Categories and Concepts

Computational models and the knowledge view

Brenden Lake

PSYCH-GA 2207

Review: Whatever is selecting the features is doing the explanatory work

Flammable? ✓

Flammable? ✓

"Flammable" applies to many things, but we only associate it strongly to some things due to its *theoretical role* (Murphy & Medin, 1985)

Review: Concepts are more than characteristic features or sets of examples

Would you classify this man as “drunk”? (Murphy & Medin)

What characteristic feature tells you this? Would you need a similar previous example in order to tell you this?

Review: Ad hoc categories (Barsalou, 1983)

- e.g., “Things to carry out of a burning house”
  - [children, dog, photo albums, computer, etc.]

- “ways to escape being killed by the Mafia”
  - [changing your name, move to Montana, etc.]

- “things that could fall on your head"
- “things to take on a camping trip”
- “possible costumes to wear to a Halloween party”
- “places to look for an antique desk”

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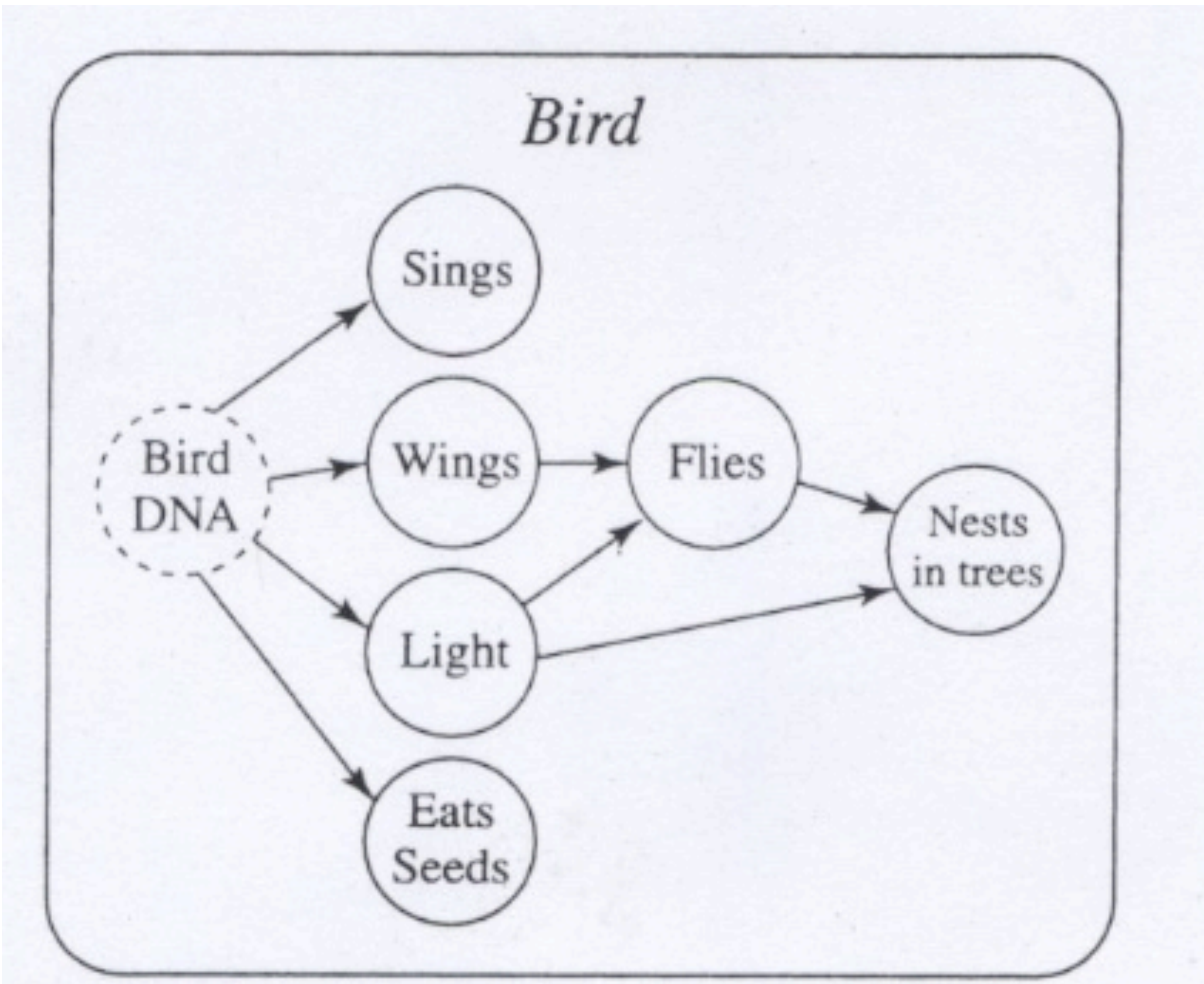
Essentialism as a Generative Theory of Classification

Bob Rehder

It is obvious that we classify the objects we encounter by their appearance, that is, by the particular features, aspects, or characteristics that they display. But, after a moment's reflection, it becomes clear that appearance is sometimes not all there is to it, that there are other factors not available to immediate inspection that might contribute to an object's identity. A study of Rips's (1989) work serves to illustrate. College students were told a story about a bird that had normal birdlike features (wings, ate seeds, lived in a nest in a tree, etc.) and was exposed to hazardous chemicals. As a result, the bird began to take on properties more characteristic of an insect: The wings with feathers were replaced with wings made of a transparent membrane; the nest was abandoned in favor of living on the underside of tree leaves; it developed a brittle iridescent outer shell; and so on. When asked whether the animal was now a bird or an insect, most students judged that it was still a bird. The important point to note is that they made this decision despite the fact that the animal no longer looked like a bird at all; apparently, there is something more to category membership than just how an object appears. In fact, there is evidence that even children as young as 3 years old believe that the "insides" of objects are relevant in determining its class membership (Gelman & Wellman, 1991; also see Gelman, 2003; Keil, 1989).

The idea that different aspects or characteristics of objects might have different implications for category membership is not (to say the least) new. In philosophy, it dates at least as far back as Aristotle, who distinguished between an entity's *essential properties* (which define what something is) from its *accidental properties* (which determine how it is, that is, which properties just happen to inhere in it). The idea that essential properties might be inaccessible to perception has an equally impressive legacy. Even as central a British empiricist as John Locke distinguished *real essences* (what an object really is, which, according to the Locke, was unknowable in principle) from *nominal essences*, which could be perceived and which formed the basis for everyday categorization.

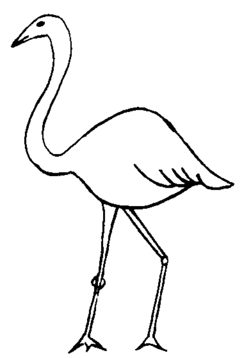
Rehder's causal-model theory of categorization



- Concepts are more than a collection of features
- Concepts can have essential features, and use causal relations to hold features together in a coherent explanation
- "Categorization as a case of causal reasoning, in which properties like weight, body` size, singing etc. provide inferential support for [defining] properties like DNA" (Rehder)
- Examples are judged by how well they fit our causal model of categories

Essentialism in categorization and category-based induction (Gelman & Markman, 1986)

Provided

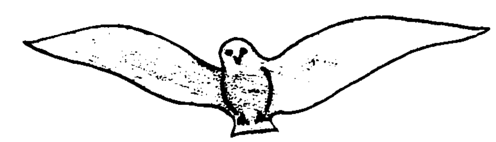


“This bird’s heart has a right aortic arch only”

“This bat’s heart has a left aortic arch only”

Query

“What does this bird’s heart have?”



Results: 4 year olds generalize based on category membership ~68% of time, overriding a distractor chosen for strong perceptual similarity

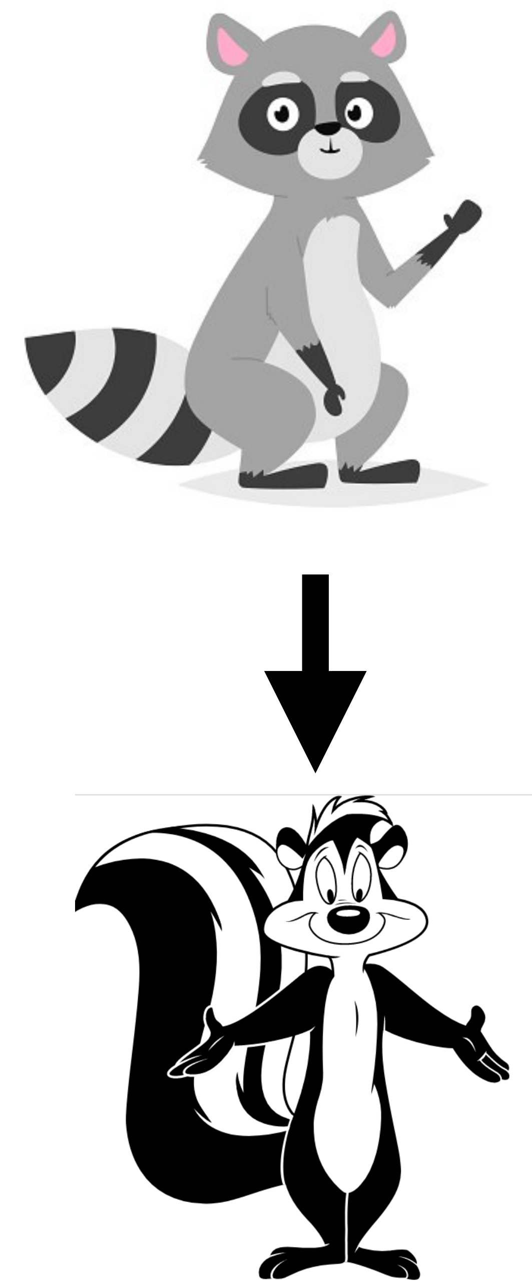
Keil's (1989) transformation study of essentialism

Participants were kids in grades K, 2, and 4 (ages approx. 5, 7, and 10 years old)

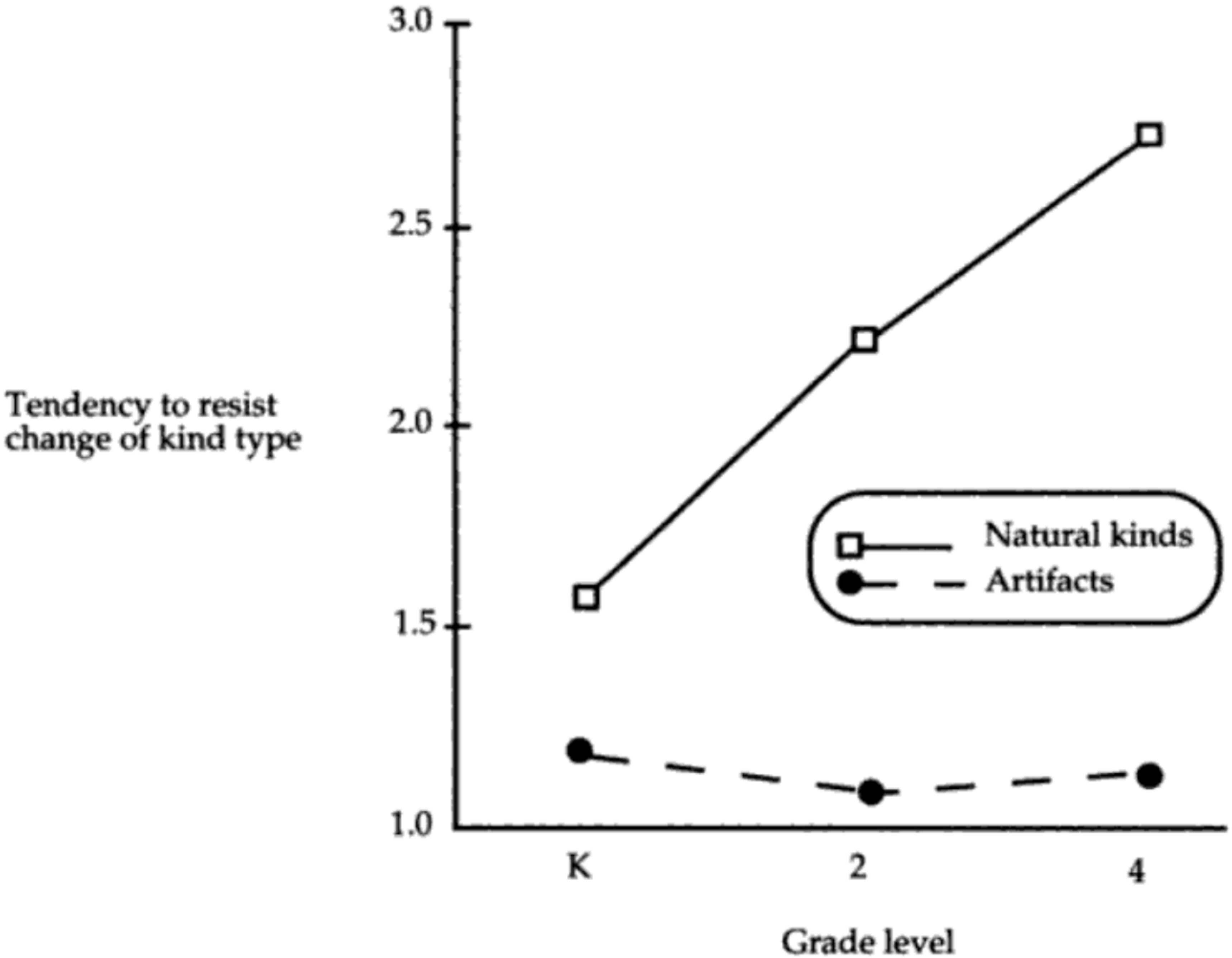
Examples of two descriptions used in the first transformations study

Natural kind: Raccoon/skunk
The doctors took a raccoon (show picture of raccoon) and shaved away some of its fur. They dyed what was left all black. Then they bleached a single stripe all white down the center of its back. Then, with surgery (explained to child in preamble), they put in its body a sac of super smelly odor, just like a skunk has (with younger children "odor" was replaced with "super smelly yucky stuff"). When they were all done, the animal looked like this (show picture of skunk). After the operation was this a skunk or a raccoon? (Both pictures were present at the time of the final question.)

Artifact: Coffeepot/birdfeeder
The doctors took a coffeepot that looked like this (show picture of coffeepot). They sawed off the handle, sealed the top, took off the top knob, sealed closed the spout, and sawed it off. They also sawed off the base and attached a flat piece of metal. They attached a little stick, cut a window in it, and filled the metal container with birdfood. When they were done, it looked like this (show picture of birdfeeder). After the operation was this a coffeepot or a birdfeeder? (Both pictures were present at the time of the final question.)



Keil's (1989) transformation study of essentialism



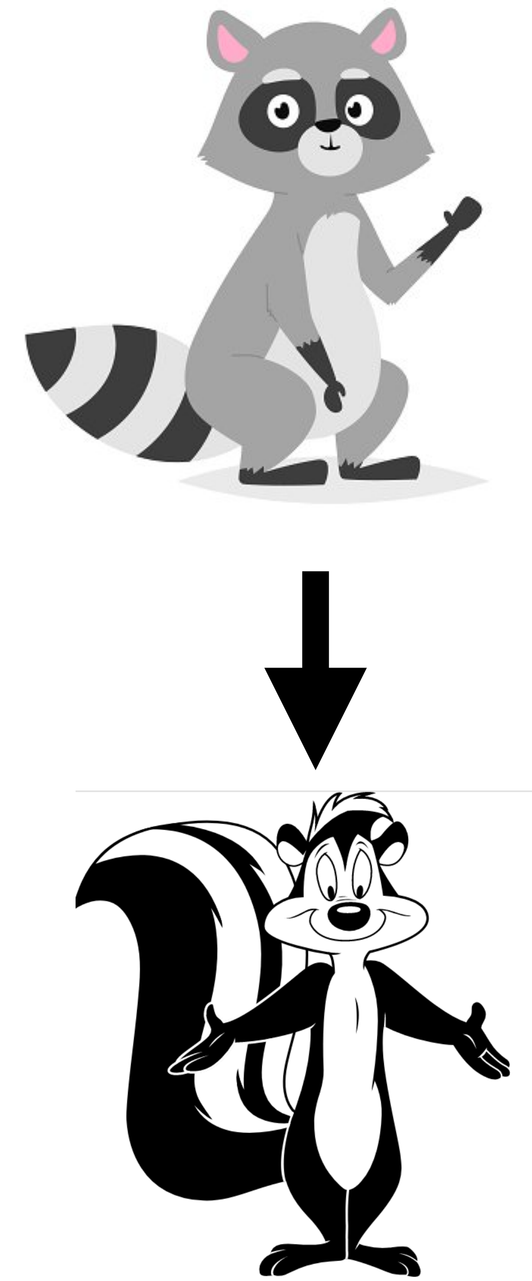
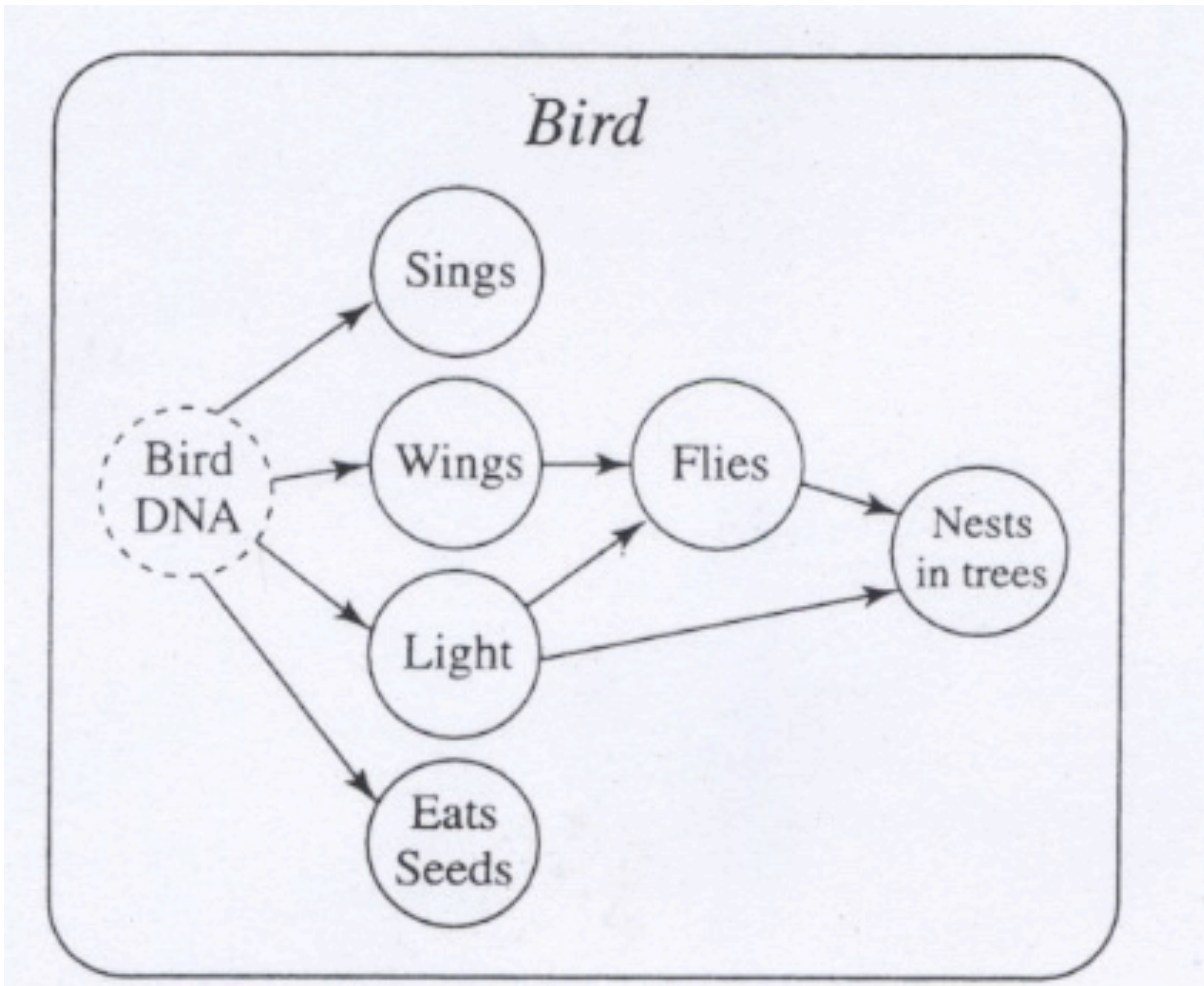


Figure 9.1
Mean scores for natural kind and artifact terms in the first transformations study. 1 = judgment that operation changed kind type, 2 = judgment indicating indecision as to whether operation changed kind type, 3 = judgment that operation did not change kind type.

Essentialized categories as causal models with essential features and surface features



Artificial categorization task

(Rehder (2003), JEP:LMC)

Task: Learn and make predictions about a new category, e.g., “Lake Victoria Shrimp”

Four binary features

F_1: High amounts of ACh neurotransmitter.

F_2: Long-lasting flight response.

F_3: Accelerated sleep cycle.

F_4: High body weight.

Base rate information: 75% of Lake Victoria Shrimp have each feature, e.g., 75% have feature F_4

Artificial categorization task

participants assigned to one of two conditions

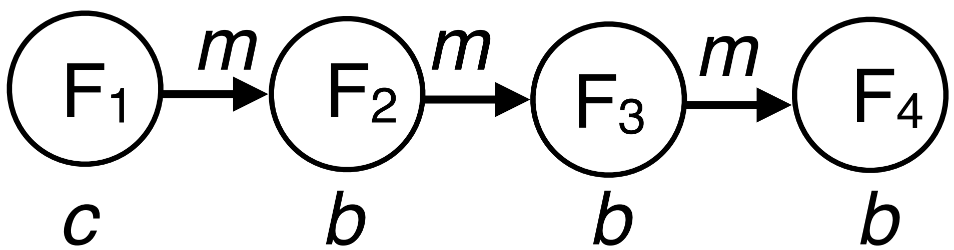
F_1: High amounts of ACh neurotransmitter.

F_2: Long-lasting flight response.

F_3: Accelerated sleep cycle.

F_4: High body weight.

chain (causal framing) condition



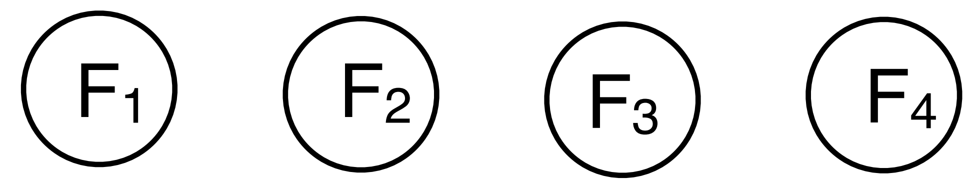
free parameters *c, b* (background mechanism) and *m* (causal strength)

$F_1 \rightarrow F_2$ A high quantity of the ACh neurotransmitter causes a long-lasting flight response. The duration of the electrical signal to the muscles is longer because of the excess amount of neurotransmitter.

$F_2 \rightarrow F_3$ A long-lasting flight response causes an accelerated sleep cycle. The long-lasting flight response causes the muscles to be fatigued, and this fatigue triggers the shrimp's sleep center.

$F_3 \rightarrow F_4$ An accelerated sleep cycle causes a high body weight. Shrimp habitually feed after waking, and shrimp on an accelerated sleep cycle wake three times a day instead of once.

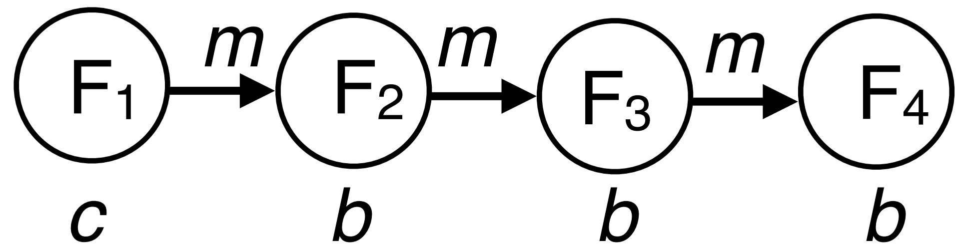
control condition (no causal framing)



exactly the same instructions, but without causal information between features

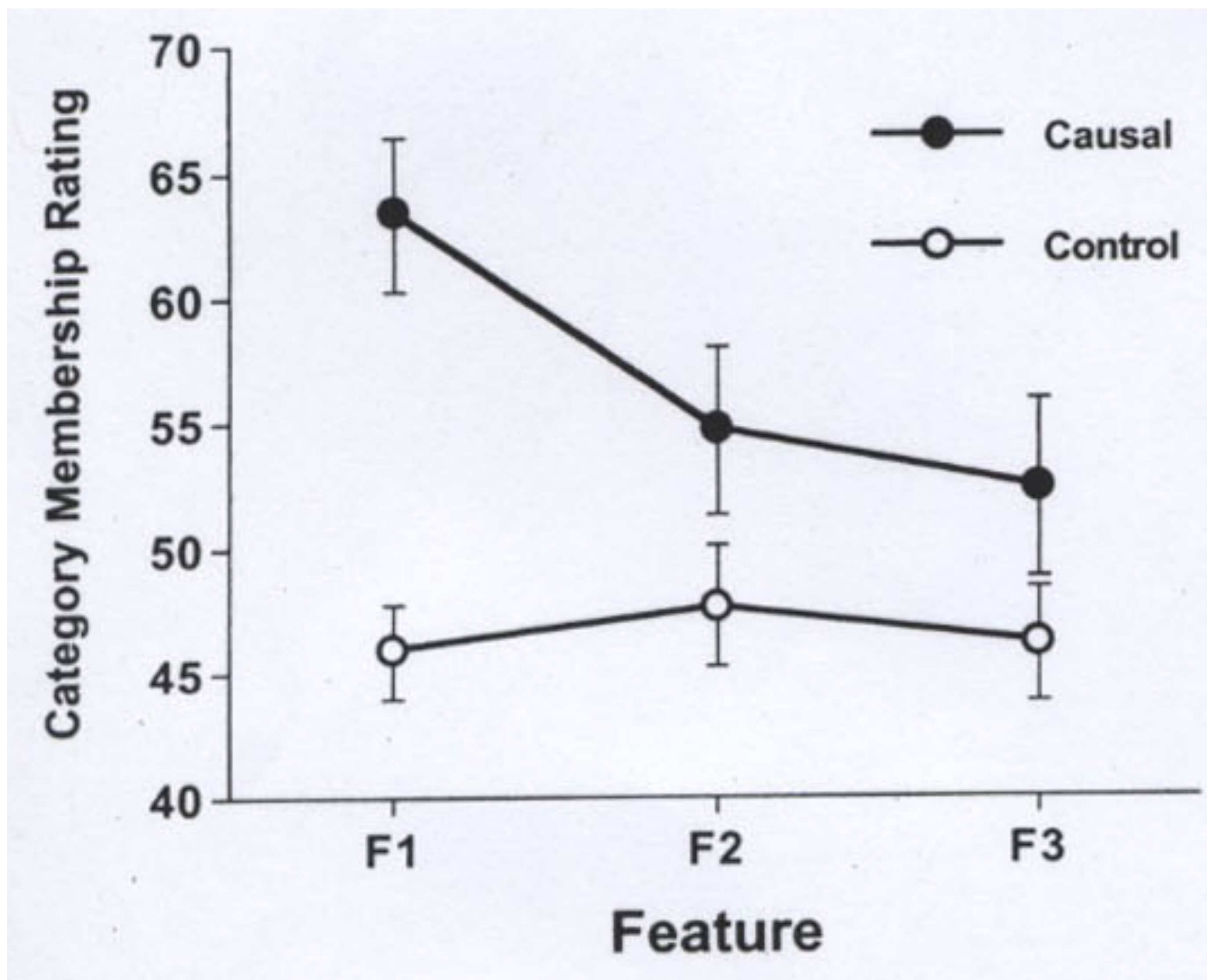
Artificial categorization task: Results

Task: Rate the category membership (0-100) of an example with one of the observable feature: “This shrimp has a long-lasting flight response — is it a Lake Victoria Shrimp?”



Result: Features earlier in the chain lead to better category members

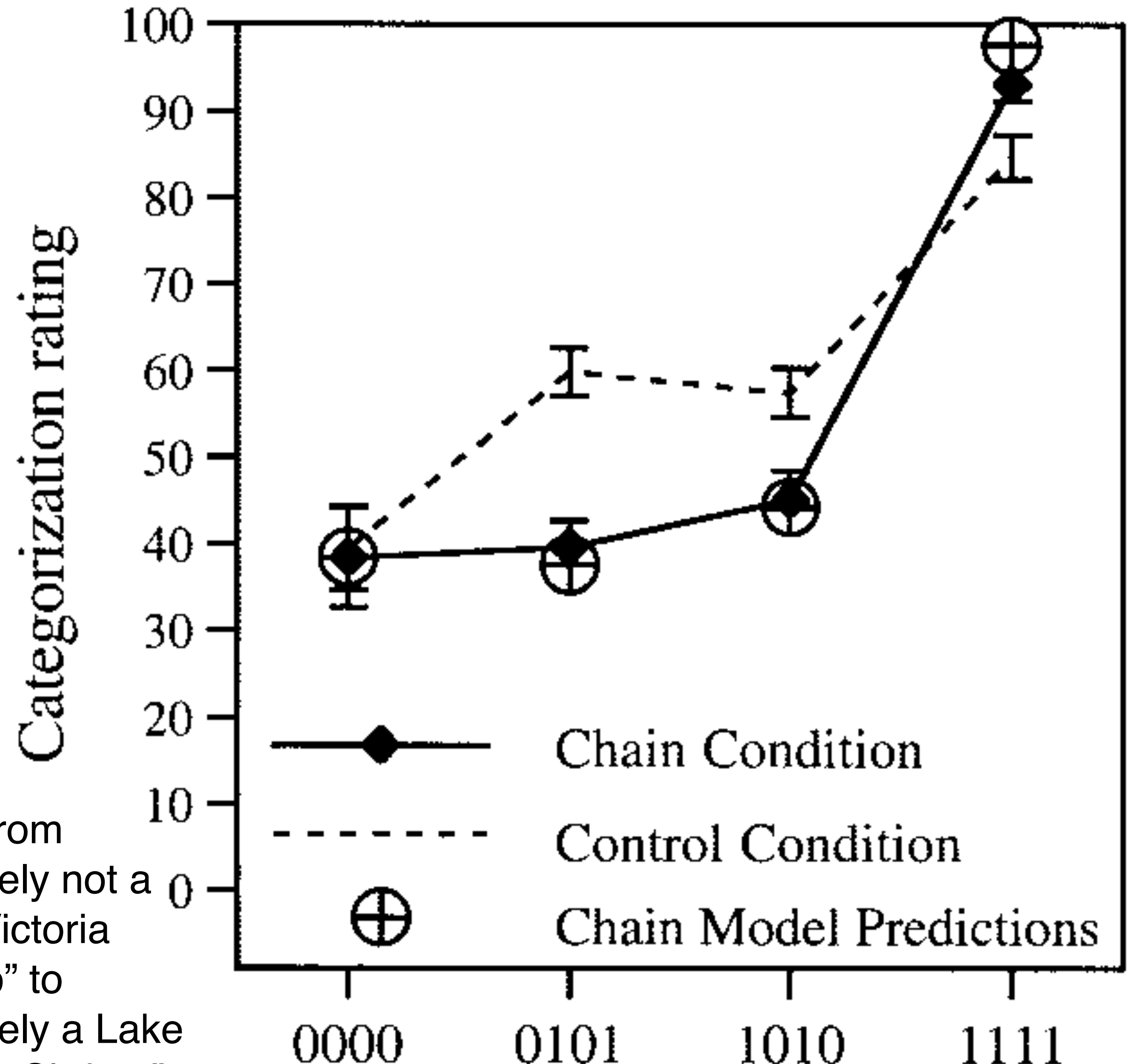
scale from “definitely not a Lake Victoria Shrimp” to “definitely a Lake Victoria Shrimp”



Similar experiment from Rehder (2003), JEP:LMC

Task: How likely is this example to be a Lake Victoria Shrimp?

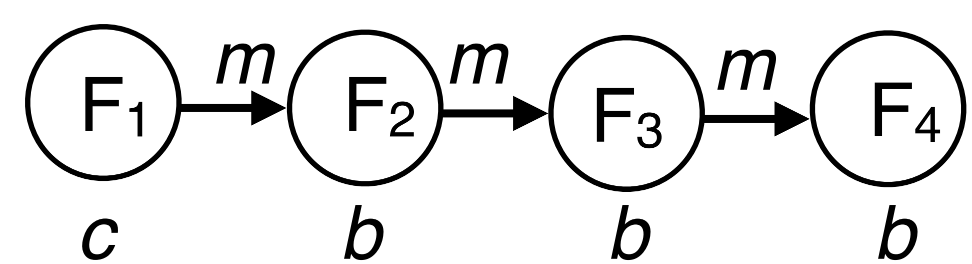
Conclusion: Causal/structural information influences people's categorization decisions, in a way predicted by a causal chain model.



scale from "definitely not a Lake Victoria Shrimp" to "definitely a Lake Victoria Shrimp"

new object for category judgment

(0101 means both F_2 and F_4 are present, and the others absent)

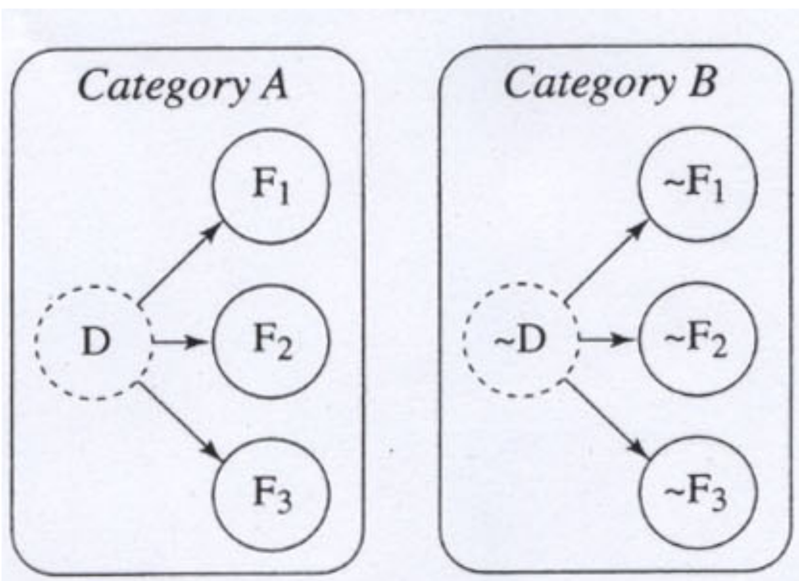


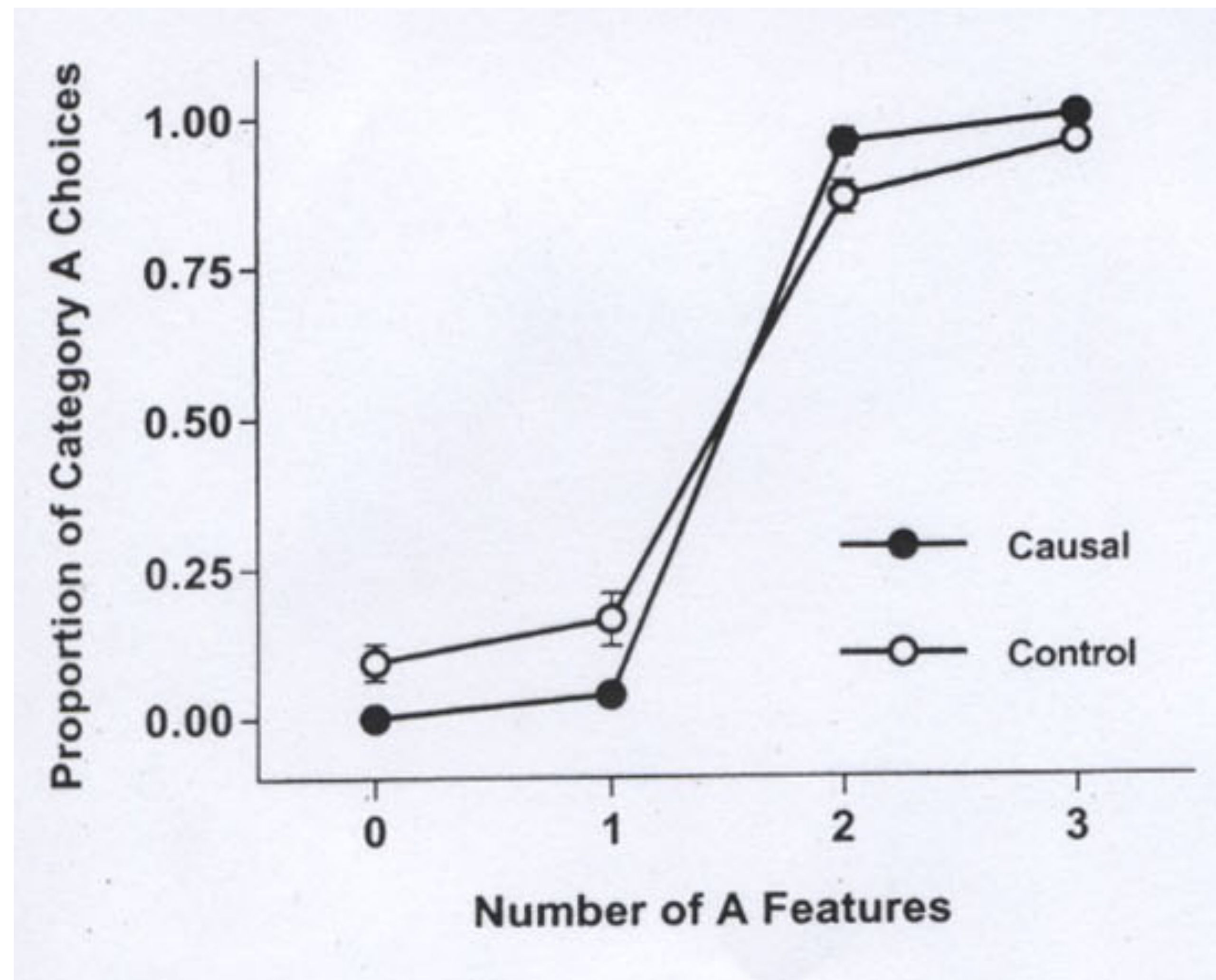
Causal structure predicts boundary intensification

Task: How likely is this example to be a Lake Victoria Shrimp?

Conclusion: Causal condition shows boundary intensification, consistent with the computational model that predicts stronger correlation between features

Causal condition



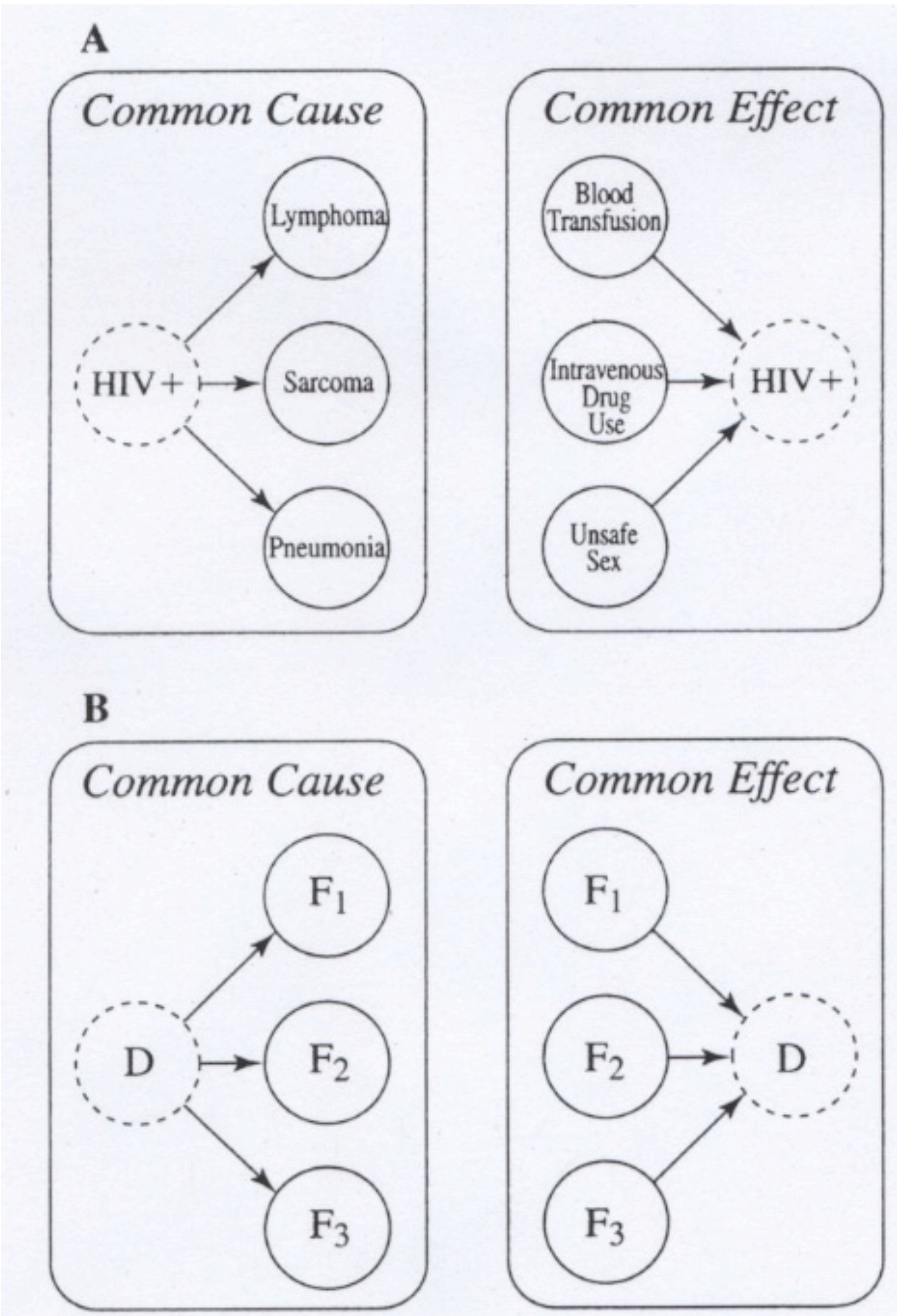


Control condition:

Same features but with no causal connections

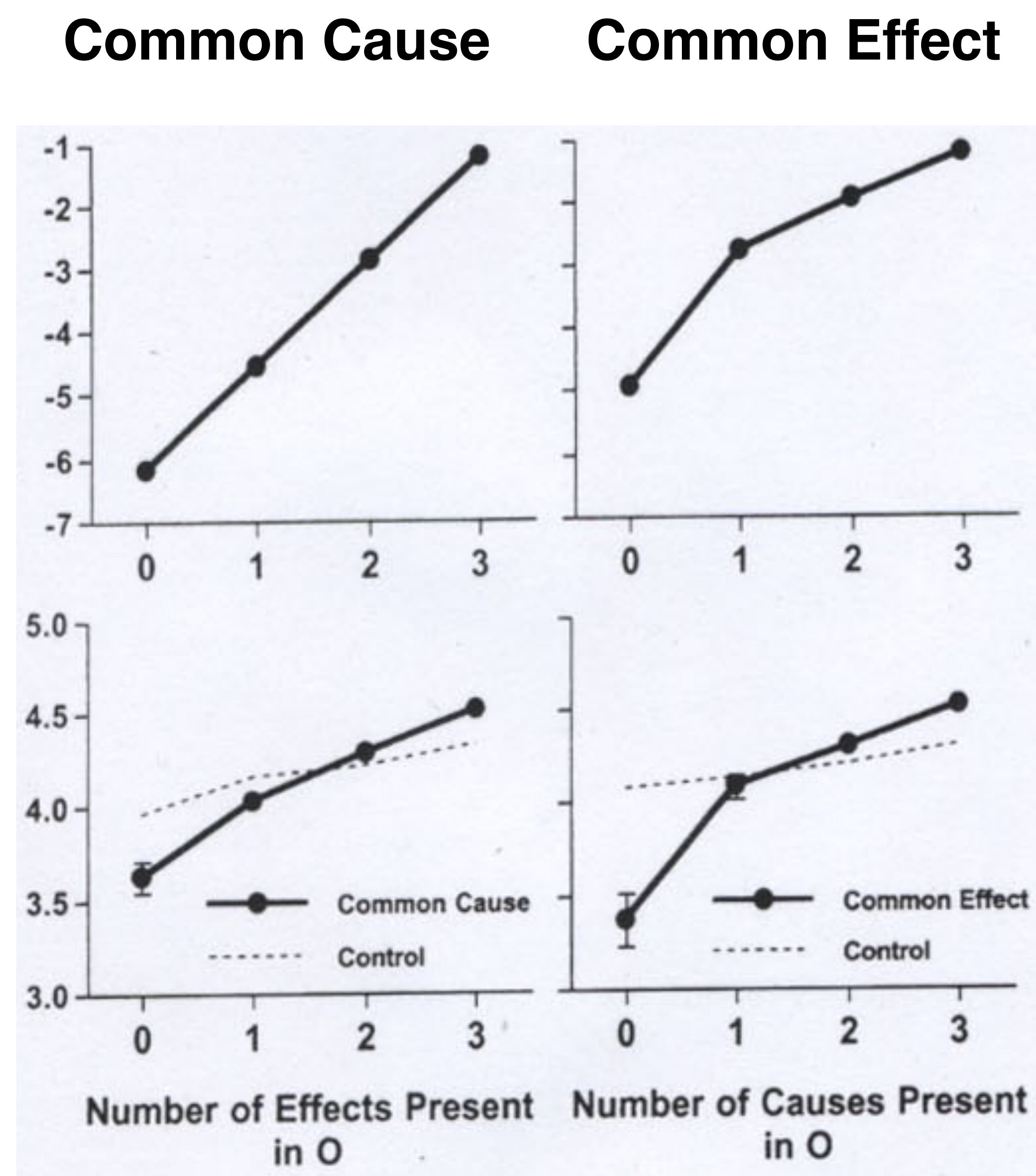
Causal structure matters in categorization judgments

Task: How likely is this example to be HIV+?



Model's categorization ratings (log-scale)

People's categorization ratings (log-scale)



Accounting for a perceptual to essentialized shift

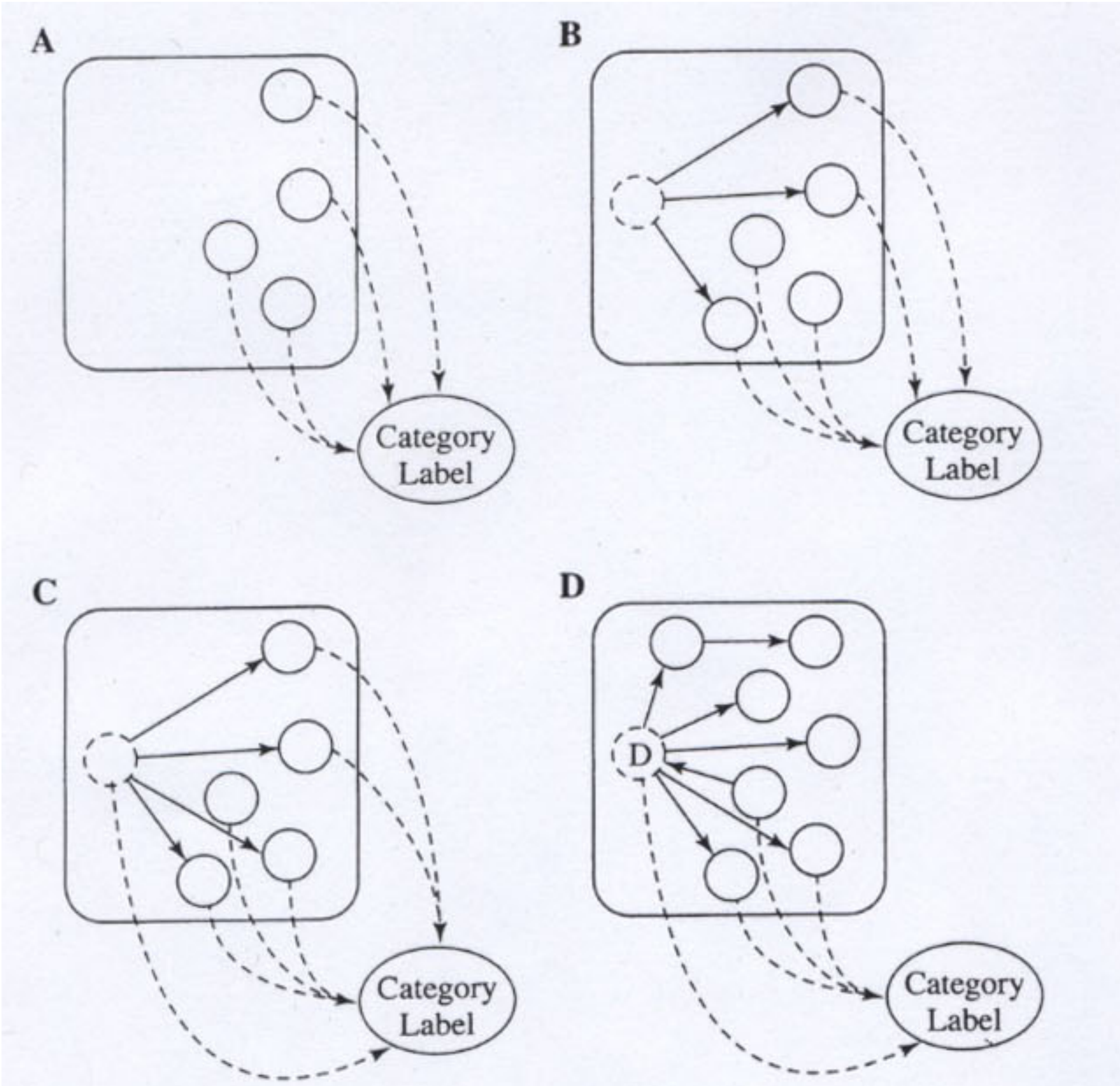


FIGURE 12-11 An evolving set of causal models.

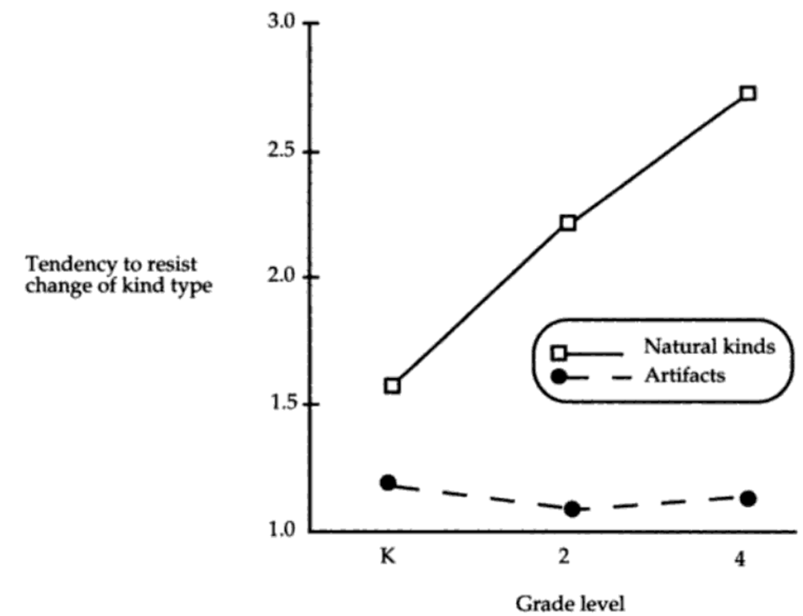


Figure 9.1
Mean scores for natural kind and artifact terms in the first transformations study. 1 = judgment that operation changed kind type, 2 = judgment indicating indecision as to whether operation changed kind type, 3 = judgment that operation did not change kind type.

Review: Murphy & Allopenna (1994). JEP:LMC

Prototypes of Two Categories: Knowledge Condition

Category 1
- Made in Africa
- Lightly insulated
- Green
- Drives in jungles
- Has wheels

Category 2
- Made in Norway
- Heavily insulated
- White
- Drives on glaciers
- Has treads

(pictures not shown in experiment)

(Plus some nonpredictive features)

Prototypes of Two Categories: Neutral Condition

Category 1
- Green
- Manual
- Radial tires
- Air bags
- Vinyl seat covers

Category 2
- White
- Automatic
- Non-radial tires
- Automatic seat belts
- Cloth seat covers

Review: Murphy & Allopenna (1994)

Results:

- Knowledge condition: learned in 2.2 blocks
- Neutral condition: learned in 4.1 blocks

- It's easy to learn categories that build a coherent model of the object

KNOWLEDGE SELECTION IN CATEGORY LEARNING

Evan Heit
Lewis Bott

I. Introduction

In our ordinary experience, we make countless observations every hour, with no observation perfectly resembling a previous case. We face a daily parade of unique events. Every time we walk into a building, for example, the building is unlike any other building in many ways. Even one particular building itself would be constantly undergoing various small changes. It has been suggested that to make better use of past experiences and simplify the processing that would be required for so many unique events, we learn about equivalence classes or categories of observations (e.g., Markman, 1989). For example, rather than treating every built architectural structure as being a unique construction, we form equivalence classes such as houses, office buildings, libraries, theaters, and pubs. These classes would facilitate many activities such as reasoning and communication. For example, just knowing that some building is a house would help to make predictions about its organization and layout, as well as help describe it to someone else. Categories allow us to greatly reduce the number of separate items we need to consider.

Although at first glance, categorization would seem to simplify our lives, it has been pointed out that category formation itself entails further complexities. Medin and Ross (1997) noted that just 10 objects can be parti-

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Experiment 1: Murphy & Allopenna follow-up

- Task is to learn "Doe buildings" vs. "Lee buildings"
  - corresponds to church-like vs. office-like
- Training was 5 blocks of 4 examples per building, and task was to memorize examples
- Had both "critical" (knowledge based) and "filler" (arbitrary) features, and not all features were trained
- Evaluation: participants made feature association judgments after every block

CRITICAL AND FILLER FEATURES FOR BUILDING STIMULI

Critical features	
Has steeply angled roof	church-like
Has wooden furniture	
Has an interesting structure	
Old building	
Quiet building	
Lit by candles	
Ornately decorated	
Built with stone	
Has a flat roof	office-like
Has metal furniture	
Has a repetitive structure	
New building	
Busy building	
Lit by fluorescent light	
Blandly decorated	
Built with metal and concrete	
Sample filler features	
Near a bus station	
Designed by a local architect	
Has gas central heating	
Not near a bus station	
Designed by an international architect	
Has electric central heating	

Experiment 1: Results

Task: Categorization of individual features as “Doe” vs. “Lee” buildings, after attempting to memorize the category examples

Conclusion: knowledge-based features are learned better, and knowledge interacts with learning throughout the entire learning process

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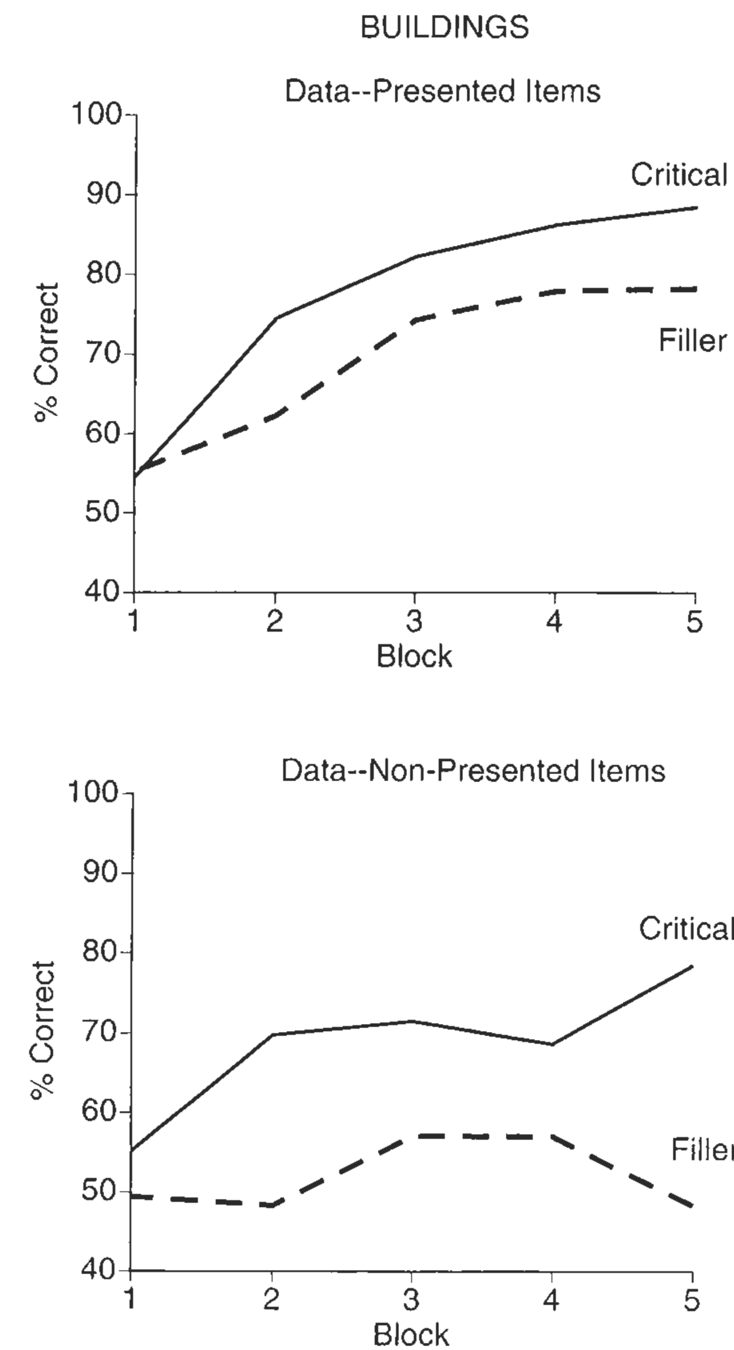
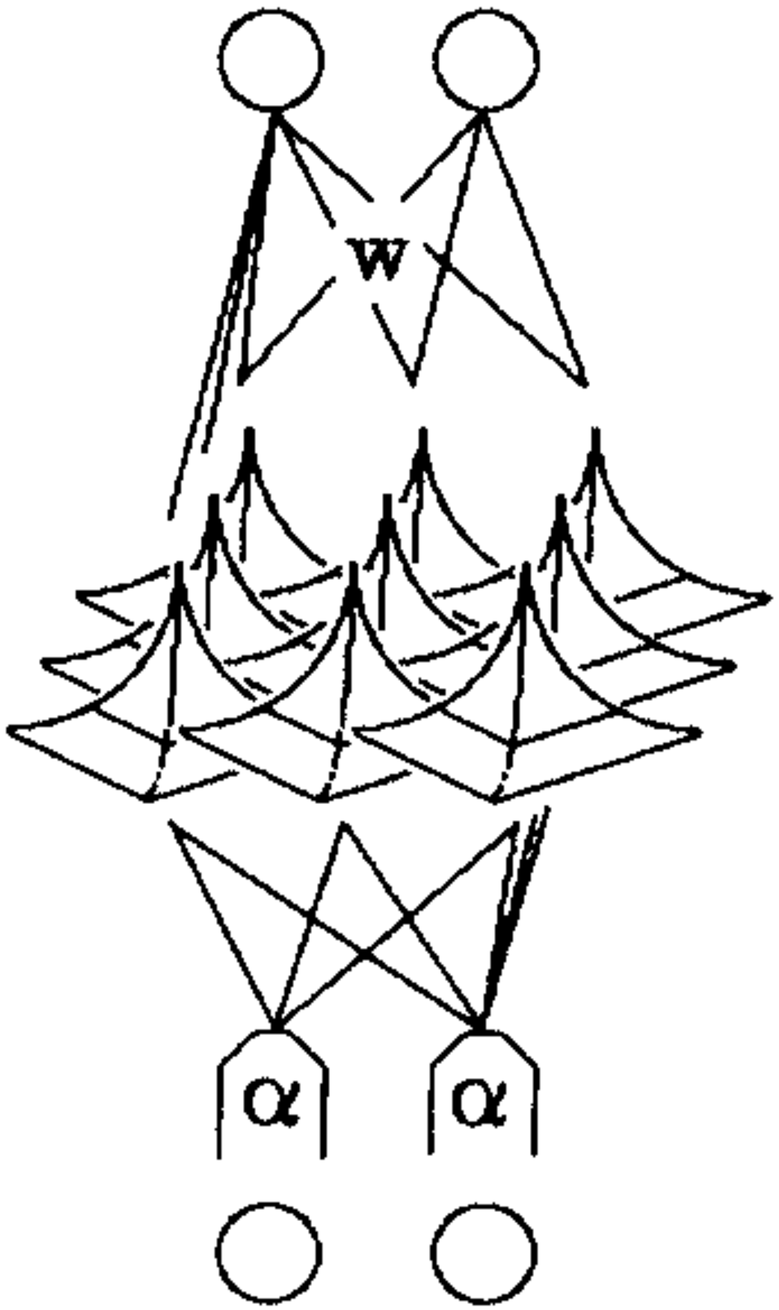


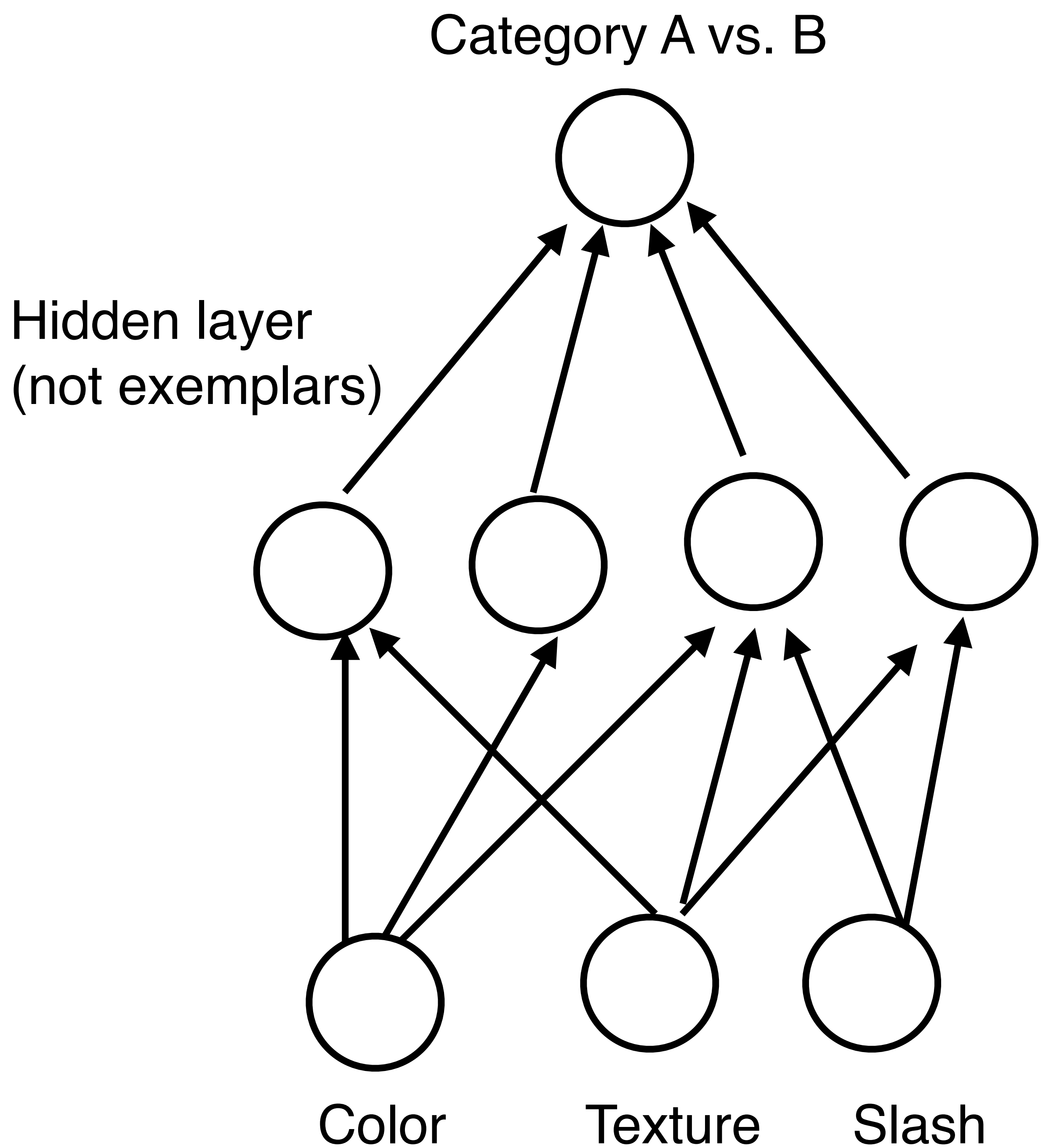
Fig. 6. Results for Experiment 1.

Neural network models of classification

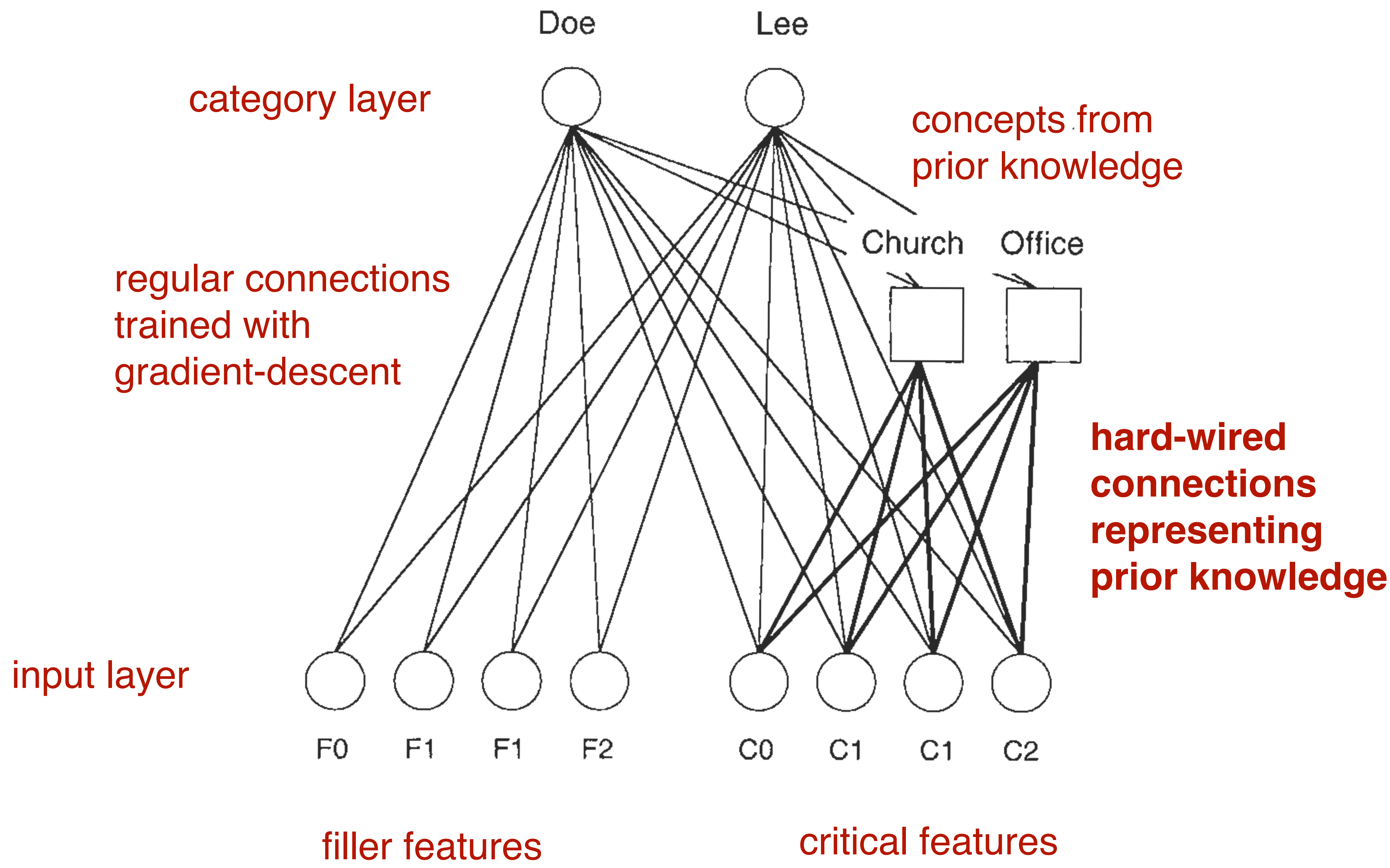
ALCOVE



standard multi-layer network



Heit and Bott neural net model of knowledge effects

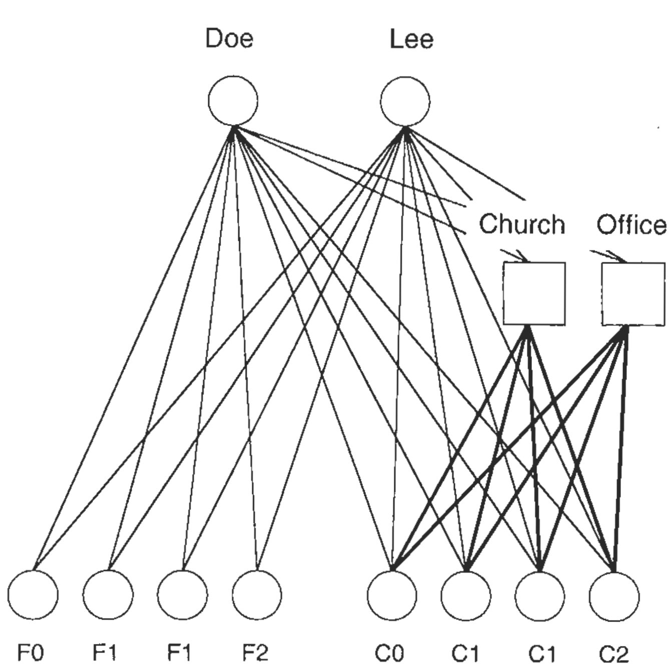


Heit and Bott model of knowledge effects

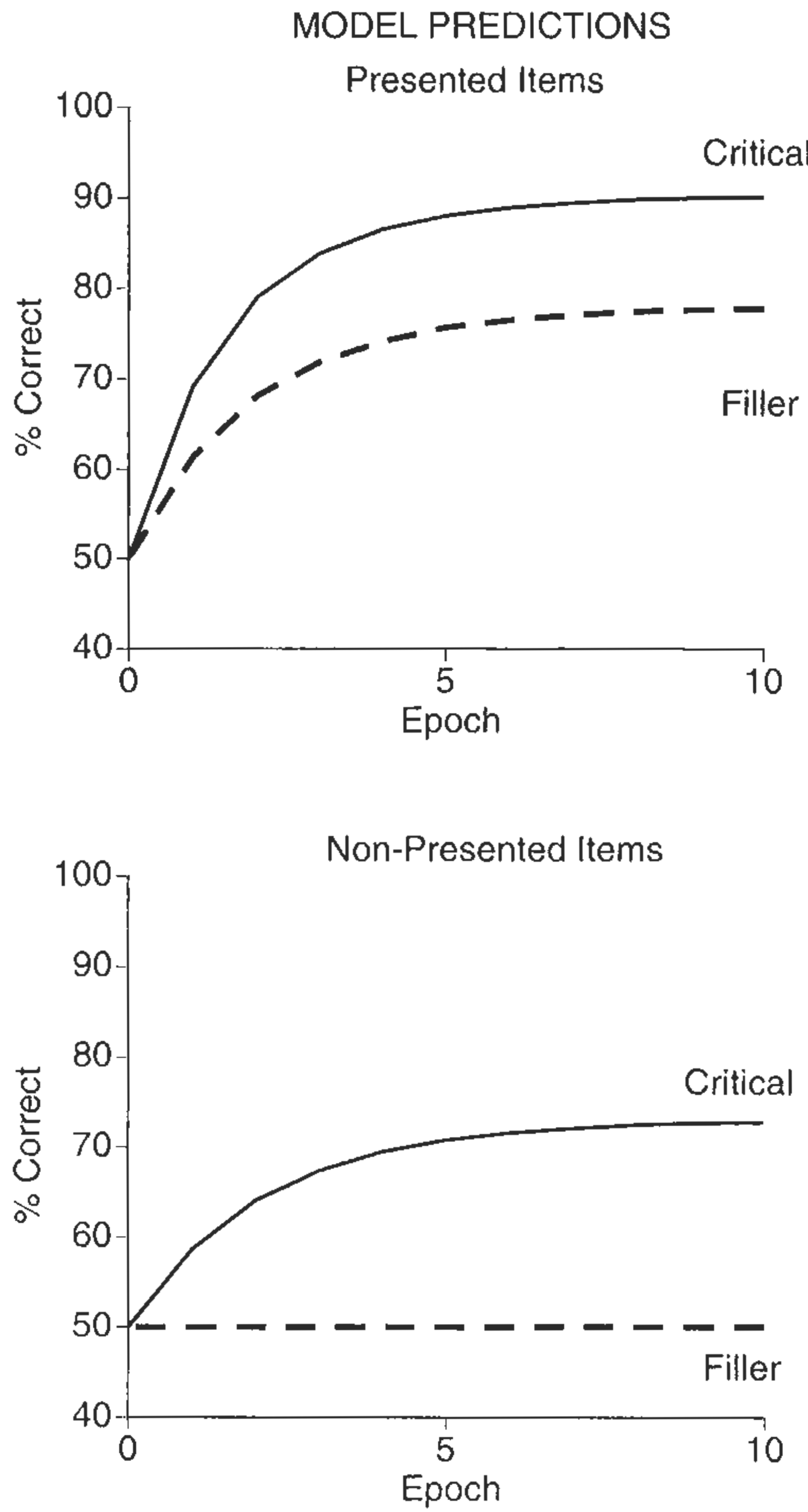
The model captures that:

- Critical features learned better/faster than Filler features, for presented features
- Non-presented critical features are (weakly) associated with categories

Task: categorization of individual features as "Doe" vs. "Lee" buildings, after attempting to memorize the category examples



Model



Human

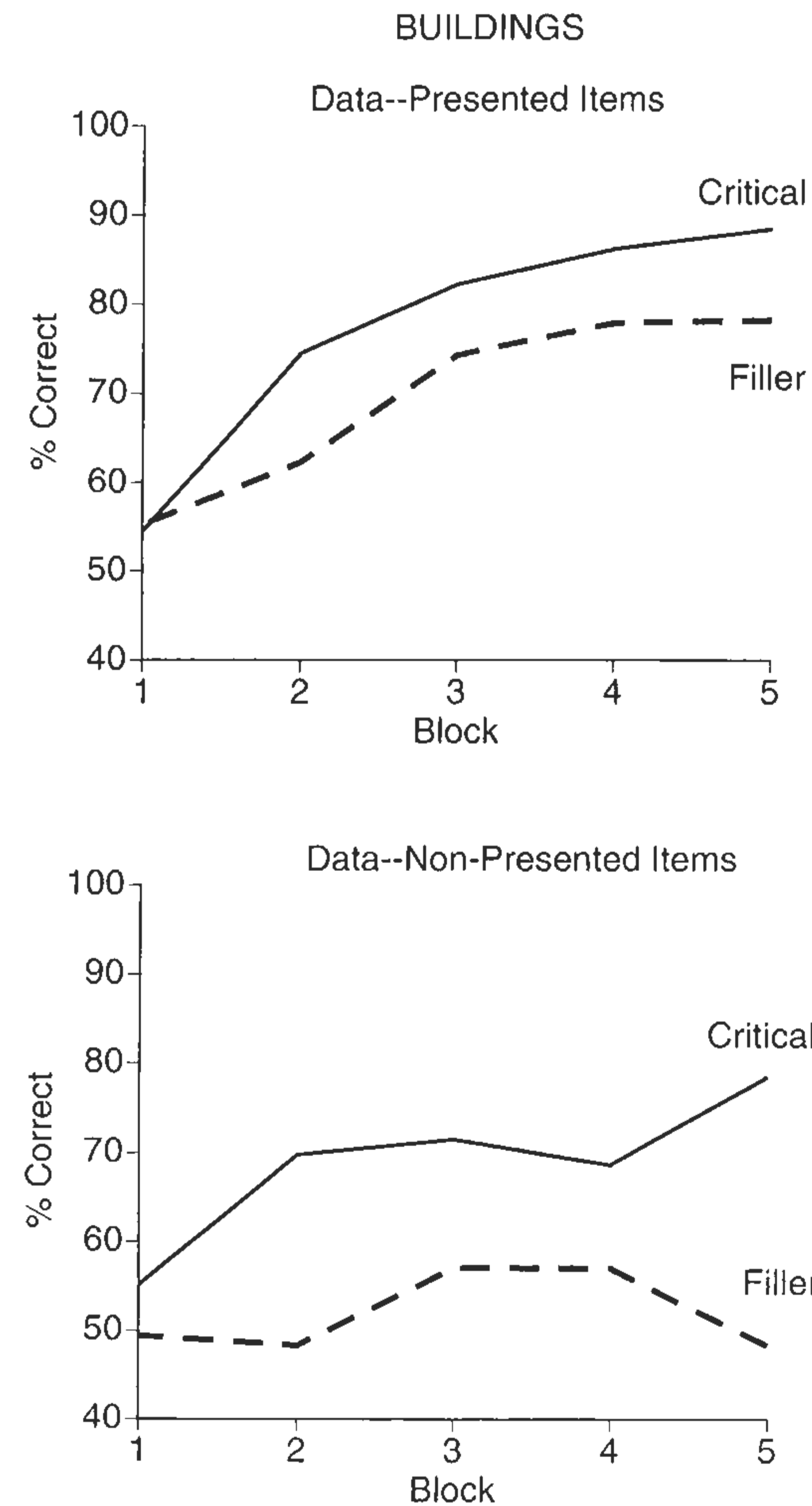


Fig. 6. Results for Experiment 1.

What happens when we remove prior knowledge?

- Prior knowledge facilitates associations with the critical features and labels

- Prior knowledge slightly diminishes the associations with filler features and labels, due to error-driven learning and stronger signal from other features