



# Cognition: Methods and Models

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PSYC 2040

L9: Cognitive Models

Part 1

# logistics: project milestone #4

- feedback returned to most groups
- use APA format to cite papers/references in first draft and final submission
  - [Purdue OWL](#) has a nice tool to obtain refs!
  - [Google Scholar](#) also has a straightforward tool
- focus on effective visualizations when making connections!
- milestone #5 (first draft) is due April 30!

## Reference List

Resources on writing an APA style reference list, including citation formats

Cite your source automatically in APA

Journal article

Infants preferentially approach and exp

Cite

Full view

× Cite

MLA	Sim, Zi L., and Fei Xu. "Infants preferentially approach and explore the unexpected." <i>British Journal of Developmental Psychology</i> 35.4 (2017): 596-608.
APA	Sim, Z. L., & Xu, F. (2017). Infants preferentially approach and explore the unexpected. <i>British Journal of Developmental Psychology</i> , 35(4), 596-608.
Chicago	Sim, Zi L., and Fei Xu. "Infants preferentially approach and explore the unexpected." <i>British Journal of Developmental Psychology</i> 35, no. 4 (2017): 596-608.
Harvard	Sim, Z.L. and Xu, F., 2017. Infants preferentially approach and explore the unexpected. <i>British Journal of Developmental Psychology</i> , 35(4), pp.596-608.
Vancouver	Sim ZL, Xu F. Infants preferentially approach and explore the unexpected. <i>British Journal of Developmental Psychology</i> . 2017 Nov;35(4):596-608.

BibTeX EndNote RefMan RefWorks

# recap: Apr 4/6, 2023

- what we covered:
  - memory tasks & phenomena
  - memory principles
- your to-dos were:
  - *finish*: L8 quiz/writing assignments
  - *submit*: project milestone #4 (outline)



# today's agenda

- first part:
  - TIP/TAP review
- second part:
  - cognitive models

# TIP/TAP > levels of processing

- claim: the tasks performed at encoding and retrieval take precedence over the nature of processing (shallow vs. deep)
- evidence: Morris, Bransford, and Franks (1977)
  - participants encoded words in a semantic or rhyming context
  - the test phase was either a standard recognition test or a rhyming-based recognition test

acquisition mode

The \_\_\_\_ flew in the sky

EAGLE

\_\_\_\_ rhymes with legal.

EAGLE

standard  
recognition

EAGLE

OLD

NEW

LAUGH

OLD

NEW

rhyming  
recognition

REGAL

OLD

NEW

LAUGH

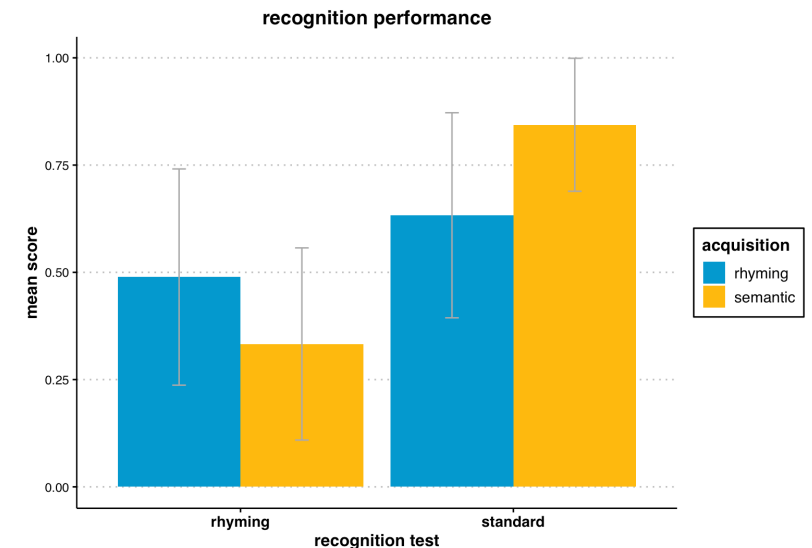
OLD

NEW

# TIP/TAP > levels of processing

- claim: the tasks performed at encoding and retrieval take precedence over the nature of processing (shallow vs. deep)
- evidence: Morris, Bransford, and Franks (1977)
  - on standard test, recognition was higher for semantic vs. rhyme words
  - on rhyme test, recognition was higher for rhyme vs. semantic words

Acquisition mode	Recognition test	
	Standard	Rhyming
Semantic–Yes	.844 (.155) <sup>a</sup>	.333 (.224)
Rhyme–Yes	.633 (.239)	.489 (.252)



# other principles

- **task-appropriate processing/probe dependency**: memory performance is influenced by the nature of the task and whether a particular cue is actively generated or provided
- **resource demands**: increasing the cognitive demands during encoding/retrieval can influence retention and performance

# conceptual question #frequency

- something from our discussion of memory phenomena that interested me was the word frequency effect. It makes sense to me that low-frequency words are better recognized than high-frequency words, but I would expect this to be the same for a recall task. I know that studies have begun to explain this paradox, but why do manipulations of word frequency influence memory performance in different ways depending on the task?
  - likely has to do with task-appropriate processing, recall requires active generation and high-frequency words are easier to produce. recognition relies on familiarity and the smallest boost is useful for low-frequency words



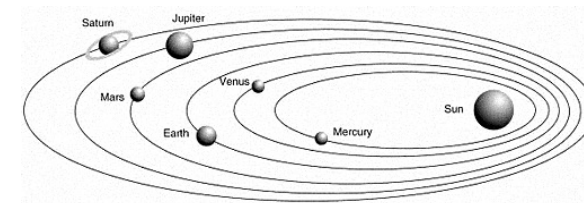
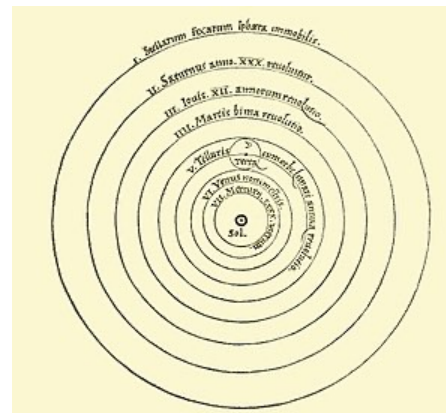
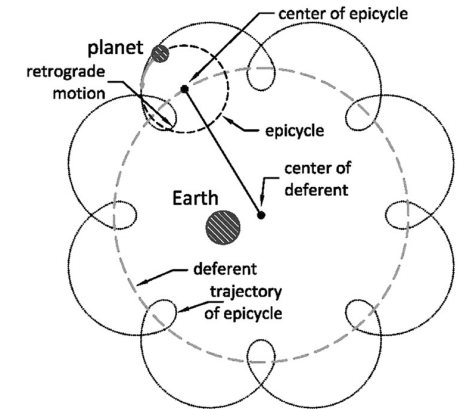
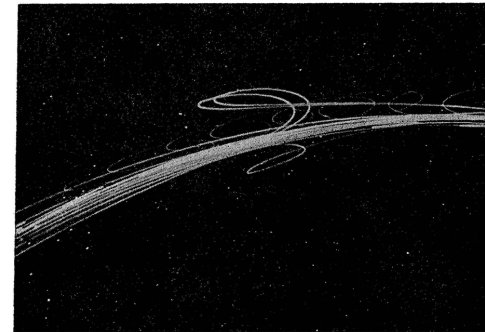


# today's agenda

- first part:
  - TIP/TAP review
- second part:
  - cognitive models

# motivating models: planetary motion

- planets typically have curvilinear paths, but appear to have strange “loops”, referred to as retrograde motion
- explaining why this happens requires **a model of an underlying process** that generates this pattern
- models do not physically *exist*, they are “abstract explanatory devices” that people use to describe, predict, and explain *real data*
- several models may explain the data and scientists must **select among different alternatives**

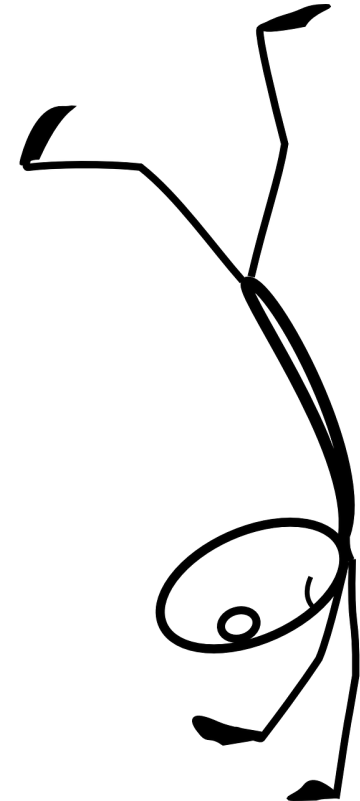


# we use models all the time!

- any type of **description of data** can be considered a model
- **averaging** a set of numbers is a *model* of the data
  - means can be informative: examples?
  - means can be misleading: examples?
- the **Rescorla-Wagner model** of associative learning
- other examples?

# theories of learning

- we know people get better over time at learning a new skill, but how exactly?
- the first time takes forever, the next few attempts lead to major improvements, and then improvements slow down
- two explanations/models:
  - power law:  $RT = N^{-\beta}$
  - exponential law:  $RT = e^{-aN}$ ,

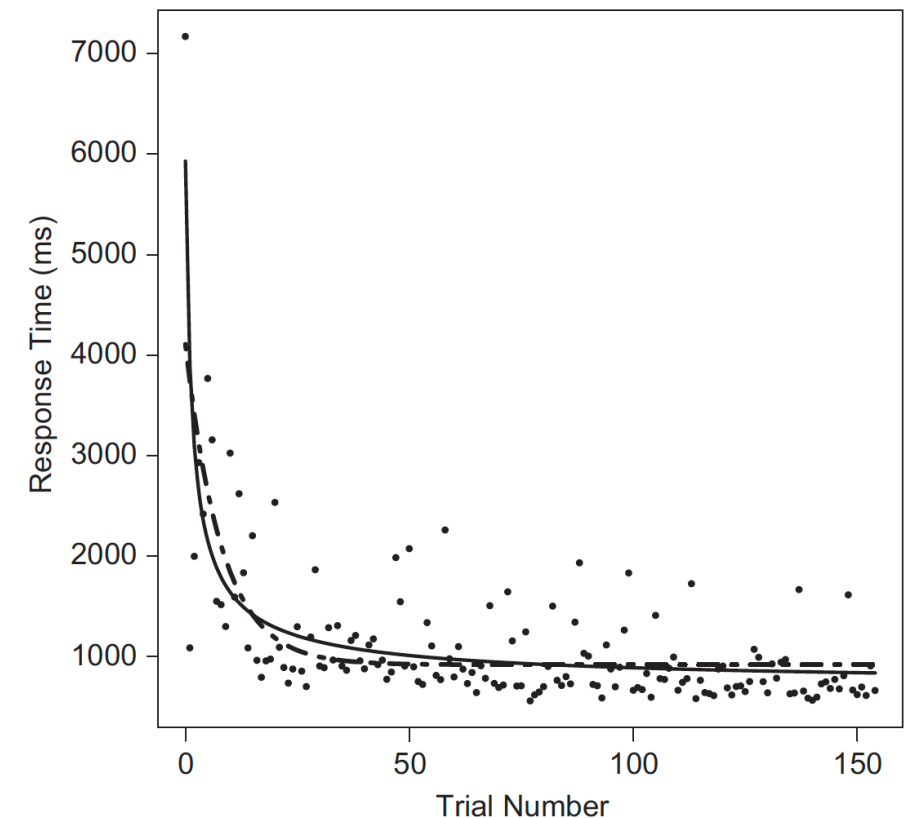


# exercise: power vs. exponential

- go to [power vs. exponential spreadsheet](#)
- find your group's tab
- inspect the formulas in columns C and D and figure out which is the power function and which is the exponential
- select columns A, C, and D, and insert a chart that shows you the time taken to learn after N trials

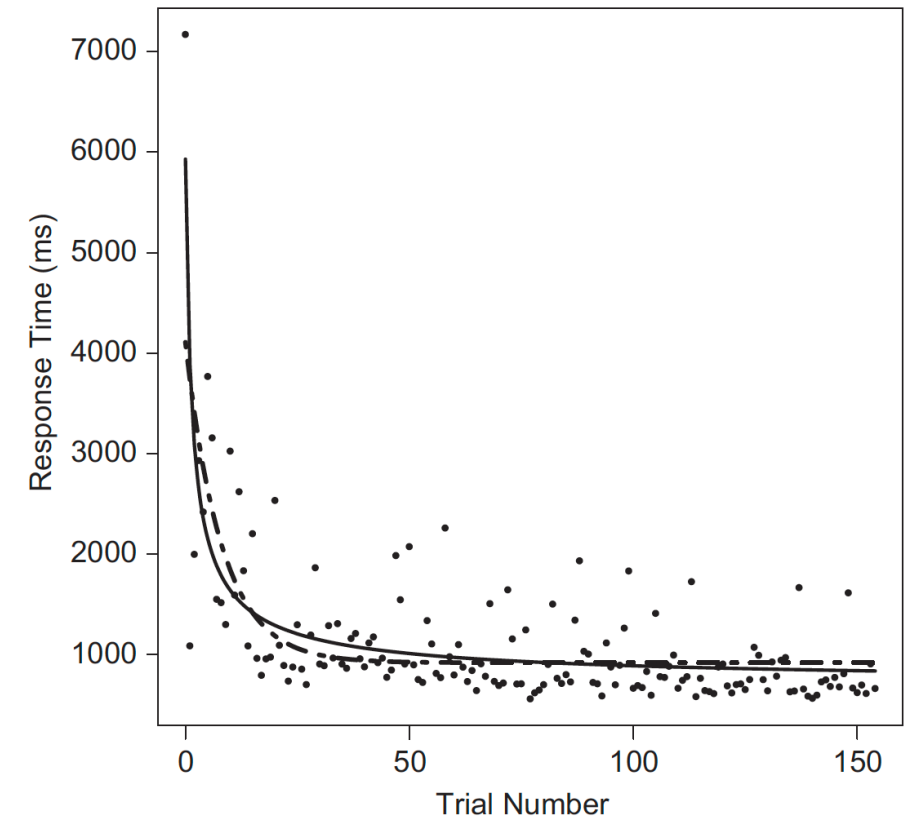
# learning: why does it matter?

- the fit of both models is very similar so **why does it matter** which one is more accurate?
- the **exponential** form suggests that the relative learning rate remains constant, i.e., regardless of practice, your learning continues to be enhanced by a constant fraction
- the **power** law suggests that the relative learning rate is slowing down, i.e., as you practice more, you are actually learning less over time
- which model is correct has important practical implications: how much should you practice a new skill?



# learning: why does it matter?

- Heathcote (2000) showed that the **exponential function better fit the trial-level data**
- learning curve is better explained by the exponential function
  - the more you learn, the more you retain
- implications for forgetting
  - **learning is not the same as forgetting**: forgetting follows a function closer to power law (Wixted, 2004), so you lose more initially and lose lesser over time



# descriptive vs. process models

- descriptive models emphasize describing the data, typically through some type of mathematical formulation and/or statistic
  - examples include the exponential/power laws, means, proportions, etc.
- process models emphasize the underlying mechanism that directly produces the data, and can often generate predictions
  - examples include the Rescorla-Wagner model



descriptive



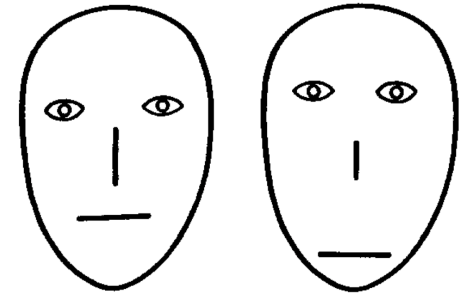
process



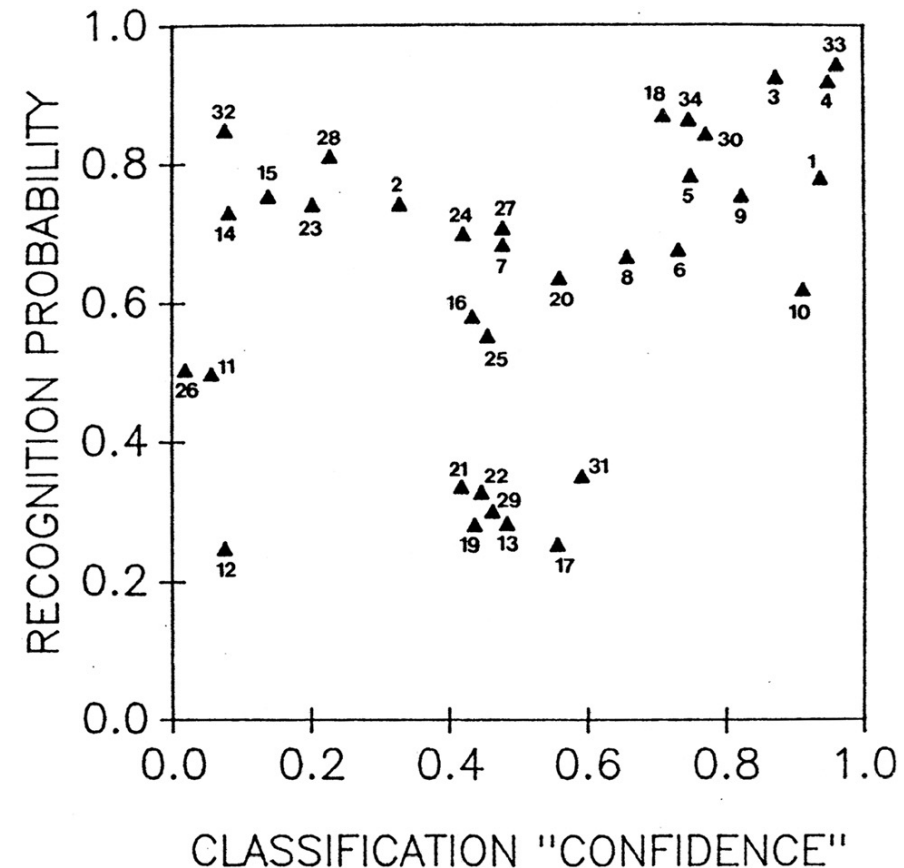
# activity: cartoon face experiment

- go to <https://lhclkdgwwg.cognition.run>
- do the experiment (use laptop!)
- come back and discuss
  - how did you do the task?
  - was there anything special about MacDonalds or Campbells?

# Nosofsky (1991) experiment



- **training** phase: classify cartoon faces
  - MacDonalds and Campbells
- **test** phase:
  - classification: classify faces and rate confidence
  - recognition: provide old/new judgments
- classification and recognition had a **moderate correlation** ( $r = .36$ ) suggesting barely much of a relationship between the two tasks
- if we knew the classification confidence, then we may not be able to predict the recognition probability

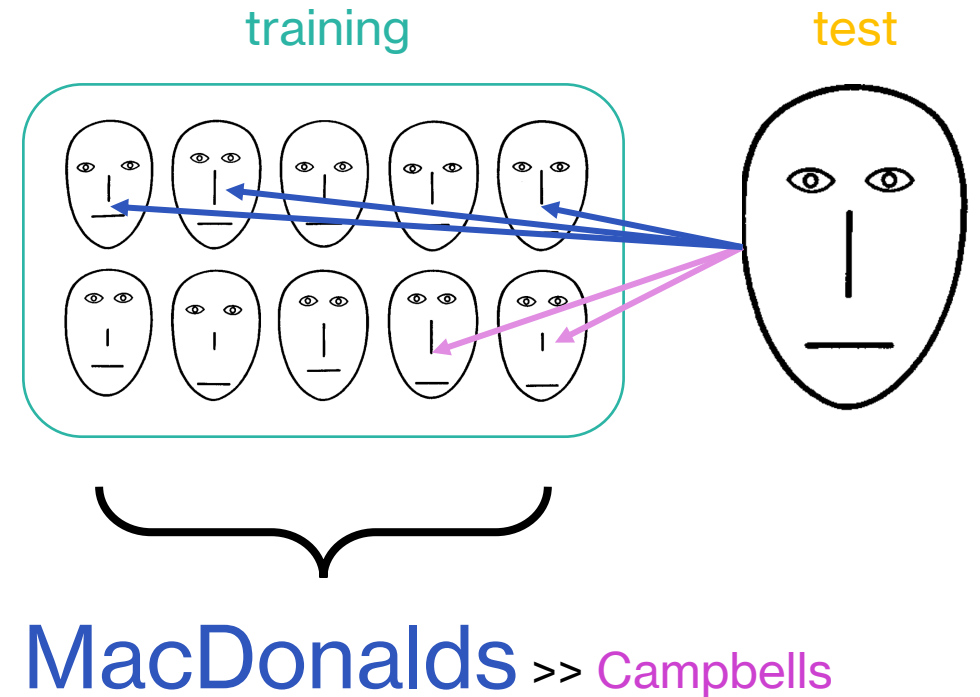


# modeling classification

- Nosofsky (1991) set out to explain *how people classify new faces* after having seen examples from two different classes
- a prominent account of classification was the *prototype model*, which suggested that people create “general” representations of concepts to which new examples are compared
- Nosofsky (1991) proposed an alternative *exemplar model*

# exemplar model: description

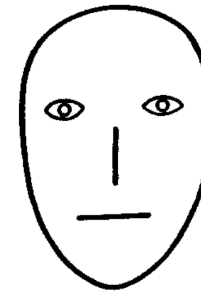
- during **training**, people store individual examples into memory
- during **test**, the training items are activated in proportion to their similarity to the test item
- the probability of responding with one label (**MacDonald**) vs. another (**Campbell**) depends on the sum of these activations



# exemplar model: training

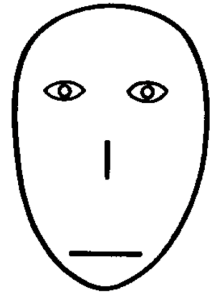
- $x_i$  denotes the  $i^{\text{th}}$  exemplar presented during training
- each exemplar can be defined along  $m$  dimensions

$x_i$



[-1.025, 0.493, 0.048, -0.666]

$x_j$



[-0.172, -0.557, 0.337, 0.163]

# activity: computing similarities

- in groups, go to the [face dimensions spreadsheet](#)
- navigate to your group's tab
- select the columns containing face dimensions
- insert a chart and choose a “bubble” chart
- can you differentiate between MacDonalds and Campbells?

# exemplar model: training

- Nosofsky (1991) varied the faces **along 4 features** (nose length, eye separation, etc.) such that there was a clear separation between the two classes (MacDonalds and Campbells)
- these features are often referred to as **dimensions** and can be placed in a multi-dimensional space

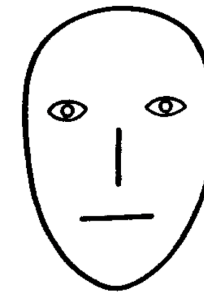


feature	face 1	face 2
eye height	23.5	19.5
eye separation	21.5	11.5
nose length	13.5	18
mouth height	16.5	12

# exemplar model: training

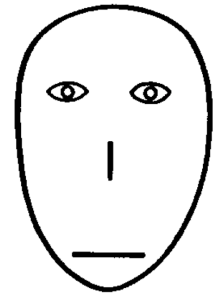
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$X_i$

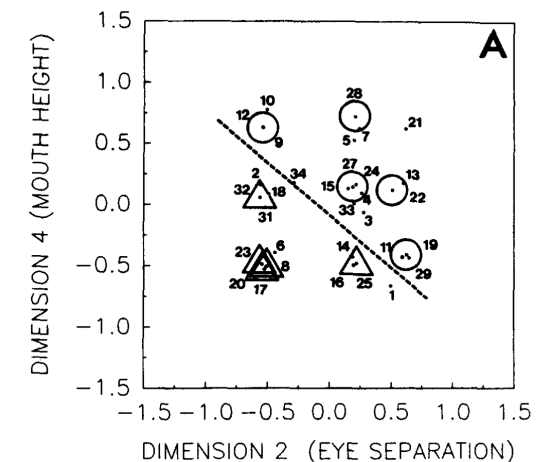


[-1.025, 0.493, 0.048, -0.666]

$X_j$



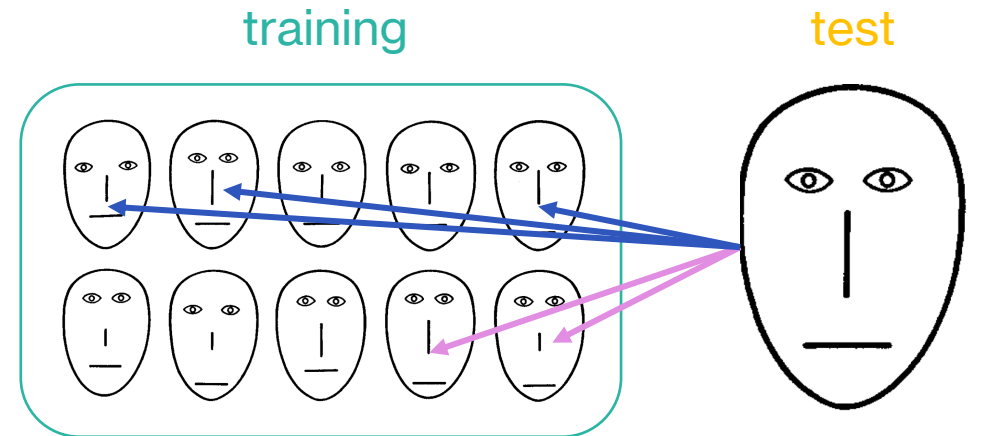
[-0.172, -0.557, 0.337, 0.163]





# exemplar model: test

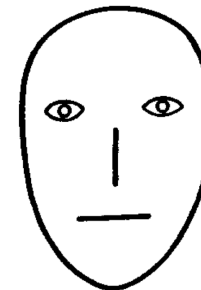
- when a new item ( $x_k$ ) is presented, each training item is activated in proportion to its similarity to the test item
- but how do we calculate similarity??



# exemplar model: similarity

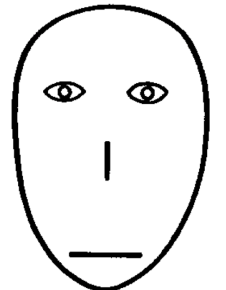
- the similarity between any two items ( $x_i$  and  $x_k$ ) can be calculated using their **coordinates** in the multidimensional space
- this requires two steps:
  - calculating the Euclidean distance  $d_{ik}$  between the items  $i$  and  $k$
  - translating distance to similarity through an exponential function

$x_i$



$[-1.025, 0.493, 0.048, -0.666]$

TEST ( $x_k$ )



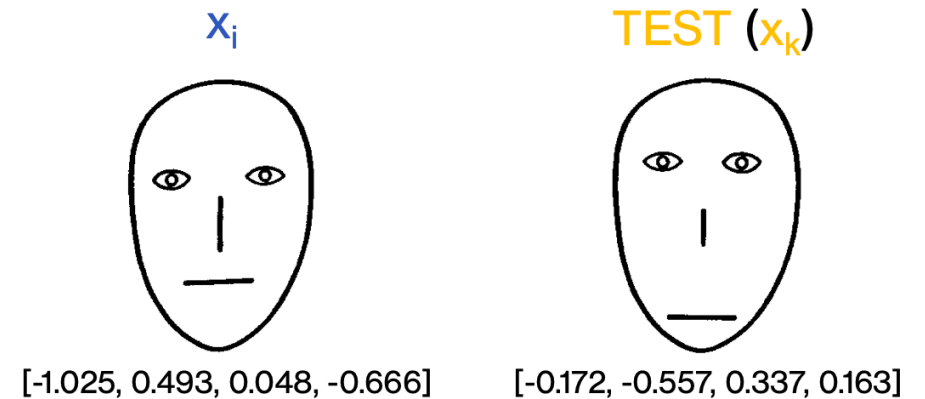
$[-0.172, -0.557, 0.337, 0.163]$

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

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

# activity: computing similarities

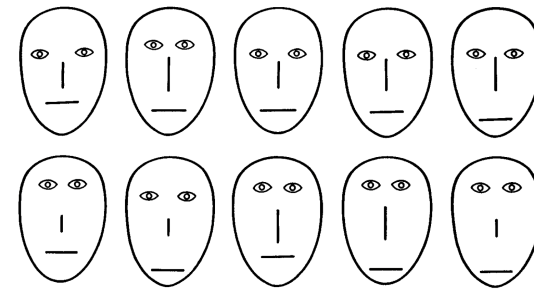
- in groups, go to [the similarity spreadsheet](#)
- navigate to your group's tab
- use the formulas in columns F and G to compute distance and similarity of each face to the test item
- report back which face has the highest and lowest similarity to the test item



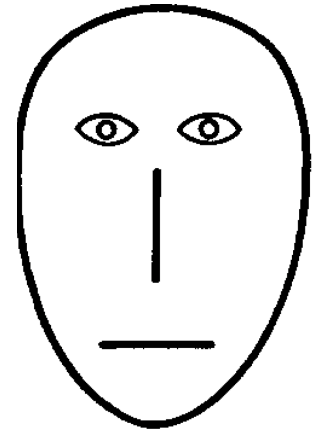
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$$s_{ik} = e^{-cd_{ik}}$$

# 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  $x_k$

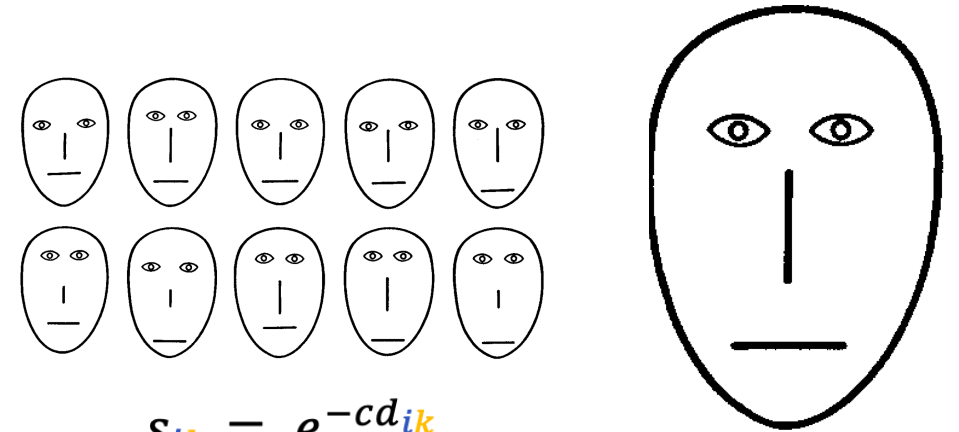


$$s_{ik} = e^{-cd_{ik}}$$



# 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**



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

$$\text{activation}(\text{MacDonald}) = \sum_k s_{ik}$$

$$\text{activation}(\text{Campbell}) = \sum_k s_{ik}$$

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

# activity: computing probabilities

- in groups, go to [the probability spreadsheet](#)
- navigate to your group's tab
- calculate the activation using the similarity values
- then calculate the probabilities
- report back the classification decision

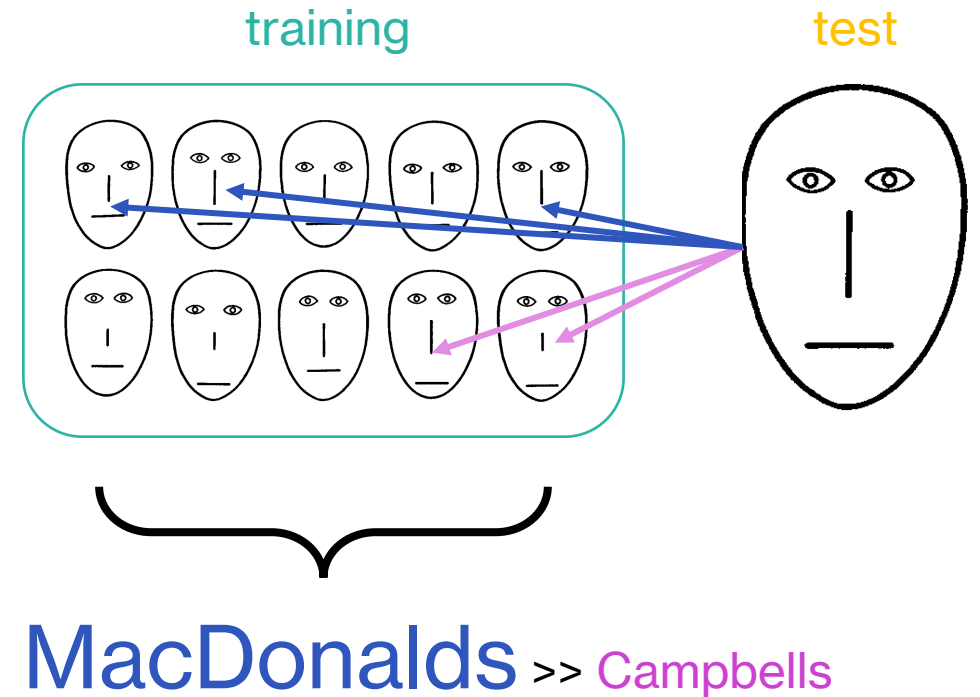
$$\text{activation}(\text{MacDonald}) = \sum_k s_{ik}$$

$$\text{activation}(\text{Campbell}) = \sum_k s_{ik}$$

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

# exemplar model: description 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





# big takeaways

- get in groups of 3 and report key takeaways from today
- [takeaways document](#)



# next class

- **before** class:
  - *finish*: L9 chapter
  - *post*: conceptual reflection
- **during** class:
  - prototype model
  - from exemplars to memory (MINERVA)