easily accessed from memory
- Common explanation for some false memory findings
  - Bed, pillow, snore, tired…
  - Did you see sleep?

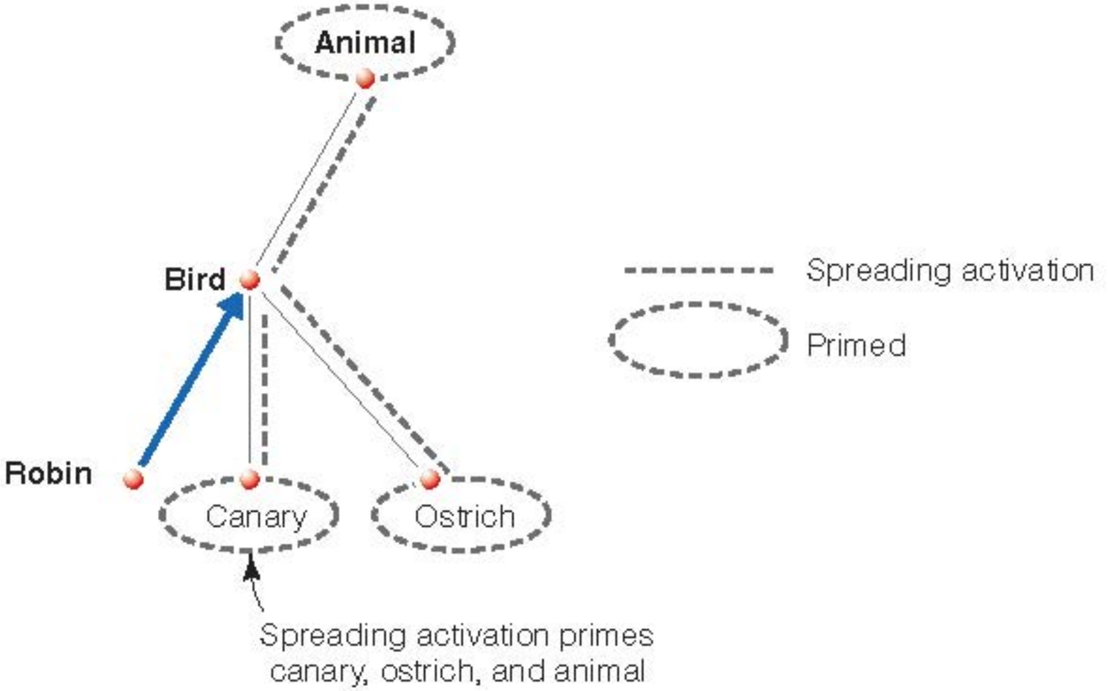



Figure 9.14 How activation can spread through a network as a person searches from "robin" to "bird" (blue arrow). The dashed lines indicate activation that is spreading from the activated bird node. Circled concepts, which have become primed, are easier to retrieve from memory because of the spreading activation. © Cengage Learning

# Semantic Networks

- Evidence for spreading activation
- Lexical decision task
  - Participants read stimuli and are asked to say as quickly as possible whether the item is a word or not
- Meyer and Schvaneveldt (1971)
  - "Yes" if both strings are words; "no" if not
  - Some pairs were closely associated
  - Reaction time was faster for those pairs
    - Spreading activation

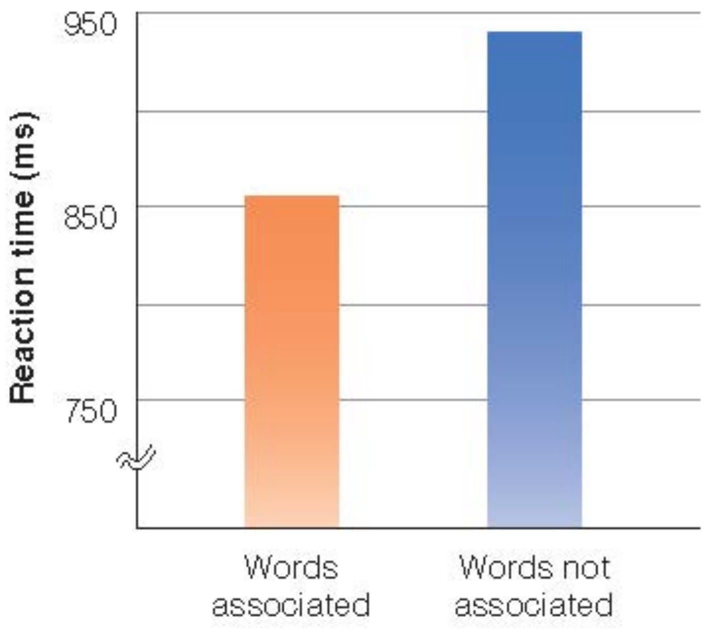



Figure 9.15 Results of Meyer and Schvaneveldt's (1971) experiment. Participants responded faster for words that were more closely associated (left bar). © Cengage Learning

# Semantic Networks

- Criticism of Collins and Quillian
  - Cannot explain typicality effects
  - Cognitive economy?
  - Some sentence-verification results are problematic for the model
- Updated Model (Loftus & Collins)
  - Distance between nodes is experience-dependent
  - However… so flexible that it becomes unfalsifiable

# The Connectionist Approach

- Creating computer models for representing concepts based on characteristics of the brain
- Also called **Parallel distributed processing (PDP)** models
  - because.. Knowledge represented in the distributed activity of many units
  - Similarly, “neural network models”

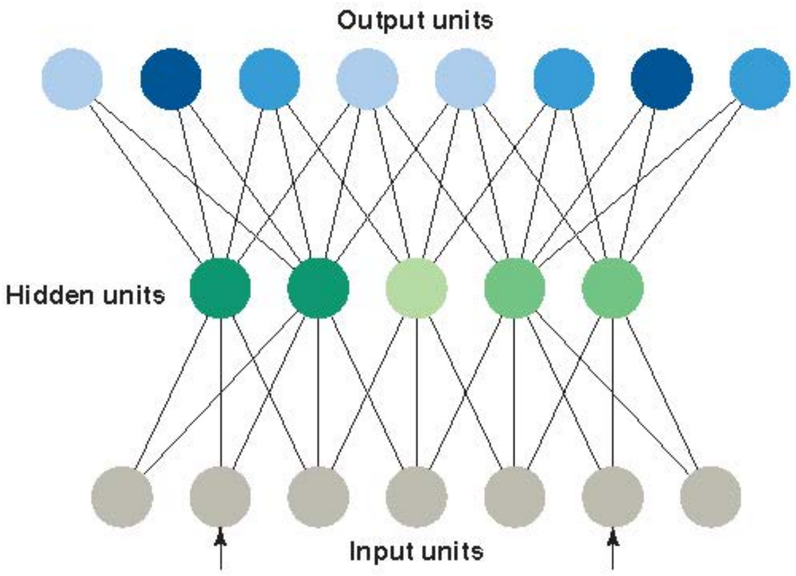
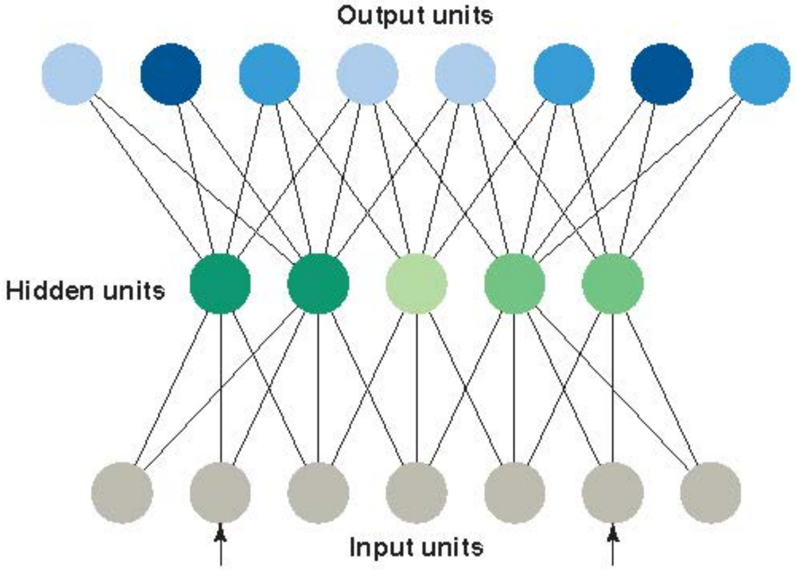



Figure 9.17 A parallel distributed processing (PDP) network showing input units, hidden units, and output units. Incoming stimuli, indicated by the arrows, activate the input units, and signals travel through the network, activating the hidden and output units. Activity of units is indicated by shading, with darker shading indicating more activity. The patterns of activity that occur in the hidden and output units are determined both by the initial activity of the input units and by the connection weights that determine how strongly a unit will be activated by incoming activity. Connection weights are not shown in this figure. © Cengage Learning

# The Connectionist Approach

- Weights determine at each connection how strongly an incoming signal will activate the next unit

- "Units"
  - Input units: activated by stimulation from environment
  - Hidden units: receive input from input units
  - Output units: receive input from hidden units

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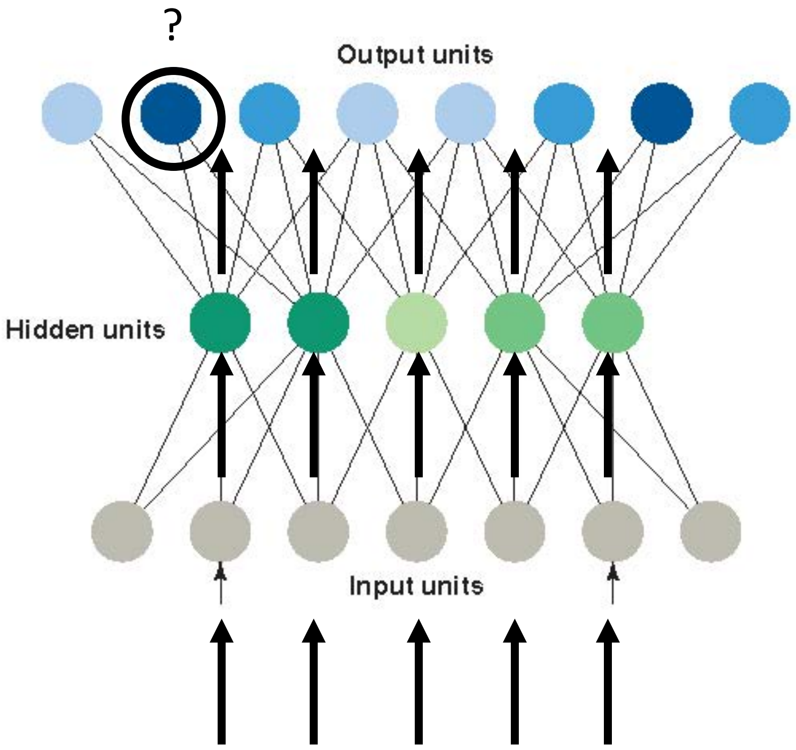
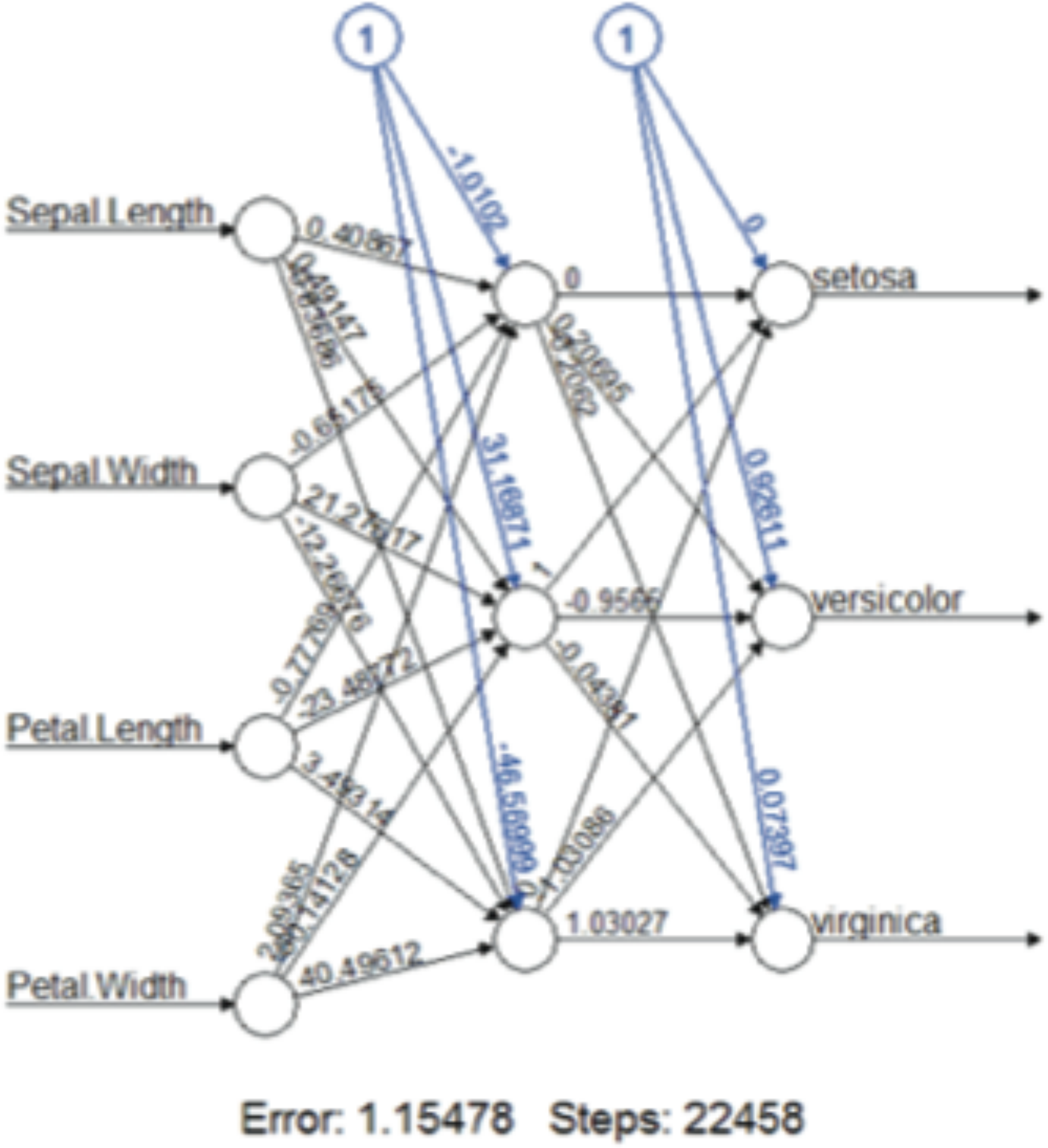
# The Connectionist Approach

- The computational model can learn with training!
  1. Network responds to stimulus
  2. Provided with correct response
     - **Error signal**
       - Difference between actual activity of each output unit and the correct activity
  3. Modifies responding to match correct response
     - **Back-propagation**
       - error signal transmitted back through the circuit
       - Indicates how weights should be changed to allow the output signal to match the correct signal
  4. The process repeats until the error signal is zero



- This model has learned to categorize species of flower based on inputs:
  - Sepal length, sepal width, petal length, petal width



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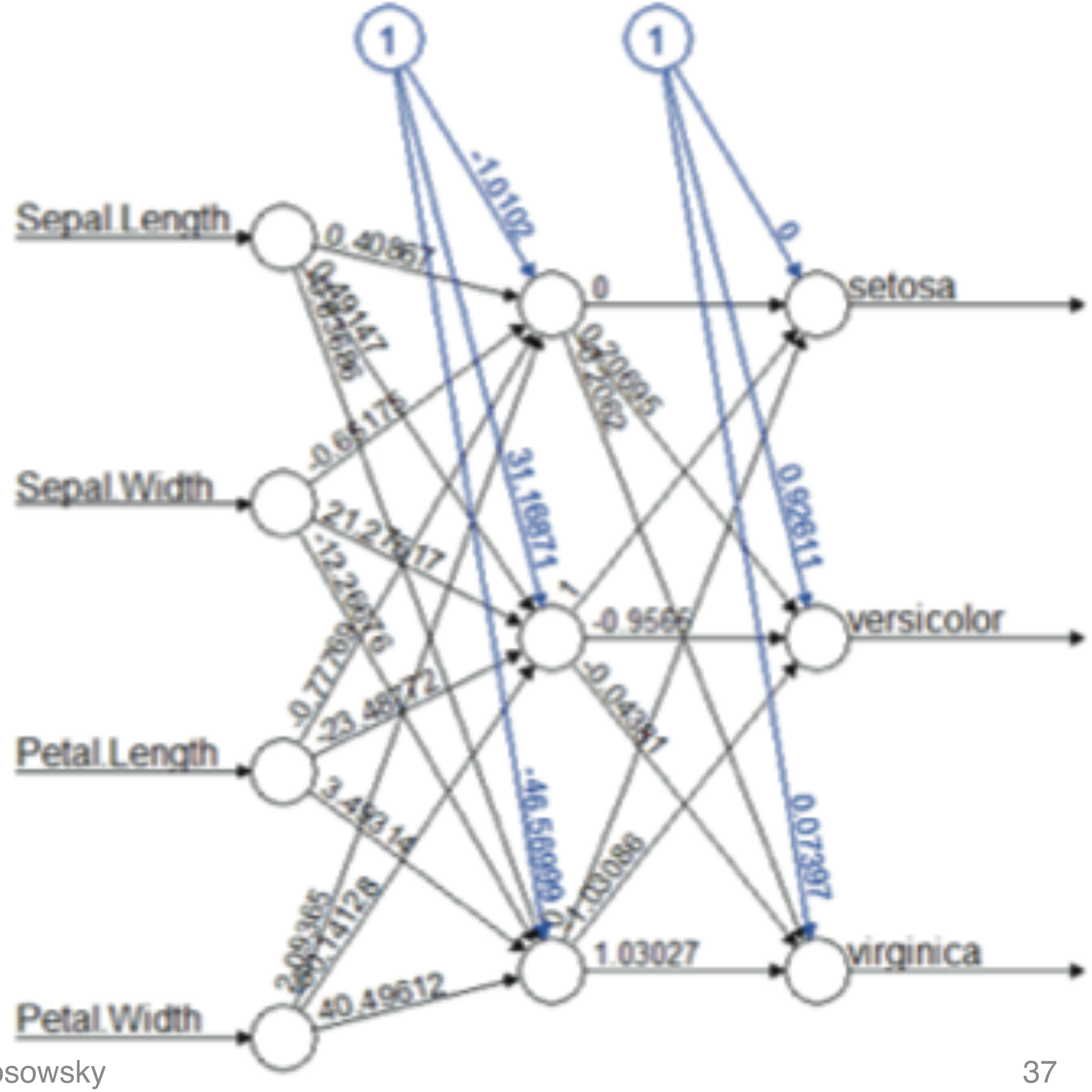
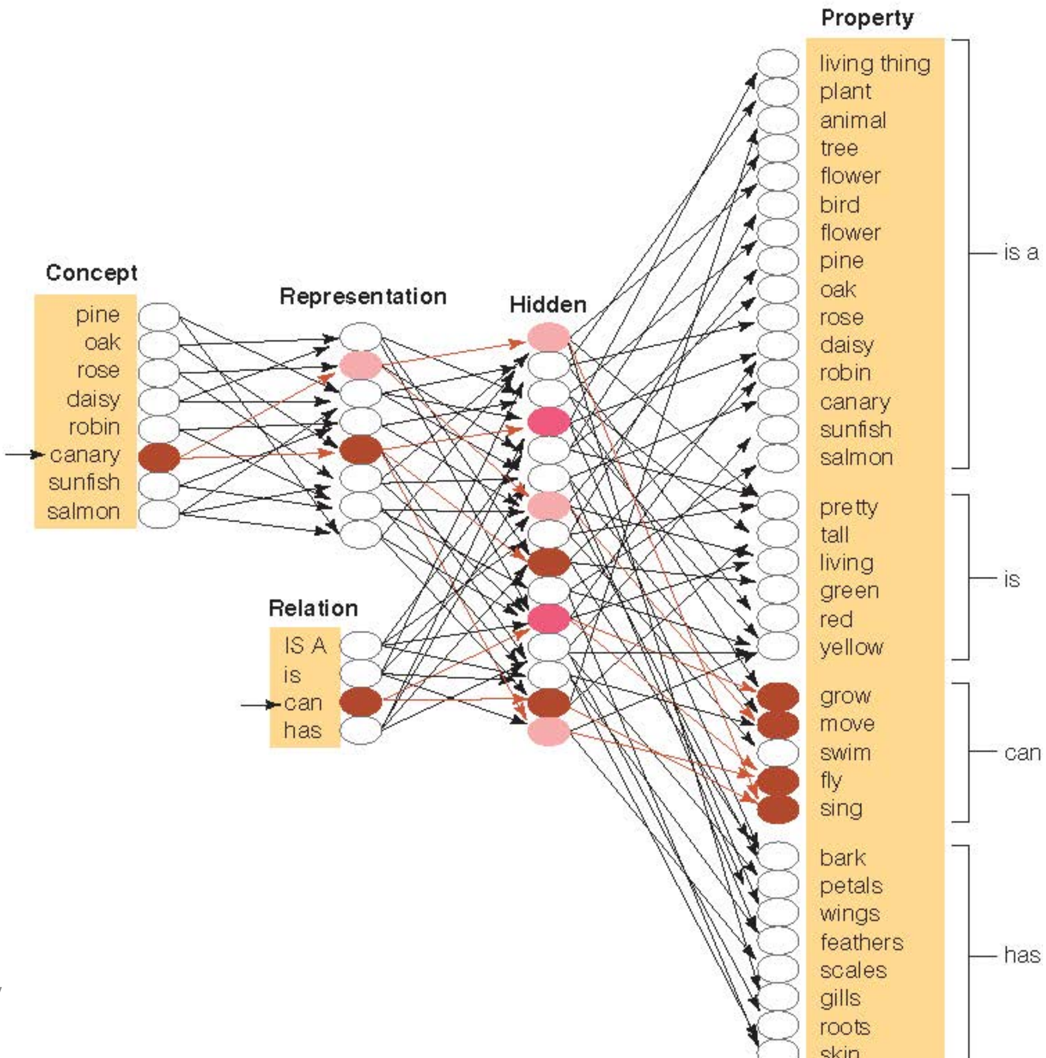


# The Connectionist Approach

- Concepts are represented by the distribution of activity needed to accurately respond
  - This is automatically determined by the computational model and its training



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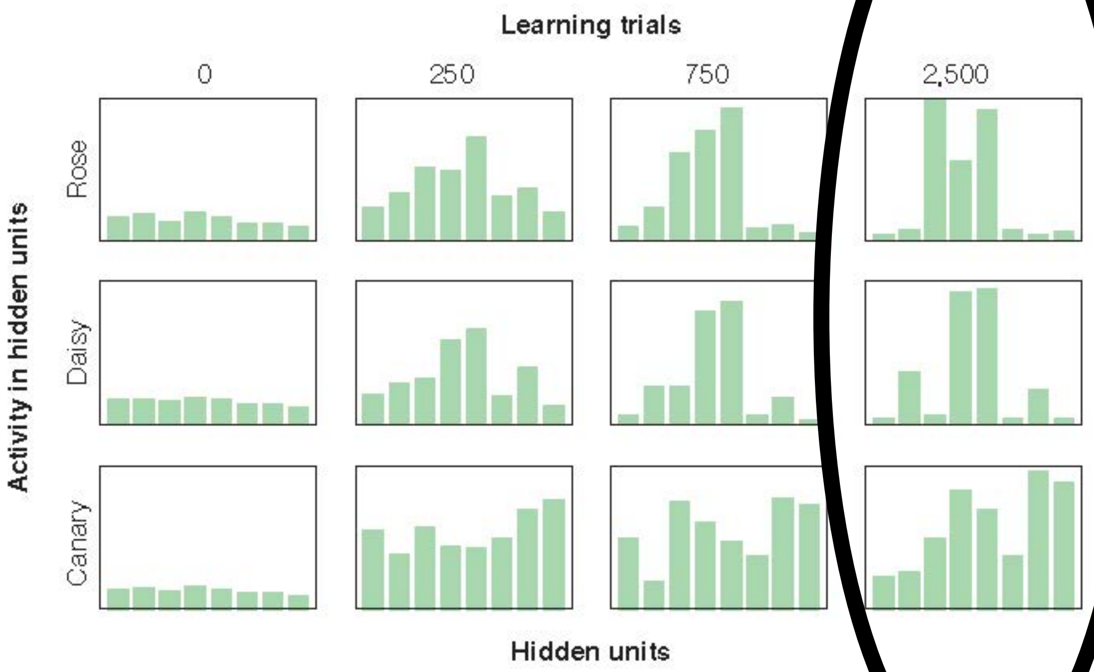


Figure 9.19 Learning in a connectionist network. Bars represent activity in the eight representation units. Notice how the pattern of activation changes as learning progresses. *(Source: Adapted from J. L. McClelland & T. T. Rogers, The parallel-distributed processing approach to semantic cognition,* Nature Reviews Neuroscience, 4, *310–320, 2003.)*

# The Connectionist Approach

- These models can simulate normal cognitive functioning
  - Language, memory, perception
- Biological plausibility
  - Models resemble our physiology
- Other evidence:
  - **Graceful degradation**: disruption of performance occurs gradually as parts of the system are damaged
  - **Generalization of learning:** Slow learning process that creates a network capable of handling a wide range of inputs
    - Learning can be generalized