Computational Cognitive Science

Lecture 1: Introduction

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Reading: Chapter 1 of Farrell and Lewandowsky.

Models and Theories

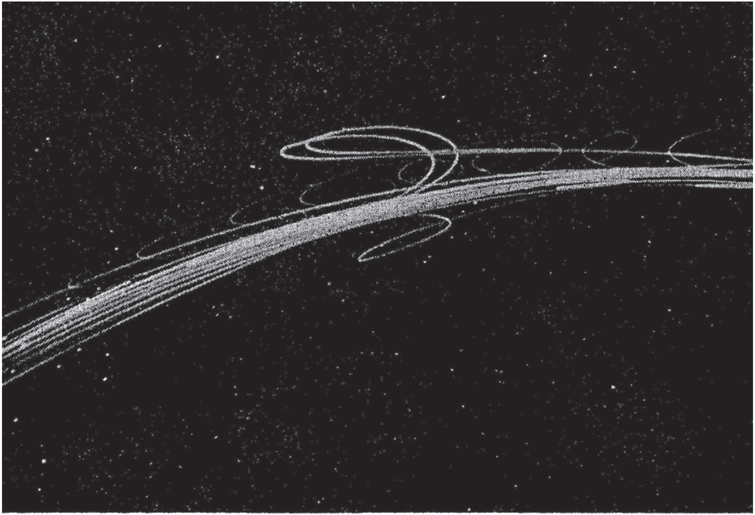
The aim of cognitive science is to understand how the mind works.

This involves *describing, explaining,* and ultimately, *predicting* human behavior.

To achieve this, analyzing data and forming verbal theories is not sufficient, we need *quantitative mathematical models.*

Example from physics: planets in the night sky move back and forth in loops.

Models and Theories



Models and Theories

Observation: *retrograde motion of planets*[1]

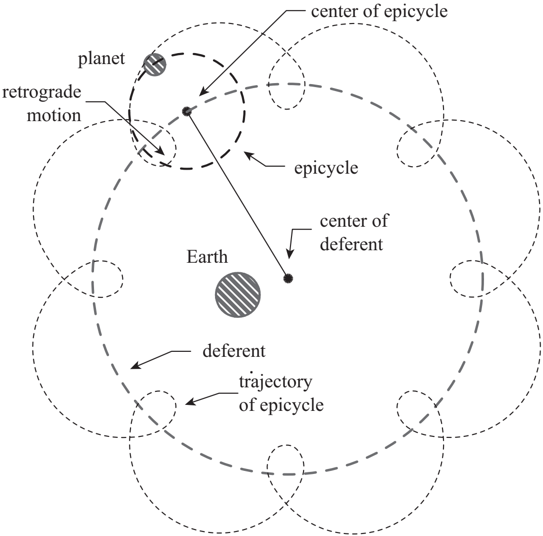
- this observation is hard to explain (or even to describe) without a model;
- the model itself (even though it may explain the data) is an unobservable, abstract device;
- there are always several possible models that explain the data.

Competing models of planetary motion:

- *Ptolemaic:* planets move around the earth in deferents and epicycles;
- *Copernican:* planets move around the sun in circles.

[1] Explainer video: https://www.youtube.com/watch?v=EtV0PV9MF88

Ptolemaic Model of Planetary Motion



Deciding between Models

Ptolemaic (geocentric) vs. Copernican (heliocentric) model:

- both predict the position of the planets to within 1° accuracy;
- Copernican model predicts latitude slightly better;
- but its main advantage is elegance and *simplicity*, not *goodness of fit* to the data.

Isn't simplicity subjective and imprecise?
Not necessarily; later we'll discuss ways to formalize simplicity.

Deciding between Models

Simpler models can also be stepping stones to other theoretical advances:

- Kepler's laws of planetary motion replace the circles in the Copernican model with ellipses (of different eccentricities);
- this small modification achieves near-perfect fit with the data.

We'll discuss model comparison in later lectures.

Models in Cognitive Science

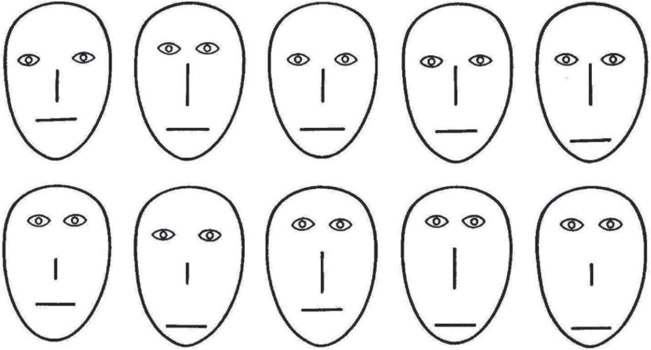
Categorization experiment (Nosofsky, 1991):

- training: participants classify cartoon faces into two categories;
- transfer: participants see a larger set, both faces they've seen before and new ones;
- they need to classify the face, say how confident they are, and whether they've seen it before.

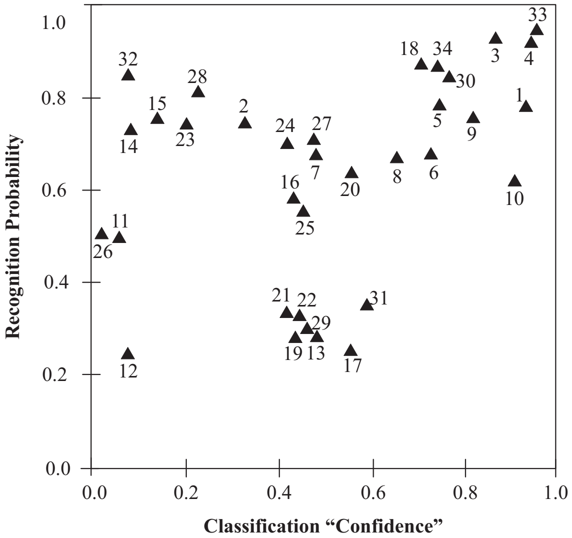
Moderate correlation between classification confidence and recognition probability.

Categorization experiment

Example instances (Nosofsky, 1991):



Models in Cognitive Science



Models in Cognitive Science

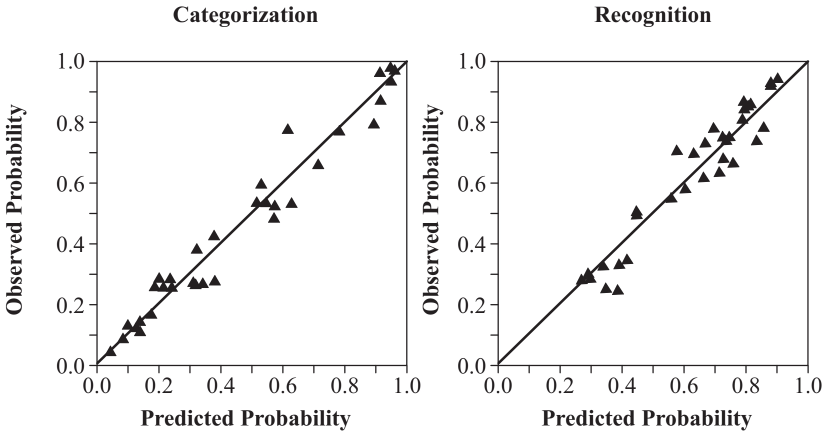
No strong relationship between classification and recognition.

Can we conclude that whether you confidently classify a face doesn't depend on whether you remember it?

No, there is a cognitive model (the GCM, details below), which relates classification and recognition and predicts both accurately.

The data don't speak for themselves, but require a quantitative model to be described and explained.

Models in Cognitive Science



Types of Models

A model is supposed to describe existing data, predict new observations, and provide an explanation for the relevant behavior.

Farrell and Lewandowsky divide models into two kinds:

- *data descriptions:* summarize the data in mathematical form, typically involving parameters estimated from the data;
- *process models:* make commitments about the underlying processes and/or mental representations. Model parameters and features have psychological interpretations.

Aside: Other taxonomies for models

There are other ways to classify models. One of the best-known is due to David Marr (1982):

- **Goal (computational) level**: What is the organism trying to achieve? How would an ideal or rational agent solve the problem?
- **Process (algorithmic) level**: What algorithm is implementing that solution?
- **Implementation level**: How is the algorithm implemented physically?

Data Description

Example:
The relationship between the amount of practice and the response time in a learning task can be described by a *power law* function:

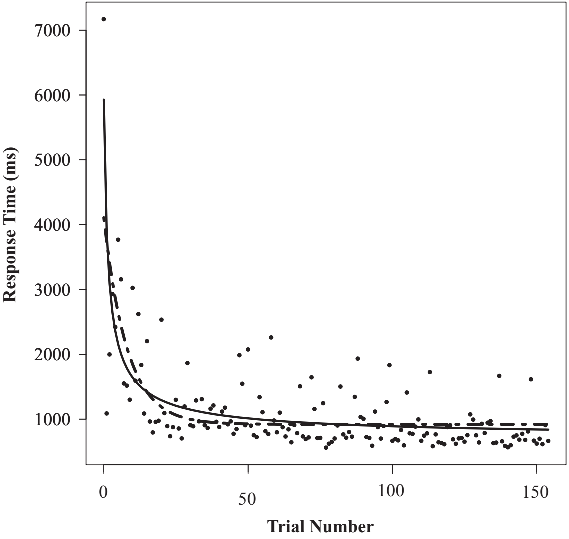
$$RT = N^{-\beta}$$

An alternative model is in terms of an *exponential function:*

$$RT = e^{-\alpha N}$$

where RT is the response time, N is the number of trials, and α and β are learning rates.

Data Description



Both models provide a good fit to the data (dashed line: power law; solid line: exponential function).

Ways to decide between them:

- *goodness of fit:* recent work shows that the exponential function provides a better fit to the data on learning;
- *empirical predictions:* the mathematical form of the power law implies that the learning rate decreases with increasing practice; the exponential function implies it stays constant.

Ideally, however, we want to tie the parameters in the model to psychological processes.

Cognitive process models

We want more than a mathematical description of the data.
Proper models ("cognitive process models"):

- **explain** and **predict** cognition and behavior;
- have psychological content – their elements can be interpreted in psychological terms.

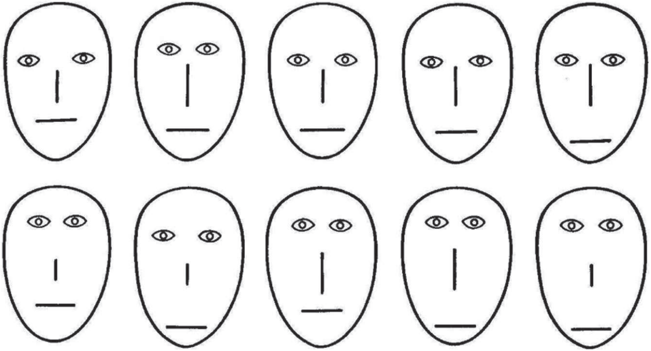
Cognitive process models

Example: *Generalized Context Model* (GCM; Nosofsky, 1986), an exemplar model of categorization:

- during training, the model stores every instance of a category;
- during testing, a new instance activates all stored exemplars depending on similarity;
- response probability depends on the sum of the similarity with each member of the category.

Generalized Context Model

Example instances (Nosofsky, 1991):



Features: eye height, eye separation, nose length, and mouth height.

Generalized Context Model

The distance d_{ij} between two instances i and j, where each has K features with values x_{ik} and x_{jk}, is:

$$d_{ij} = \left(\sum_{k=1}^{K} |x_{ik} - x_{jk}|^2 \right)^{\frac{1}{2}}$$

The similarity between i and j is (where c is a parameter):

$$s_{ij} = \exp(-c \cdot d_{ij})$$

Then the probability of classifying instance i into category A (rather than category B) is:

$$P(R_i = A|i) = \frac{\sum_{j \in A} s_{ij}}{\sum_{j \in A} s_{ij} + \sum_{j \in B} s_{ij}}$$

The Power of Models

In addition to helping us explain and predict human behavior, models can:

- help *classify phenomena* (e.g., by relating seemingly unrelated data, see categorization vs. recognition);
- help *explore the implications* of a theory (e.g., lesioning a model, scaling to larger data sets, exploring learning).

Course Overview

This course provides an introduction to computational cognitive modeling. There are two main parts:

- introduction to modeling methods;
- discussion of specific models.

We will cover three broad areas of cognition:

- memory;
- language;
- vision.

The textbook is *Farrell and Lewandowsky: Computational Modeling of Cognition and Behavior*. The university has an electronic subscription. This is complemented by papers, see the course resource list.

Required Background

This course requires programming skills. We will use Matlab for the assignment, and the text uses R for several examples.

The second requirement is maths background:

- probability theory: random variables, distributions, expectations, Bayes theorem;
- linear algebra: basic vector and matrix operations.

If you need a refresher, use *Sharon Goldwater's maths tutorial.*

http://homepages.inf.ed.ac.uk/sgwater/math_tutorials.html

Communication

When you sign up for the course, you will have access to:

- the course mailing list: used for all essential communication;
- the Learn page of the course, used for the assignment
- all other material will appear on the course web page.

There is also a Piazza discussion for the course:

- you can use it to post questions about the course content, including tutorials and assignment;
- the main purpose is **peer support:** students discuss course material and help each other;
- course staff will moderate and contribute

Assessment, Tutorials, Lectures

The assessment on this course will consist of:

- an assessed assignment, worth 25% of the overall mark;
- a final exam worth 75% of the overall mark.

See the course web page for:

- date of assignment and how to submit it;
- plagiarism policy;
- lecture slides, old exams.

There are weekly tutorials for this course:

- tutorials are both practical (use R) and theoretical;
- they start in **Week 3**;
- you will be automatically assigned a tutorial group; if you have a timetable clash, contact the ITO.

Feedback

Feedback students will receive in this course:

- there will some non-assessed quizzes – we may try to use Top Hat for these;
- tutorials will be based on non-assessed exercises; you should try to solve these before the tutorials!
- sample solutions will be released for tutorials;
- tutorials include a feed-forward session for the assignment;
- individual assignment comments will be provided by the marker;

References

Marr, D. (1982). *Vision: A computational investigation into the human representation and processing of visual information*. New York: W. H. Freeman.

Nosofsky, R. M. (1986). Attention, similarity, and the identification-categorization relationship. *Journal of Experimental Psychology: General*, *115*(1), 39–57.

Nosofsky, R. M. (1991). Tests of an exemplar model for relating perceptual classification and recognition memory. *Journal of Experimental Psychology: Human Perception and Performance*, *17*(1), 3–27.