Cognition: Methods and Models

PSYC 2040

L9: Cognitive Models

Part 2

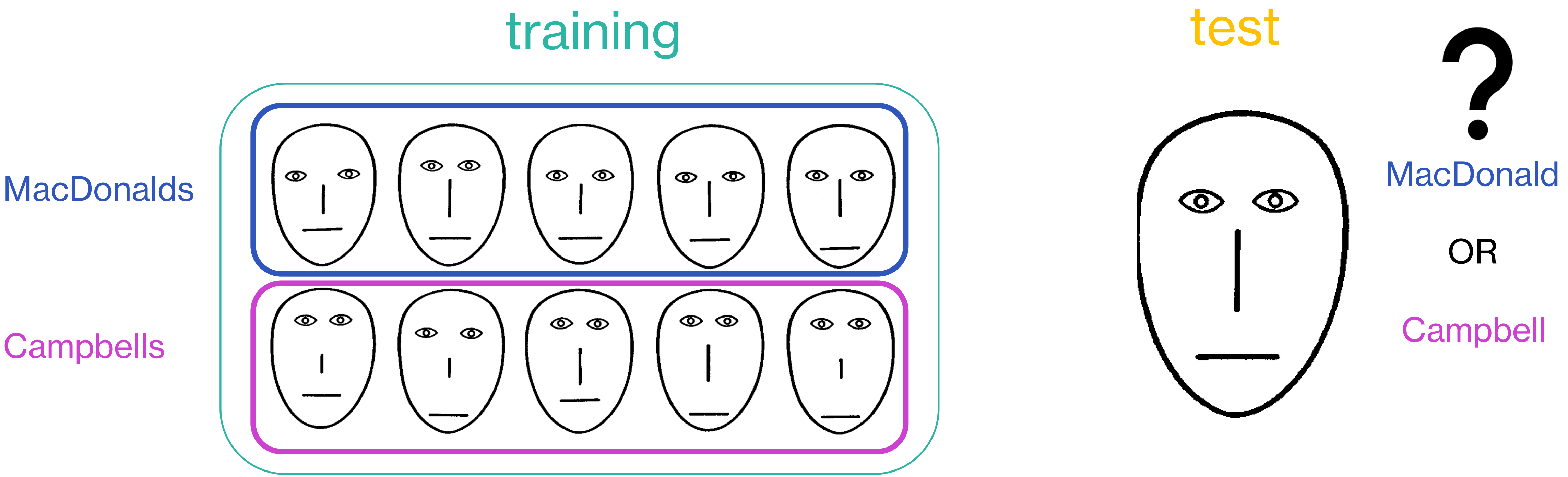
recap: Apr 11, 2023

- what we covered:
  - TIP/TAP review
  - cognitive models: learning and classification (exemplar)
- your to-dos were:
  - *finish:* L9 reading
  - *submit:* conceptual reflection

today’s agenda

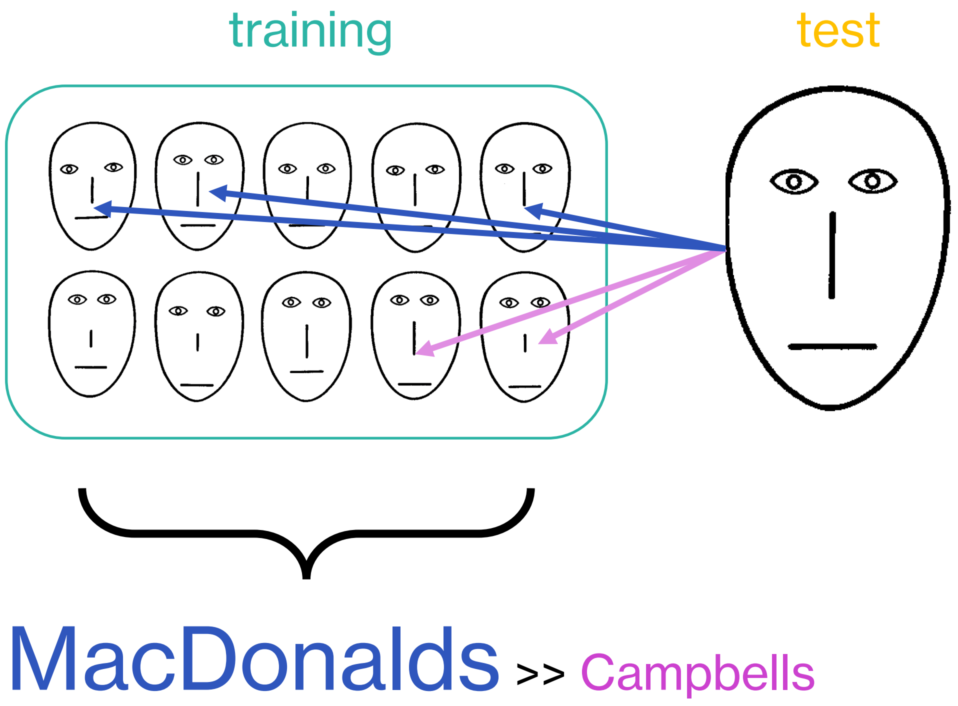
- exemplar model continued
- prototype model
- instance theory / MINERVA 2
- model scope and falsifiability

how do we classify/categorize?



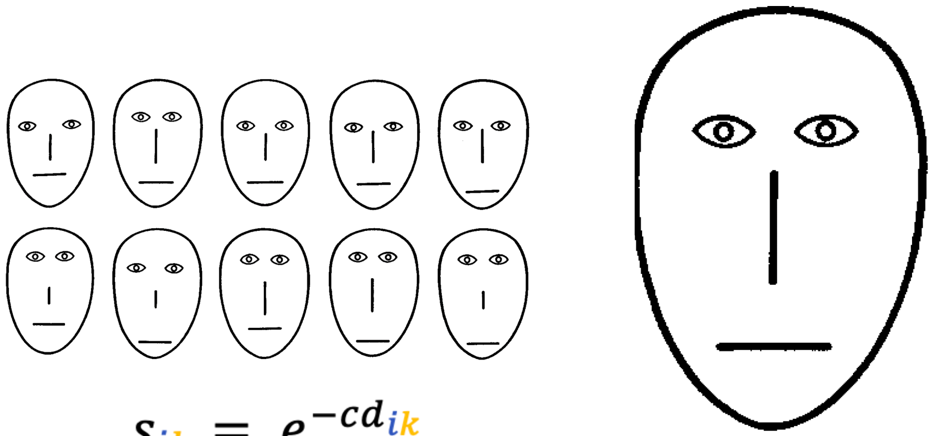
exemplar model: review

- during training, people store individual examples into memory
- during test, the training items are activated in proportion to their similarity to the test item
- the probability of responding with one label (MacDonald) vs. another (Campbell) depends on the sum of these activations



exemplar model: test

- when a new item (x_k) is presented, each training item is activated in proportion to its similarity to the test item
  - exemplar x_i is activated in proportion to its similarity to test item x_k
- activations of each exemplar in a class are added up to produce total activation for the class
- the probability of classifying the new test item is determined by whichever class has higher total activation



$$s_{ik} = e^{-cd_{ik}}$$

$$activation\ (MacDonald) = \sum_{k \in MacDonald} s_{ik}$$

$$activation\ (Campbell) = \sum_{k \in Campbell} s_{ik}$$

$$P\ (MacDonald) = \frac{activation\ (MacDonald)}{activation\ (MacDonald) + activation\ (Campbell)}$$

activity: computing distance & similarity

- in groups, go to [the probability spreadsheet]
- navigate to your group's tab
- fix the formula in column H to accurately calculate distance using the 4 dimensions instead of 2 dimensions
- extend the correct formula to all rows
- verify that distance of test item to itself is 0 and similarity is 1

x_i TEST (x_k)

[-1.025, 0.493, 0.048, -0.666] [-0.172, -0.557, 0.337, 0.163]

$$d_{ik} = \sqrt[2]{\sum_m |x_{im} - x_{km}|^2}$$

$$s_{ik} = e^{-cd_{ik}}$$

activity: computing probabilities

- calculate the total activation of MacDonalds and Campbells by adding the similarities for the respective categories
- which class is more activated overall?

$$activation\ (MacDonald) = \sum_{k \in MacDonald} s_{ik}$$

$$activation\ (Campbell) = \sum_{k \in Campbell} s_{ik}$$

activity: computing probabilities

- now calculate the probability of responding MacDonald and responding Campbell
- what is the sum of the two probabilities?
- what decision would you make about this particular test face?

$$activation\ (MacDonald) = \sum_{k \in MacDonald} s_{ik}$$

$$activation\ (Campbell) = \sum_{k \in Campbell} s_{ik}$$

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exemplar model: review

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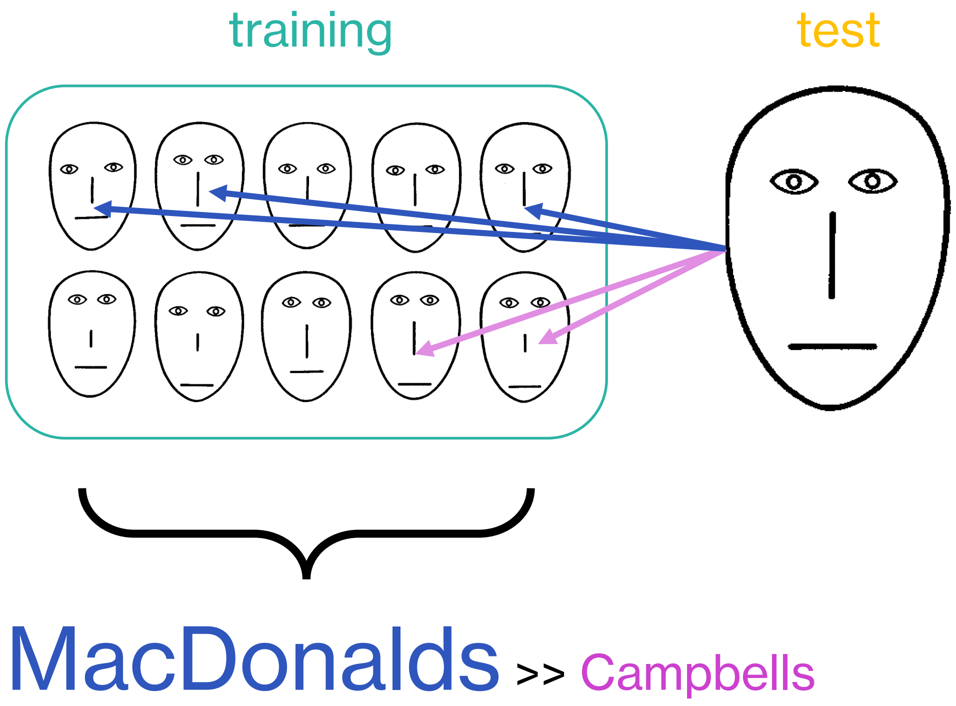
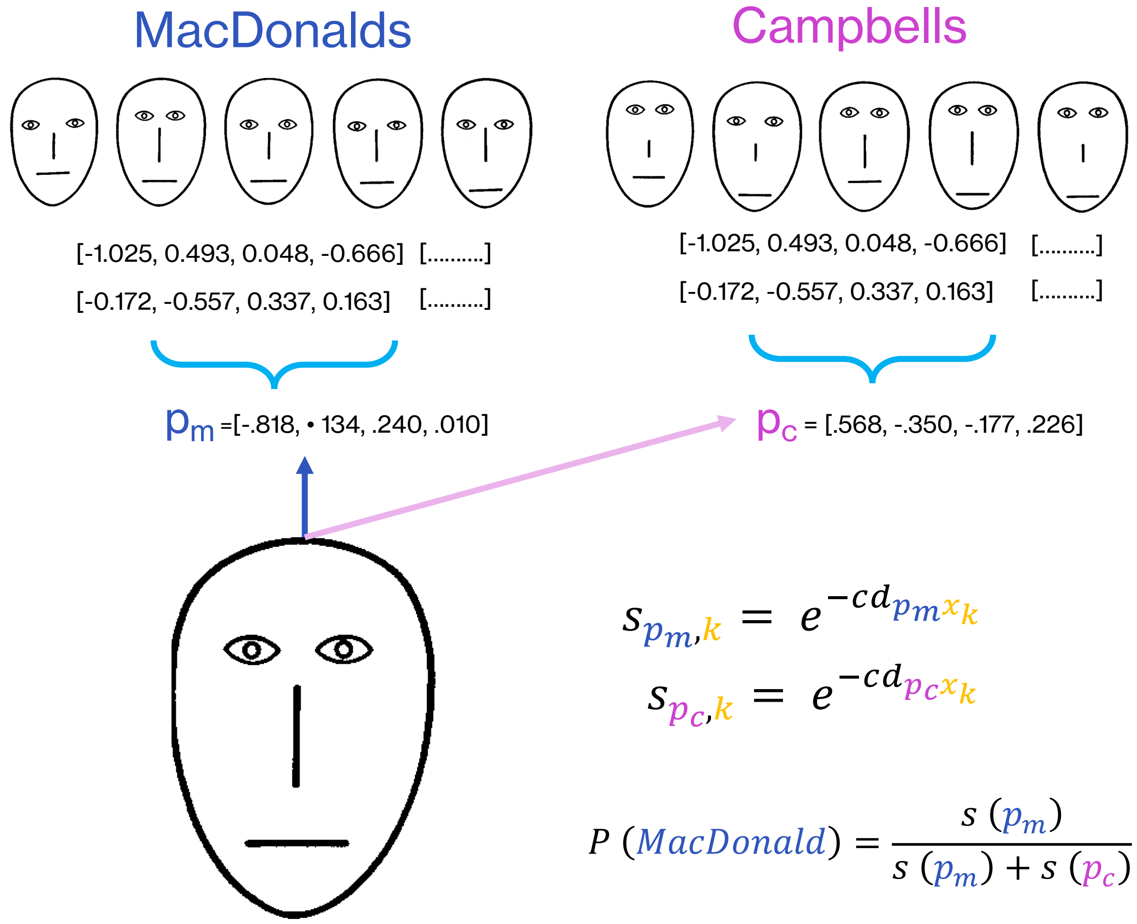


prototype model: description

- during training, all exemplars are "summarized" to form a prototype
- during test, the prototypes for each class are activated in proportion to their similarity to the test item
- the probability of responding with one label vs. another depends on whichever prototype is more activated



$$s_{p_m,k} = e^{-cd_{p_m x_k}}$$

$$s_{p_c,k} = e^{-cd_{p_c x_k}}$$

$$P\left(MacDonald\right) = \frac{s\left(p_m\right)}{s\left(p_m\right) + s\left(p_c\right)}$$

activity: prototype model

- go to the prototype spreadsheet
- using the calculation for MacDonalds, complete the calculation for the distance and similarity of the test item to Campbells
- then compute the probability of classification
- what decision would you make about this particular test face?

reviewing the evidence

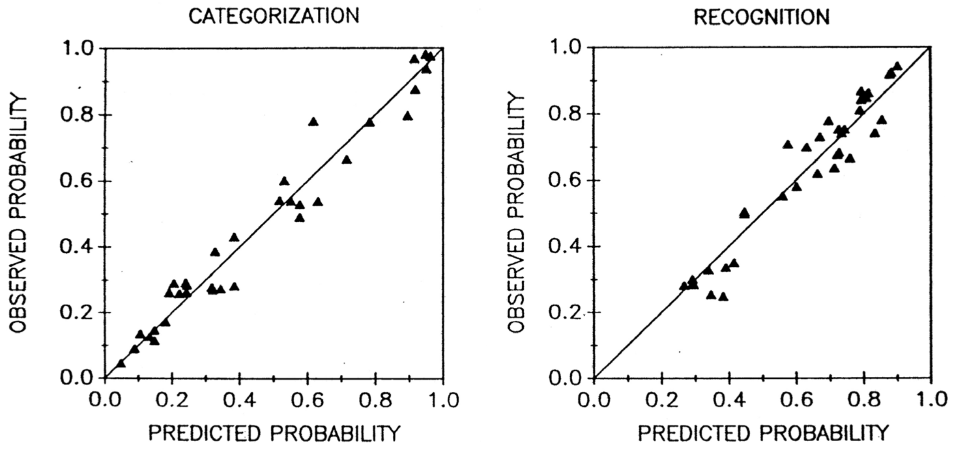
- both exemplar and prototype models have a proposal for how a classification decision may be reached, i.e., they can predict classification decisions given a set of examples and a new test item
    - they are both process/computational models
- we also have a large dataset of classification decisions from human participants who did this experiment
- how can we compare the two models?

exemplar vs. prototype model?

- the exemplar model performed *better* than the prototype model
- the generalized context model (GCM) or the exemplar model was able to successfully relate classification confidence to recognition accuracy, such that knowing one of these could predict the other with remarkable accuracy

Table 3
Maximum Likelihood Parameters and Summary Fits, Experiment 1B

Model	Parameters									Fits		
	σ	c	w_1	w_2	w_3	w_4	x_c	b	M_7	SSE	% Var	-ln L
All-subjects analyses												
Context												
Classification	.267[a]	1.077[a]	.15	.15	.29	.41		.173	1.464[a]	.097	96.5	129.2
Recognition	.267[a]	1.077[a]	.13	.56	.23	.08	5.322		1.464[a]	.076	95.4	119.2
Prototype												
Classification	.186[a]	.777[a]	.16	.14	.40	.30		.044	1.123[a]	.175	93.7	181.0
Recognition	.186[a]	.777[a]	.25	.55	.12	.07	1.231		1.123[a]	.182	89.0	156.0



exemplar vs prototype learners

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2019, Vol. 6(1) 21–28

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Recommendations From Cognitive Psychology for Enhancing the Teaching of Natural-Science Categories

Robert M. Nosofsky[1] and Mark A. McDaniel[2]

Abstract

Because of their complex structures, many natural-science categories are difficult to learn. Yet achieving accuracy in classification is crucial to scientific inference and reasoning. Thus, an emerging theme in cognitive-psychology and cognitive-science research has been to investigate better ways to instruct about categories. This article briefly reviews major findings that will help inform policies for teaching categories in the science classroom. Many of the examples come from our specific project that examines teaching rock classifications in the geologic sciences. This project uses formal models of human category learning—developed in cognitive psychology—to search for optimal teaching procedures. The model-suggested category-teaching procedures often lead to better learning outcomes than do alternative procedures motivated by teachers' and students' intuitive judgments. In addition to reviewing these enhanced procedures for teaching natural-science categories, the article points to recent broader efforts for fostering collaborations between cognitive-science researchers and education researchers.

why computational models?

- data never speak for themselves; they require a model to be understood and explained
- verbal theorizing cannot substitute for quantitative analysis
- data can be explained through several alternative models, and we must select among these alternatives
  - “all models are wrong, but some are useful” – George Box
- model selection is based on quantitative evaluation and qualitative judgments
  - quantitative: prediction errors, R^2, mean square error, log likelihood etc.
  - qualitative: less complexity (lower constants/parameters): Occam’s Razor

Farrell & Lewandowsky (2018)

exemplar models & instance theory

- exemplar models are derived from a process-oriented theory of memory and cognition, “instance theory”
- instance theory uses a general framework for cognitive processing, where ‘instances’ are defined, encoded, and retrieved
- the framework has been applied beyond memory processes, to account for many phenomena such as associative learning, language, eyewitness identification, etc.
- instance theory models have many versions/flavors and vary in descriptive or mathematical details

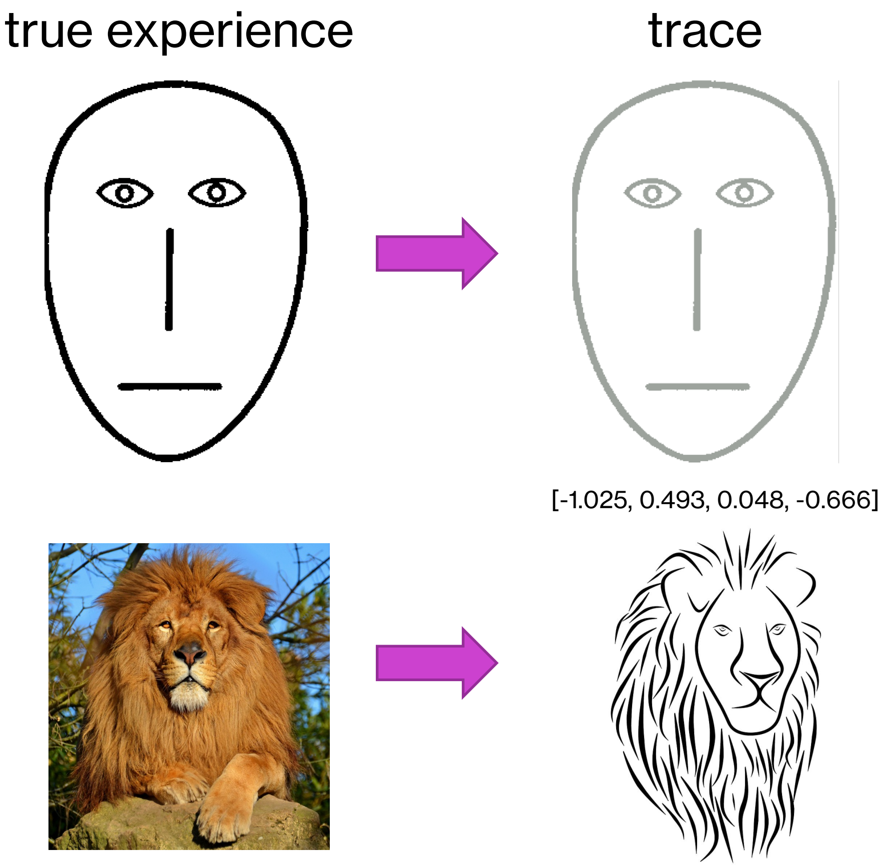
Instance theory as a domain-general framework for cognitive psychology

Randall K. Jamieson, Brendan T. Johns, John R. Vokey and Michael N. Jones

Abstract | The dominant view in cognitive psychology is that memory includes several distinct and separate systems including episodic memory, semantic memory and associative learning, each with a different set of representations, explanatory principles and mechanisms. In opposition to that trend, there is a renewed effort to reconcile those distinctions in favour of a cohesive and integrative account of memory. According to instance theory, humans store individual experiences in episodic memory and general-level and semantic knowledge such as categories, word meanings and associations emerge during retrieval. In this Perspective, we review applications of instance theory from the domains of remembering, language and associative learning. We conclude that instance theory is a productive candidate for a general theory of cognition and we propose avenues for future work that extends instance theory into the domain of cognitive computing, builds hybrid instance models and builds bridges to cognitive neuroscience.

instance theory: key assumptions

- all experiences are encoded as “traces” in memory, and capacity for traces is very larger / unlimited
- “traces” can capture many different aspects or properties of an experience
- retrieval is driven by the overlap between the current experience and its similarity to traces of previous experiences



MINERVA 2

- MINERVA 2 (Hintzman, 1984; 1986; 1988) is a computational model of memory based on instance theory
- a “probe” is a retrieval cue that activates related traces in memory based on their similarity to the cue
- an “echo” is the result of a probe being presented
- MINERVA 2 has been applied more broadly to cognitive phenomena
    - associative learning (Jamieson et al., 2010)
    - semantic memory (Jamieson et al., 2018)
    - sequence learning (Jamieson & Mewhort, 2009)
    - false memory (Arndt, 1998)

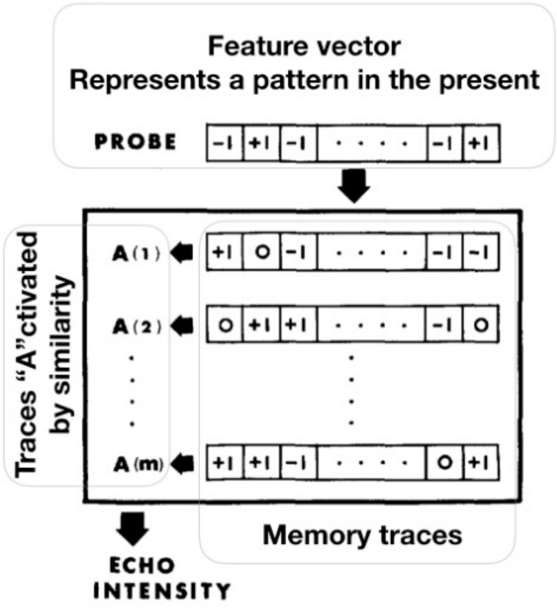


Figure 1. Trace activation. (Each trace is activated according to its similarity to the probe. Feature values [$j = 1 \ldots n$] are listed from left to right, and traces [$i = 1 \ldots m$], from top to bottom. $A(i)$, the activation level of trace i, depends on the proportion of features it shares with the probe. Echo intensity is the sum of the $A(i)$ values.)

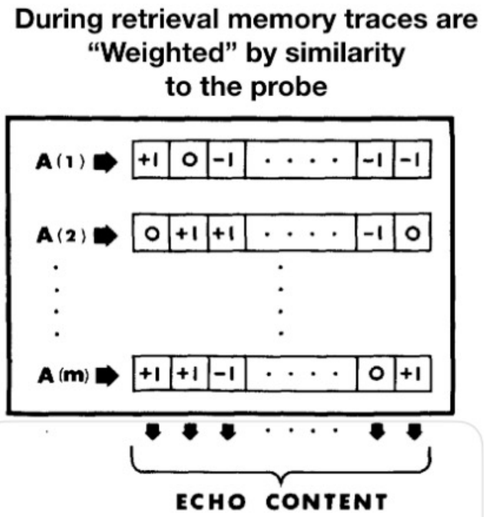
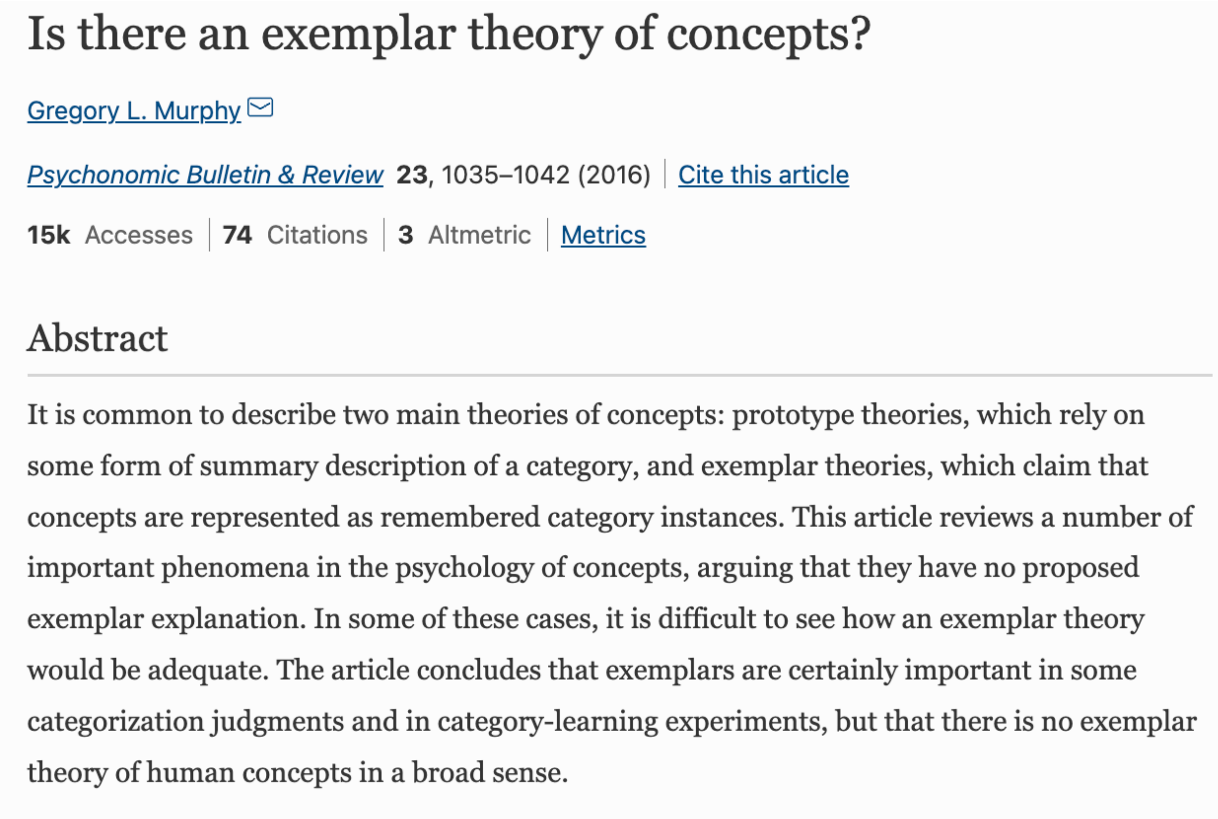


Figure 2. Retrieval of echo content. (Activation initiated by the probe [see Figure 1] is passed down to all features of each trace, as the product of $A(i)$ and the feature value. For each feature, j, the products are summed over traces to yield $C(j)$. Echo content is the set of $C(j)$ values.)

Echo is the aggregate memory response

instance theory: limitations

- rule-based categorization
- hierarchical knowledge/processing?
- inferences/induction
- capacity limitations and levels of analysis



Is there an exemplar theory of concepts?

Gregory L. Murphy

Psychonomic Bulletin & Review **23**, 1035–1042 (2016) | Cite this article

15k Accesses | **74** Citations | **3** Altmetric | Metrics

Abstract

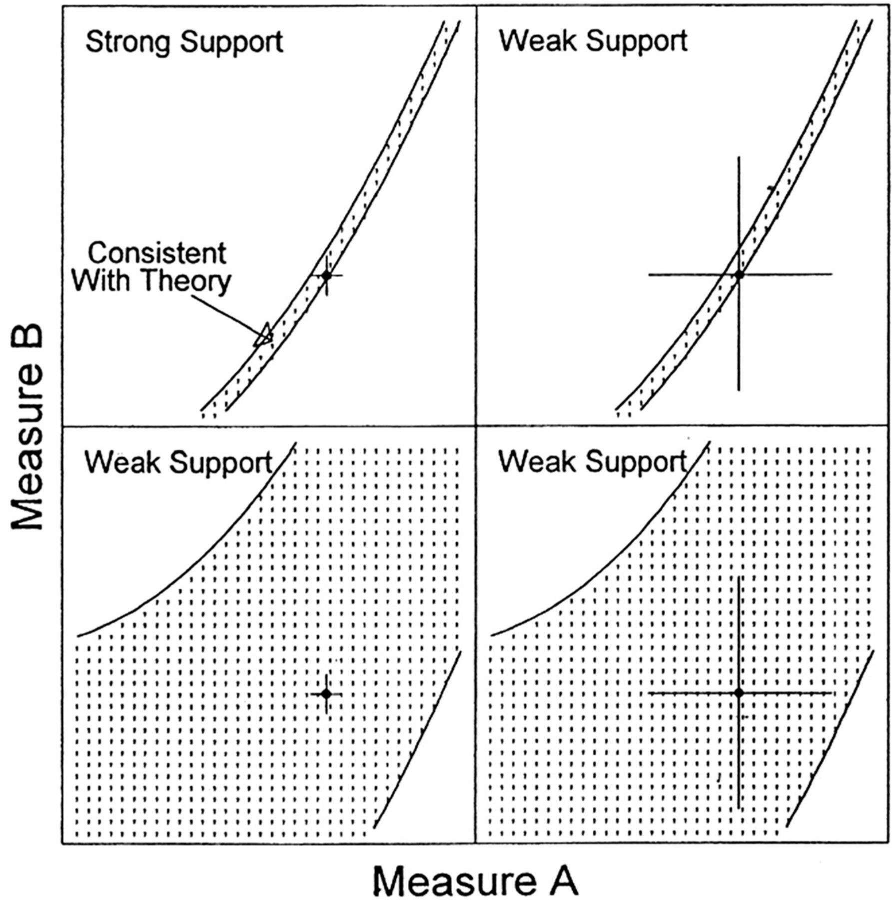
It is common to describe two main theories of concepts: prototype theories, which rely on some form of summary description of a category, and exemplar theories, which claim that concepts are represented as remembered category instances. This article reviews a number of important phenomena in the psychology of concepts, arguing that they have no proposed exemplar explanation. In some of these cases, it is difficult to see how an exemplar theory would be adequate. The article concludes that exemplars are certainly important in some categorization judgments and in category-learning experiments, but that there is no exemplar theory of human concepts in a broad sense.

alternative domain-general models

- the appeal of instance theory is its broader application to more than one instance/facet of cognition
- however, this is *one* theory: other such theories exist that do not rely on exemplar storage and retrieval mechanisms
  - domain-specific models
  - error-driven models (more next week: language!)
  - inferential models (social cognition week)

models: scope and falsifiability

- ideally, we want our models/theories to explain as much variance in the data as possible, i.e., have maximal scope
- but… we also want our models/theories to be able to separate signal from noise (hits vs. false alarms!), i.e., models/theories need to be falsifiable, not false
- examples of falsifiable or non-falsifiable theories?

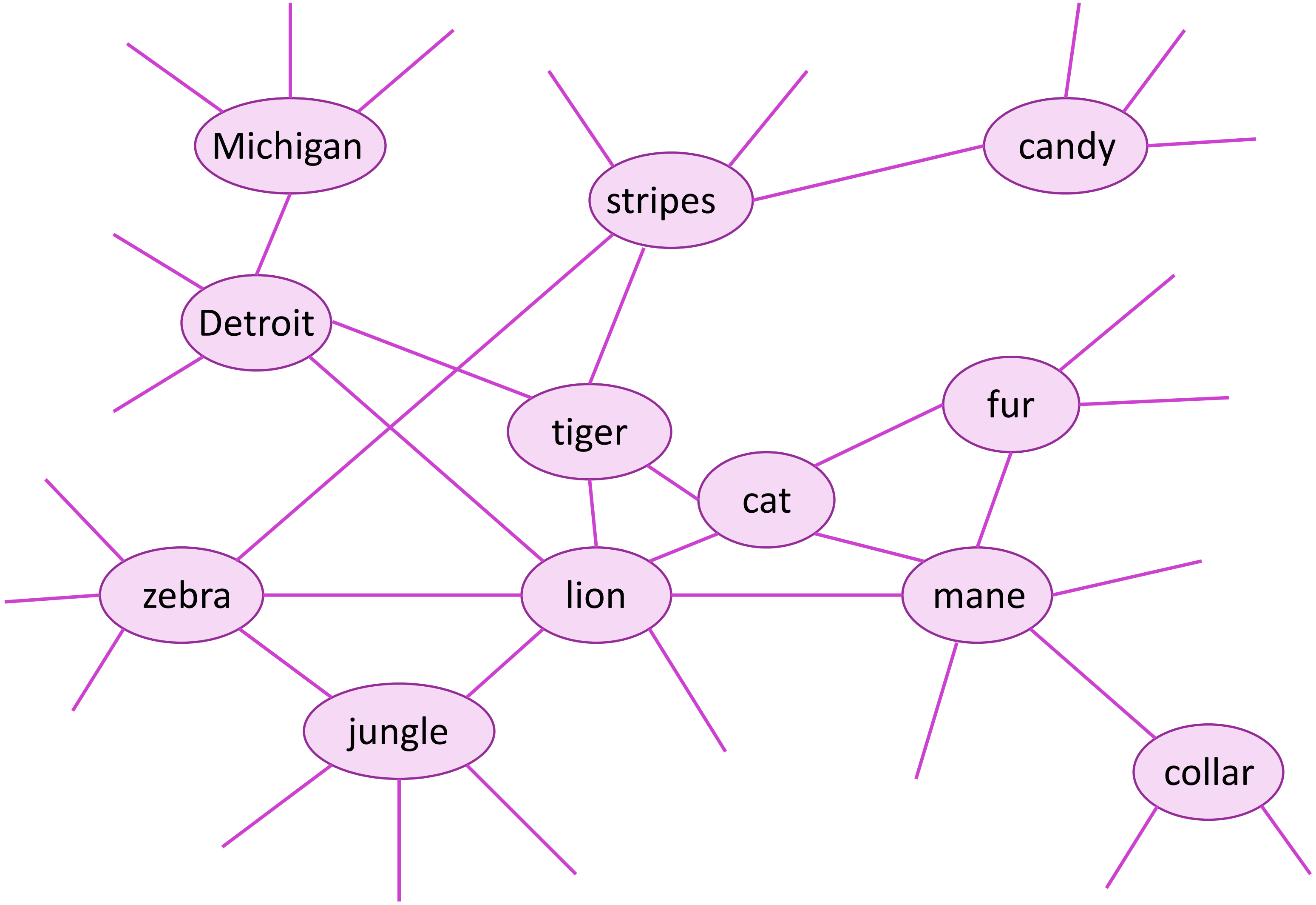


Farrell & Lewandowsky (2018)

models are cognitive aids

- metaphors are powerful but can be misleading!
- what metaphors have we encountered already?
- "spreading activation" is a broad theory of how concepts in memory can be represented as a connected network, such that activating a concept activates other related nodes in memory

Farrell & Lewandowsky (2018)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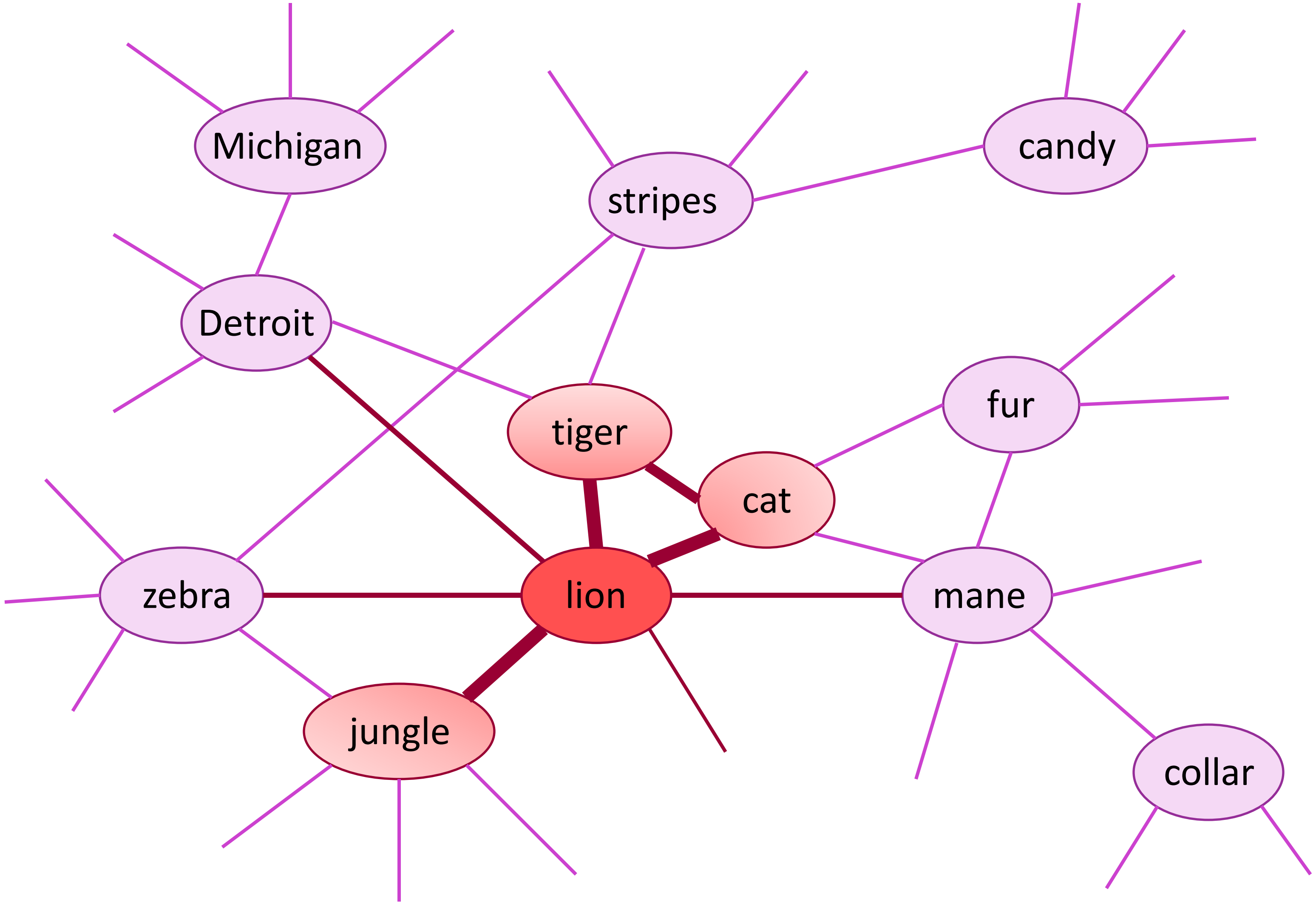
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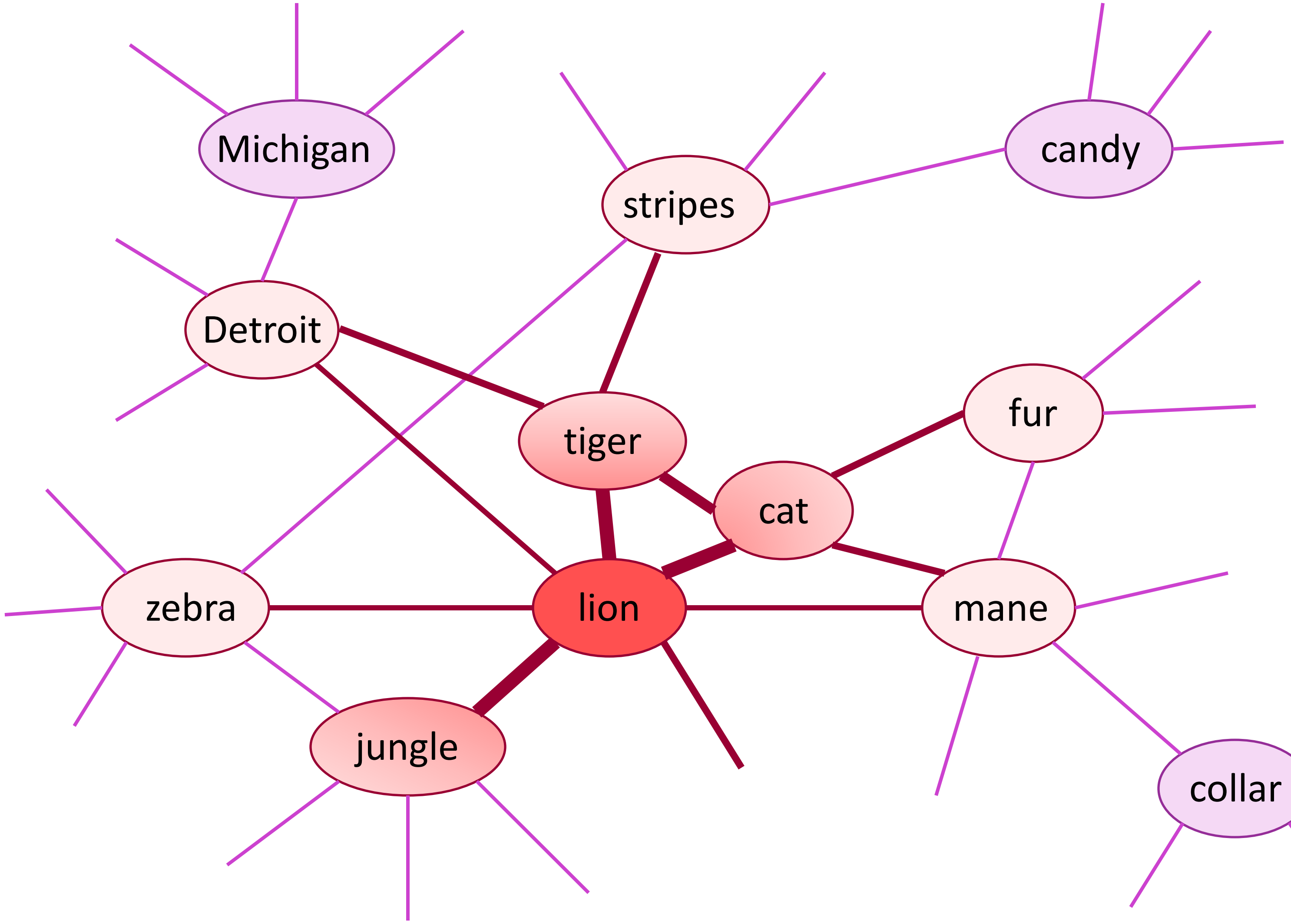
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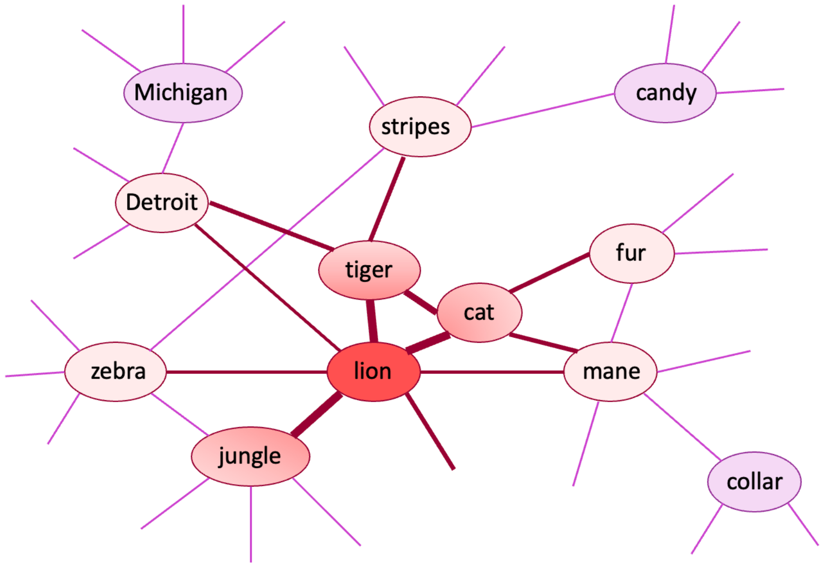
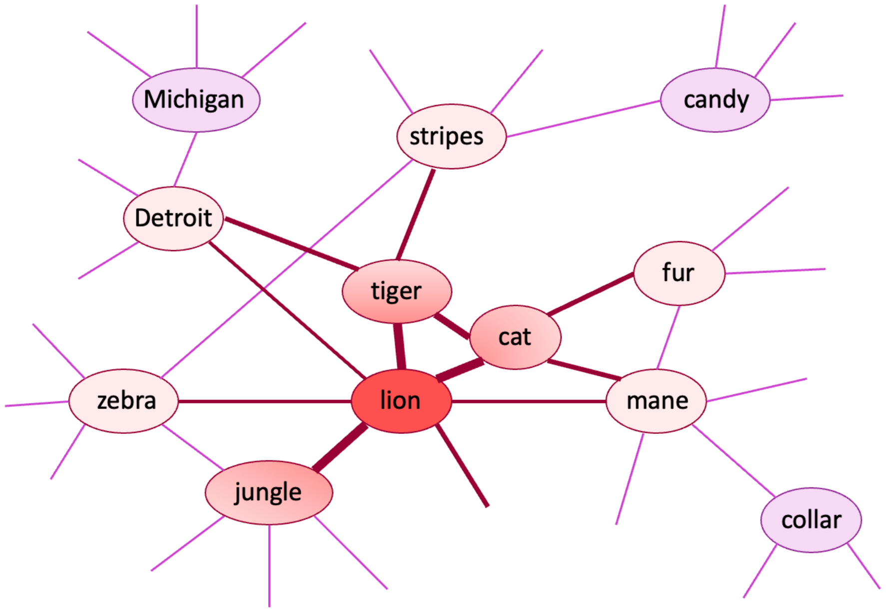
models are cognitive aids

- how exactly does spreading activation work?
  - electricity through wires?
  - water through pipes?
- models help us be specific about our assumptions and then test those assumptions against data
- models also help us communicate better as scientists



some food for thought

- how do we decide which word activates which other words?
- how is this information learned in real life?
- why does lion bring tiger to mind but not candy?



big takeaways

- get in groups of 3 and report key takeaways from today
- takeaways document

next class

- **before** class:
  - *finish:* L9 quiz + writing assignments
  - *read:* L10 reading
- **during** class:
  - L10: language (FINALLY!!)