Lecture 1: Computational Cognitive Modeling

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course website:
https://brendenlake.github.io/CCM-site/

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Logistics

course website:
https://brendenlake.github.io/CCM-site/

course discussion:
https://piazza.com/nyu/spring2018/dsga3001006/home

email address for instructors:
instructors-ccm-spring2018@nyuccl.org

lecture:
Tuesdays 6:45 PM - 8:25 PM

lab:
Tuesdays 8:25 PM - 9:25 PM

Course Overview

Key questions:

- For cognitive scientists: Can we better understand human learning and thought by developing computational cognitive models?

- For data scientists: Can we better understand behavioral data by developing computational cognitive models?

Course Overview

Pre-requisites:

- *Math:* If you had linear algebra and calculus as an undergrad, or if you have taken Math Tools in the psychology department, you will be in the best position for approach the material. We will, when needed, review some of the basic technical concepts in lab.

- *Programming:* For the homework/assignments, we will assume some basic familiarity with programming in Python using the Jupyter Notebook system (http://jupyter.org). We will review some of the programming basics in lab.

Course Overview

Grading:

- The final grade is based on homeworks (50%), final project (35%), and attendance/participation (15%).

Final project:

- Final project will be done in groups of 2-4 students. A short paper will be turned in describing the project. The project will represent either an substantial extension of one of the homeworks (e.g., exploring some new aspect of one of the assignments), implementing and replicated an existing cognitive modeling paper, or a written paper discussing one of the core modeling topics. The final projects will need to be approved by the instructor at least 6 weeks before the end of the semester.

Course Overview

Collaboration policy:

- We encourage you to discuss the homework assignments with your classmates. We expect you to run the simulations and complete the write-ups for the homeworks on your own. Under no circumstance should students look at each other's write ups.

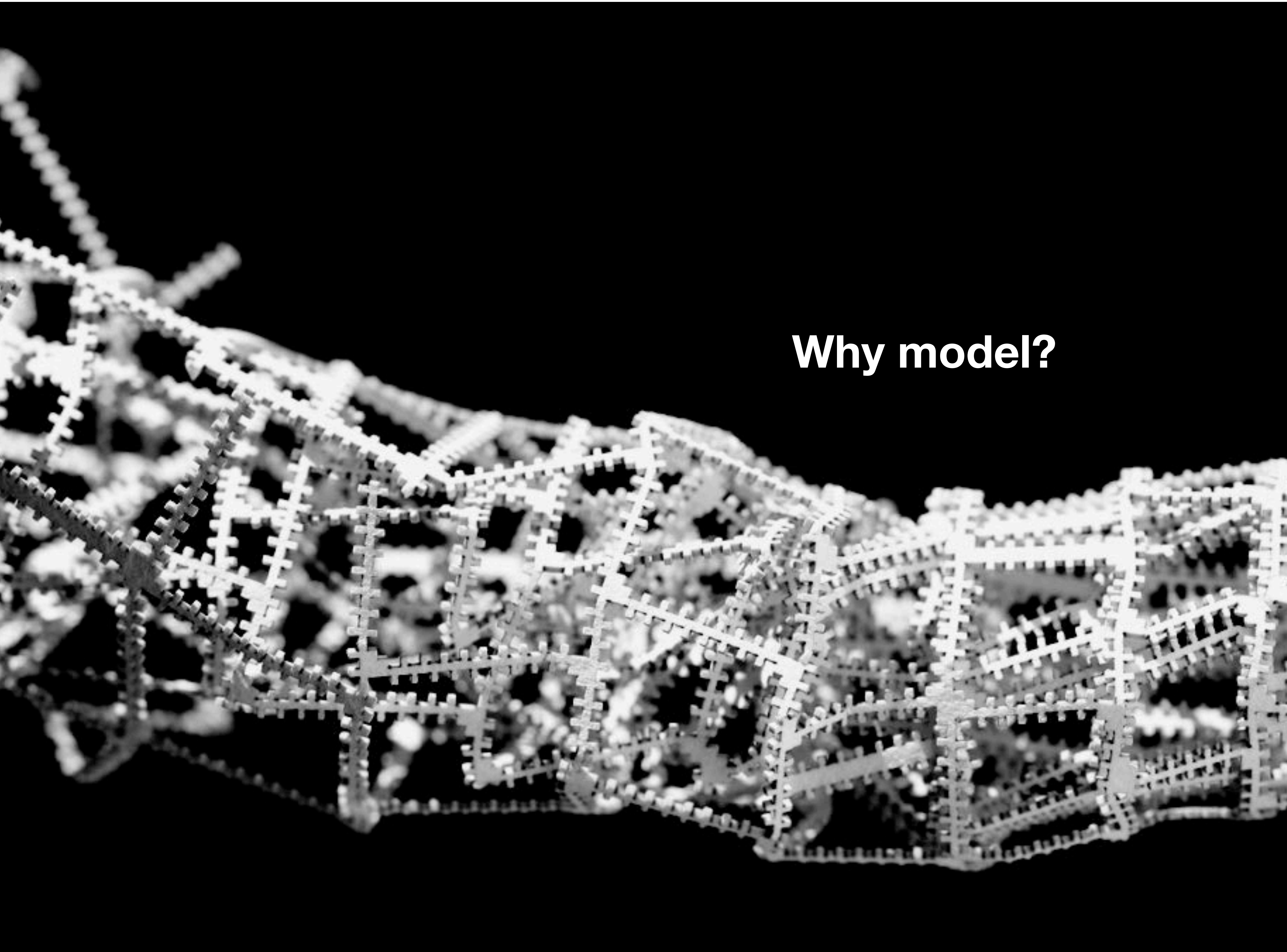
Late work:

- We will take off 10% for each day a homework or final project is late.

What is Computational Cognitive Modeling?

- Computational Cognitive Modeling is a field devoting to unlocking the mystery of the human mind/brain in terms of underlying computational processes.
- A core goal is to build simulations that *mimic* the intelligent behavior of humans, and to use these types of model to predict and explain behavior.

Why model?



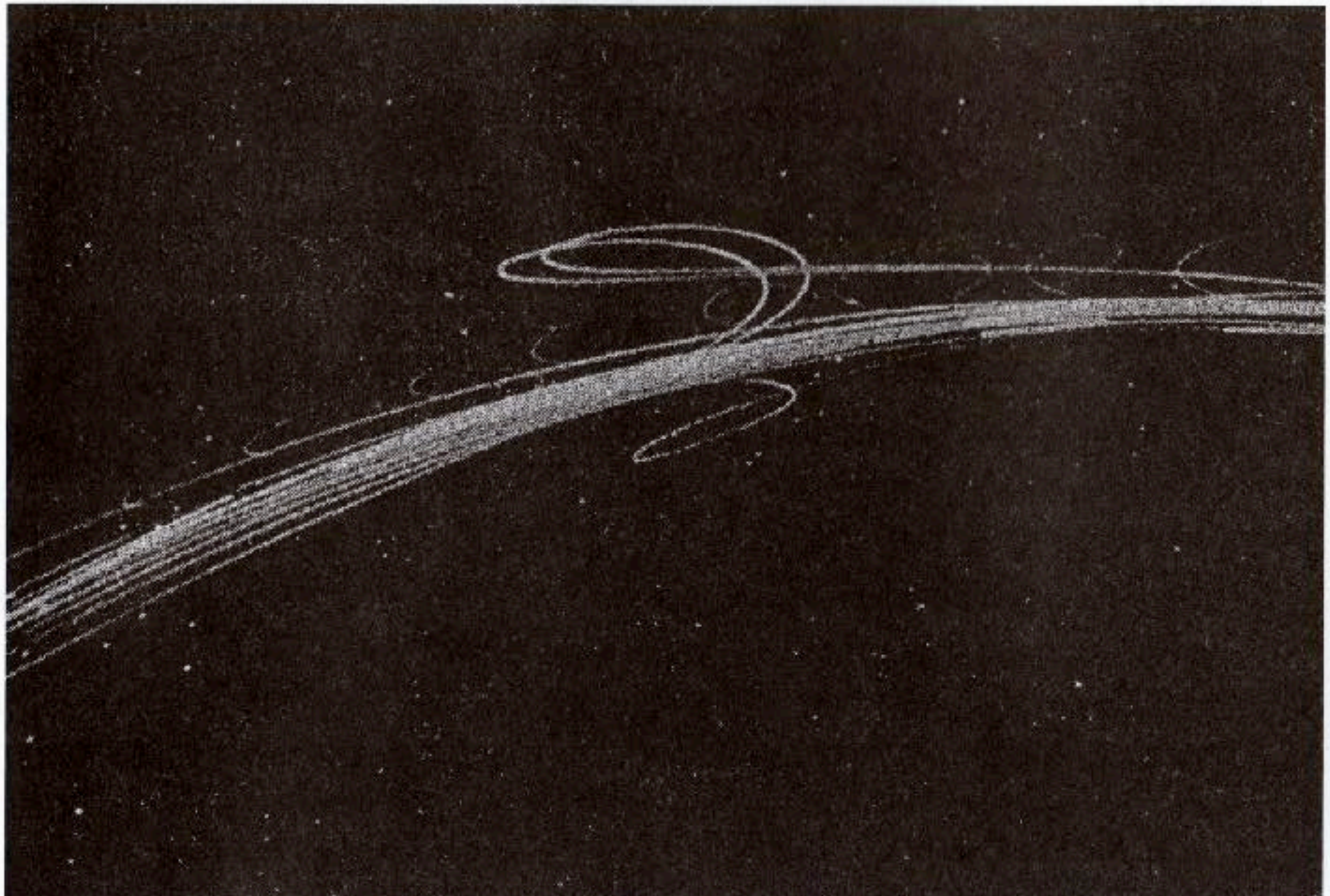


Figure 1.1 An example of data that defy easy description and explanation without a quantitative model.

Ptolemy

Copernicus

Kepler

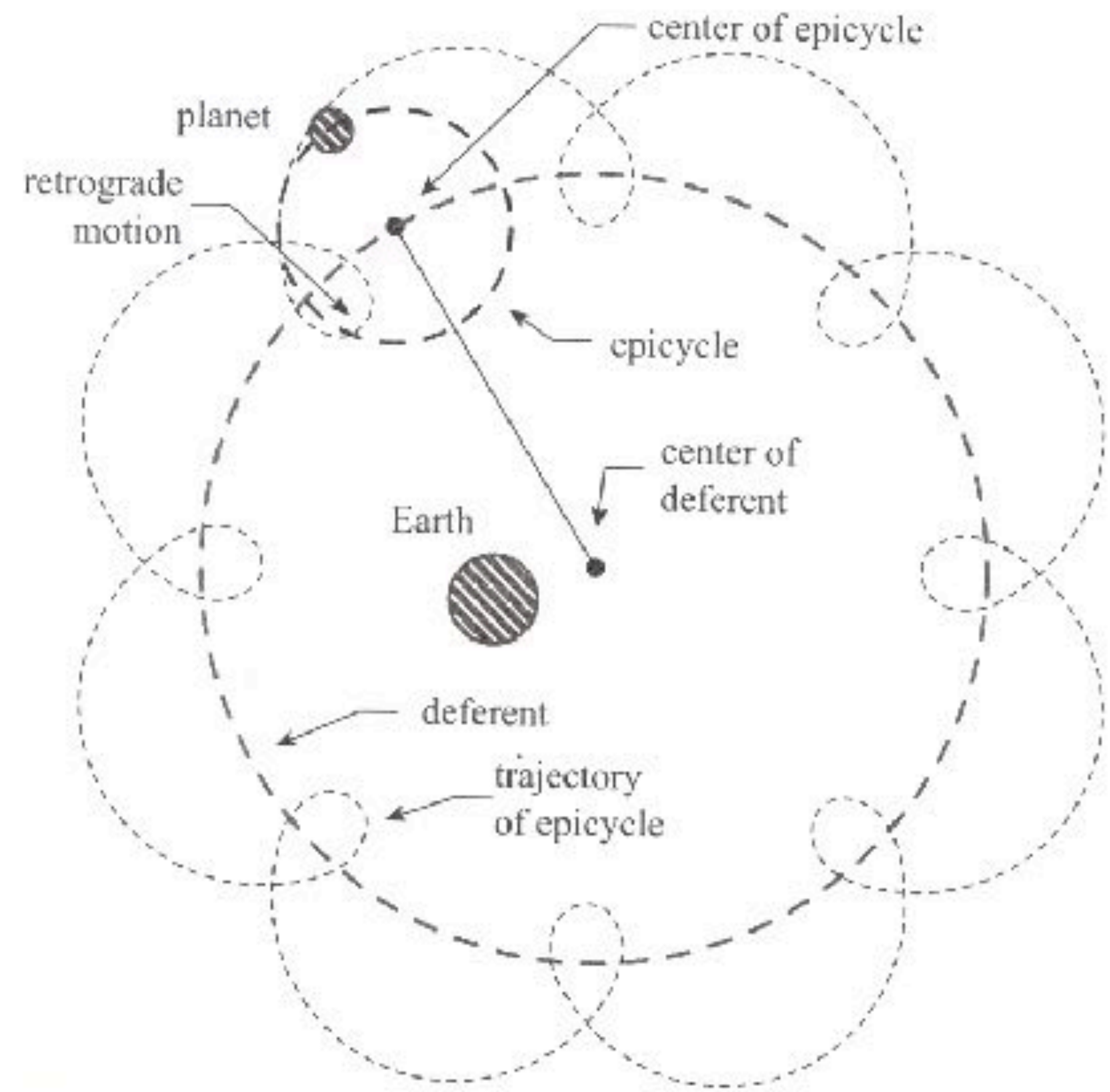


Figure 1.2 The geocentric model of the solar system developed by Ptolemy. It was the predominant model for some 1,300 years.

Why model?

- Data never speak for themselves but require a model to be understood and to be explained

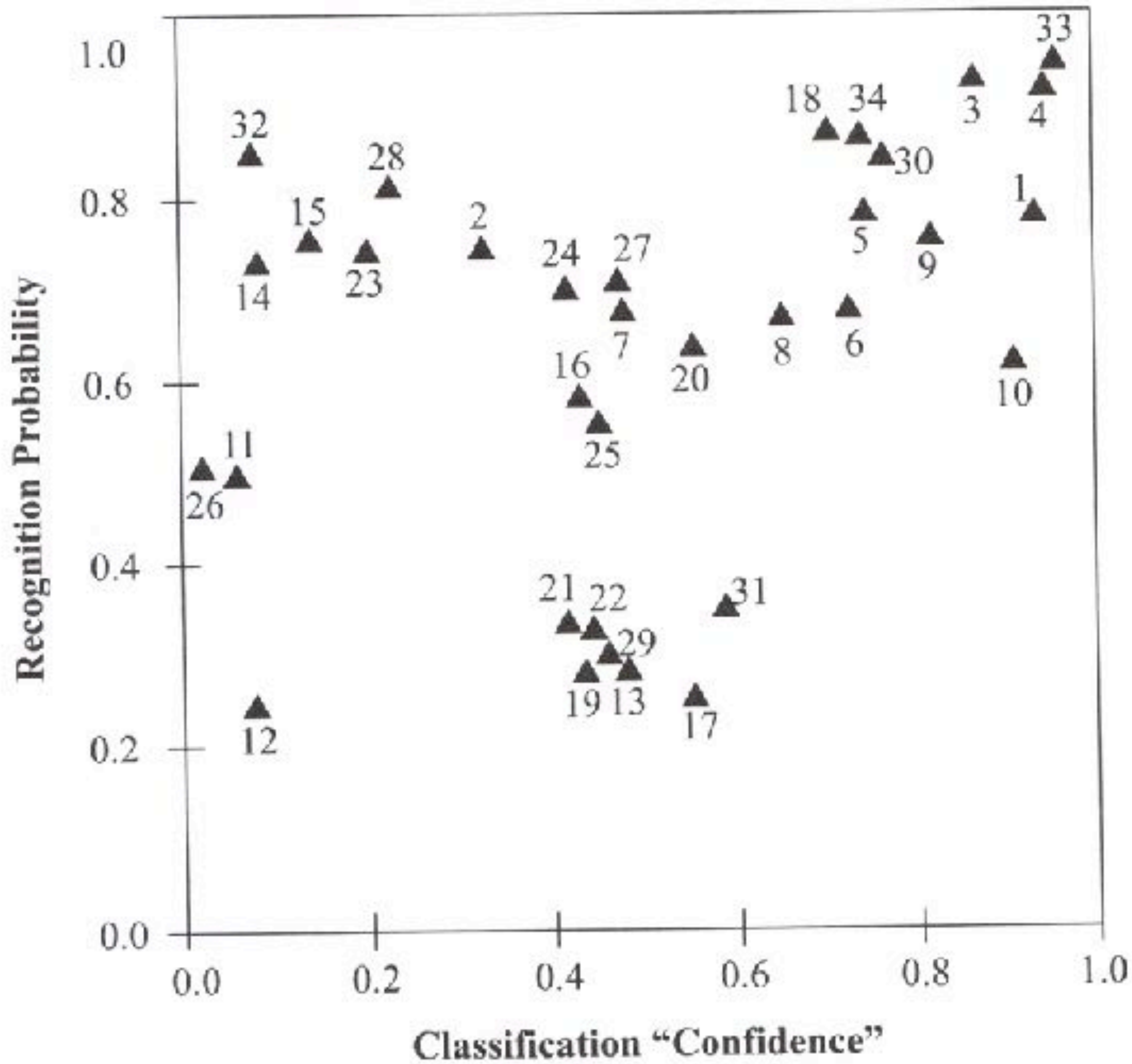


Figure 1.3 Observed recognition scores as a function of observed classification confidence for the same stimuli (each number identifies a unique stimulus). See text for details. Figure reprinted from Nosofsky, R. M. (1991). Tests of an exemplar mode for relating perceptual classification and recognition memory. *Journal of Experimental Psychology: Human Perception and Performance*, *17*, 3–27. Published by the American Psychological Association; reprinted with permission.

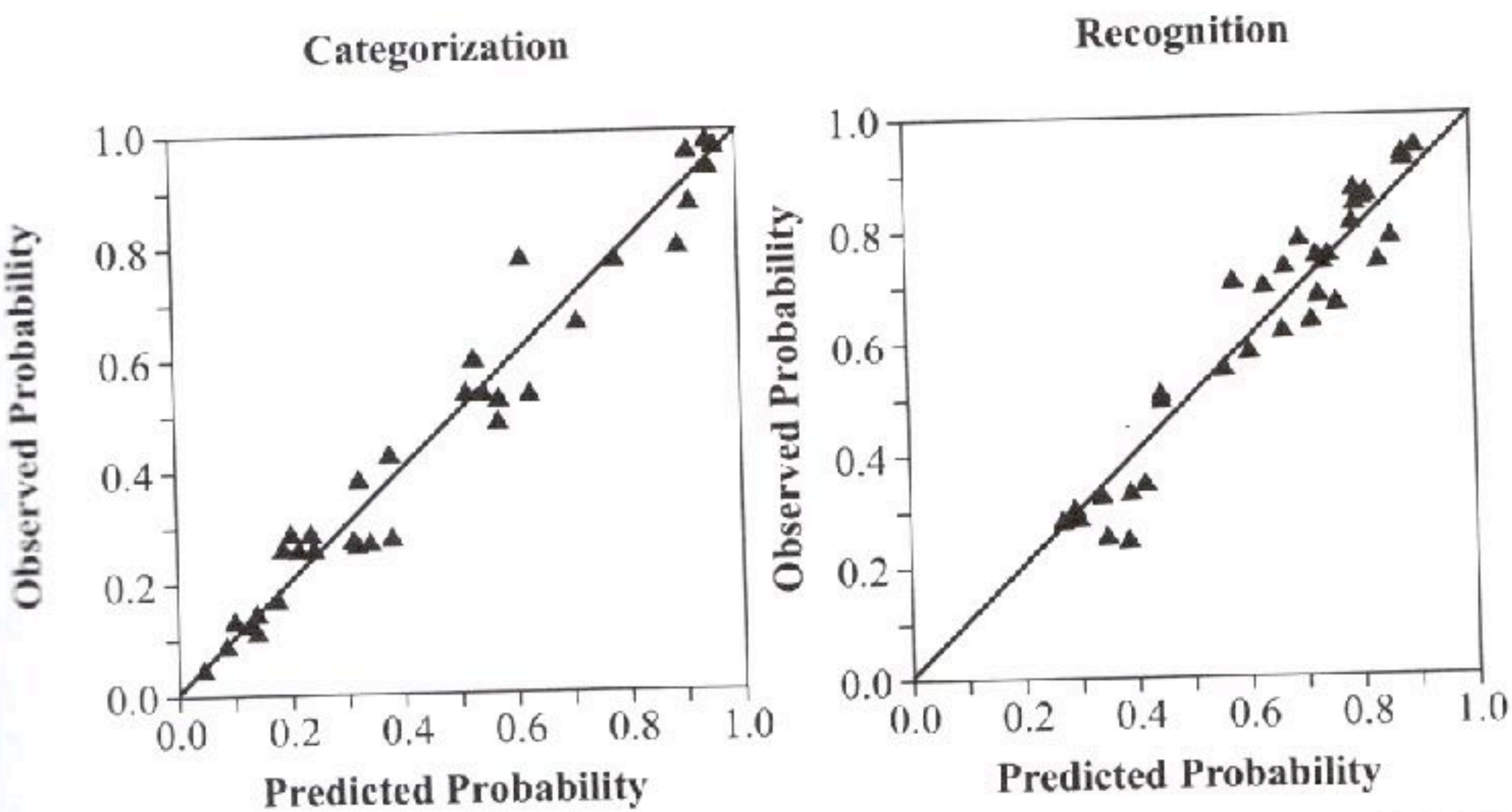


Figure 1.4 Observed and predicted classification (left panel) and recognition (right panel). Predictions are provided by the GCM; see text for details. Perfect prediction is represented by the diagonal lines. Figure reprinted from Nosofsky, R. M. (1991). Tests of an exemplar mode for relating perceptual classification and recognition memory. *Journal of Experimental Psychology: Human Perception and Performance*, *17*, 3–27. Published by the American Psychological Association; reprinted with permission.

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- There are always several alternative models that vie for explanation of data, and we must select between them

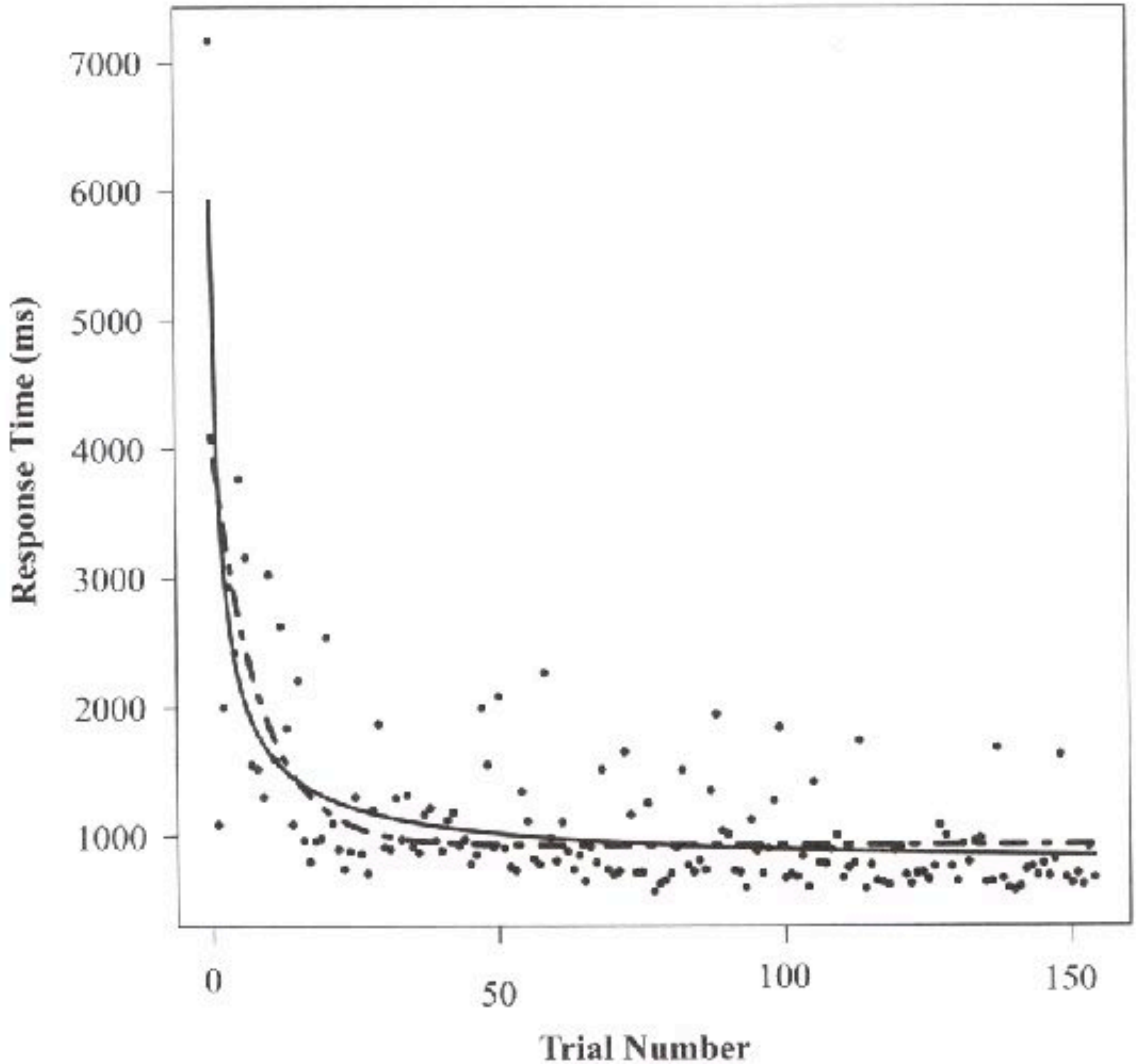

Figure 1.5 Sample power law learning function (dashed line) and alternative exponential function (solid line) fitted to the same data. Data are represented by dots and are taken from Palmeri's (1997) Experiment 3 (Subject 3, Pattern 13). To fit the data, the power and exponential functions were a bit more complex than described in Equations 1.1 and 1.2 because they also contained an asymptote (A) and a multiplier (B). Hence, the power function took the form $RT = A_P + B_P \times (N+1)^{-\beta}$, and the exponential function was $RT = A_E + B_E \times e^{-\alpha N}$.

Why model?

- Data never speak for themselves but require a model to be understood and to be explained
- Verbal theorizing alone ultimately cannot substitute for quantitative analysis
- There are always several alternative models that vie for explanation of data, and we must select between them
- Model selection rests on both quantitative evaluation and intellectual and scholarly judgment

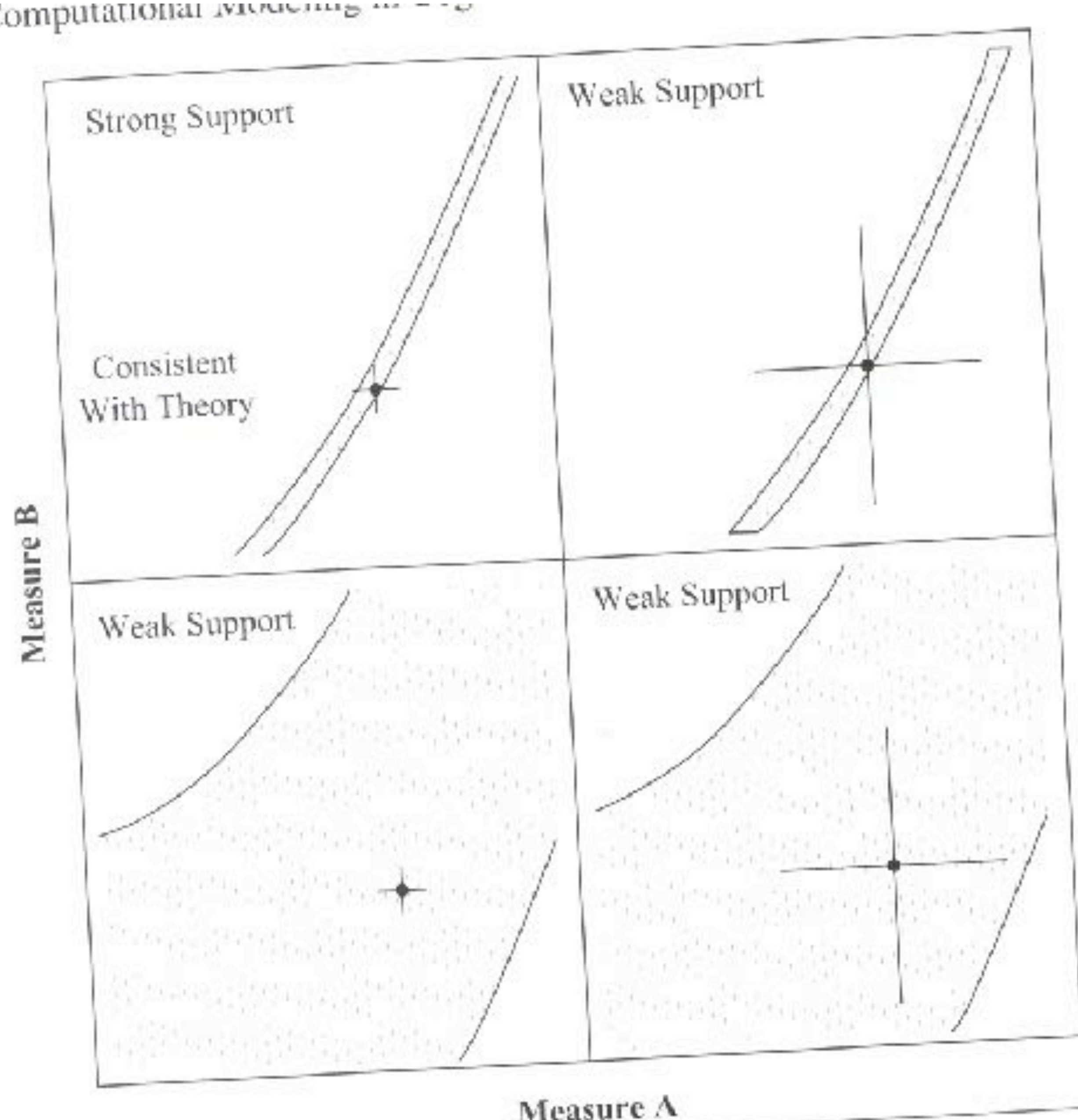

Figure 1.10 Four possible hypothetical relationships between theory and data involving two measures of behavior (A and B). Each panel describes a hypothetical outcome space permitted by the two measures. The shaded areas represent the predictions of a theory that differs in predictive scope (narrow and broad in the top and bottom panels, respectively). The error bars represent the precision of the observed data (represented by the black dot). See text for details. Figure reprinted from Roberts, S., & Pashler, H. (2000). How persuasive is a good fit? A comment on theory testing. *Psychological Review, 107*, 358–367. Published by the American Psychological Association; reprinted with permission.

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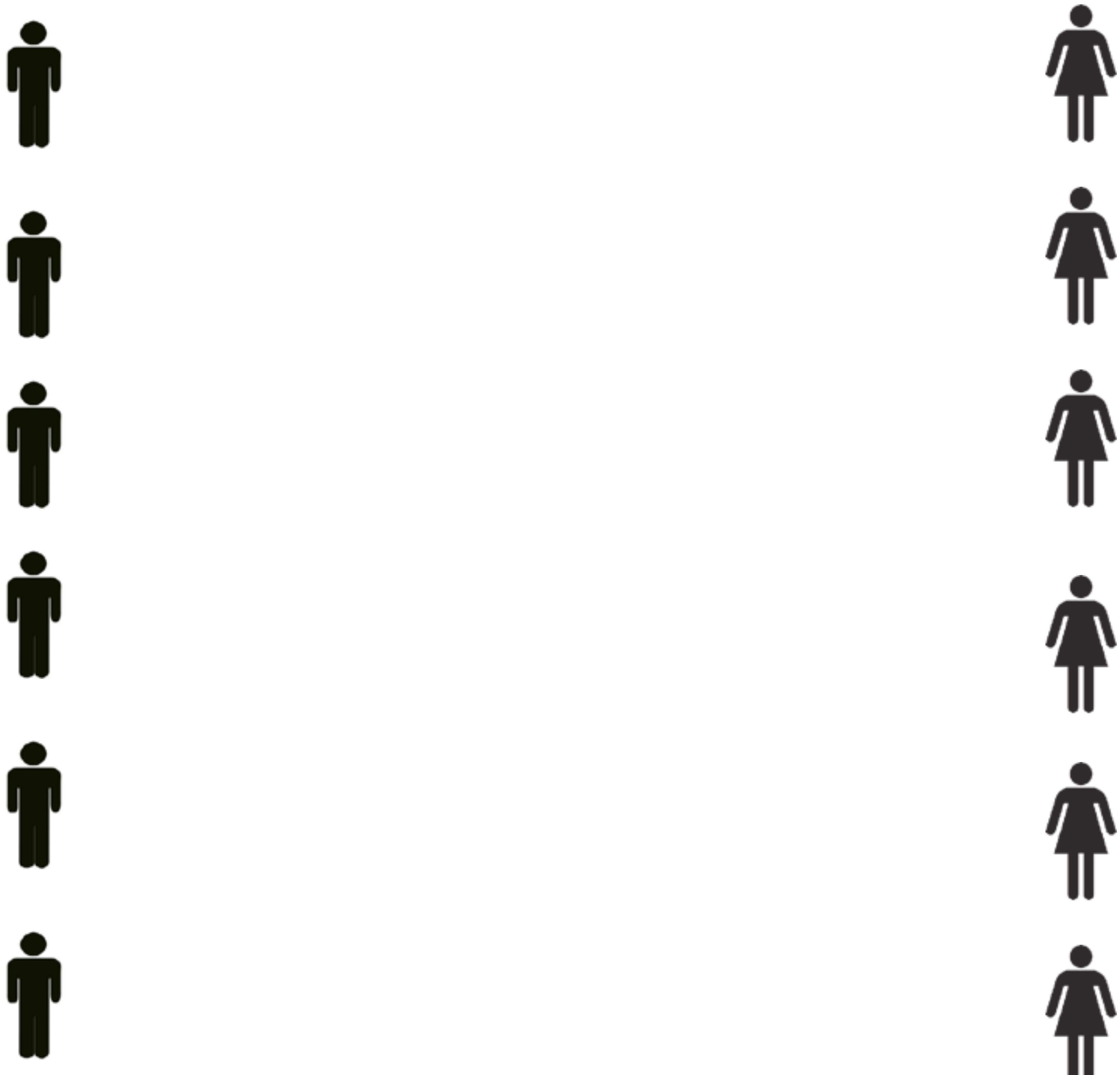
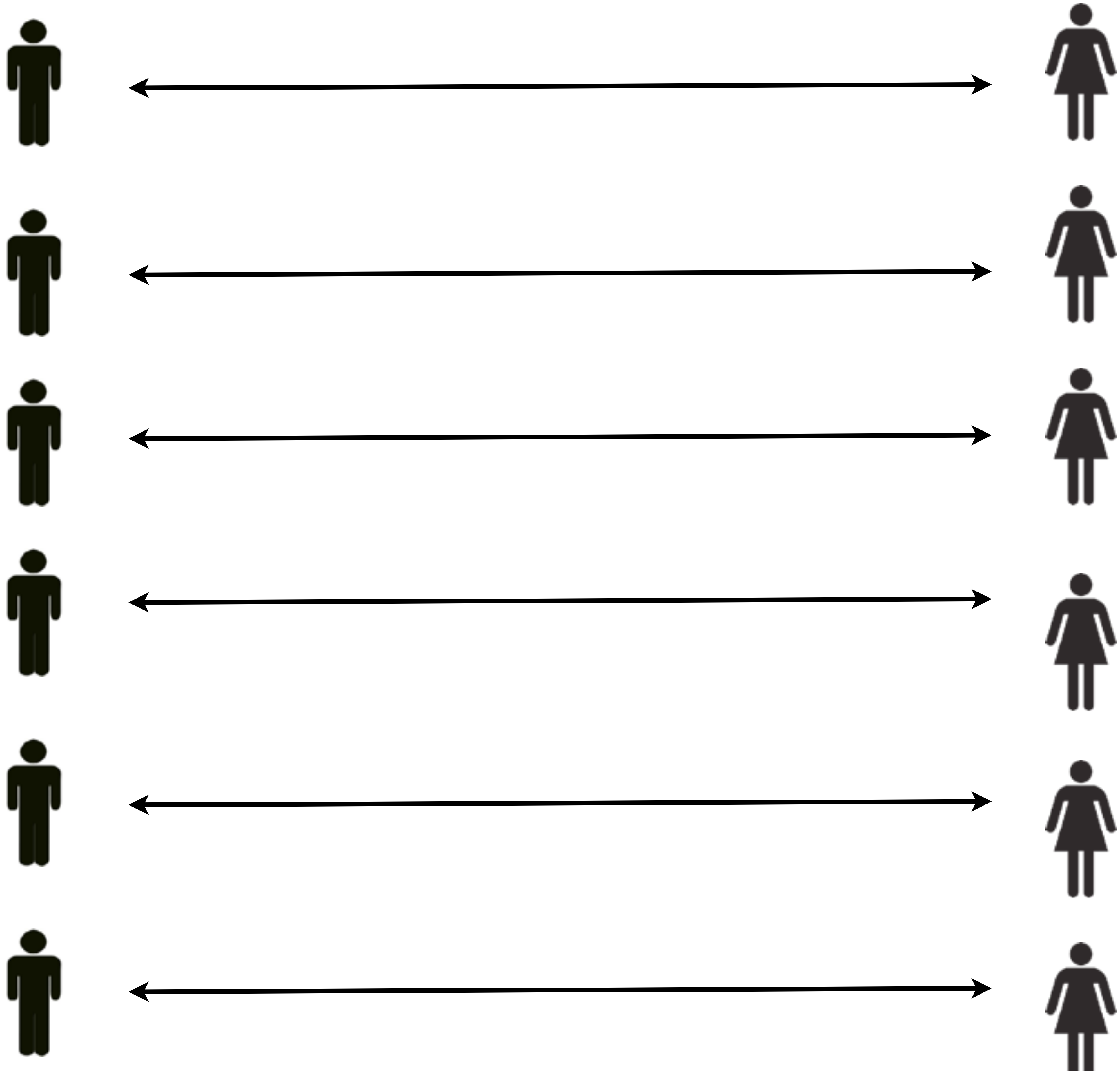
- Even seemingly intuitive verbal theories can turn out to be incoherent or ill-specified

“While adultery rates for men and women may be equalizing, men still have more partners then women do, and they are more likely to have one night stands; the roving male seeks sex, the female is looking for a better partner” (Leahey & Harris, 1989)





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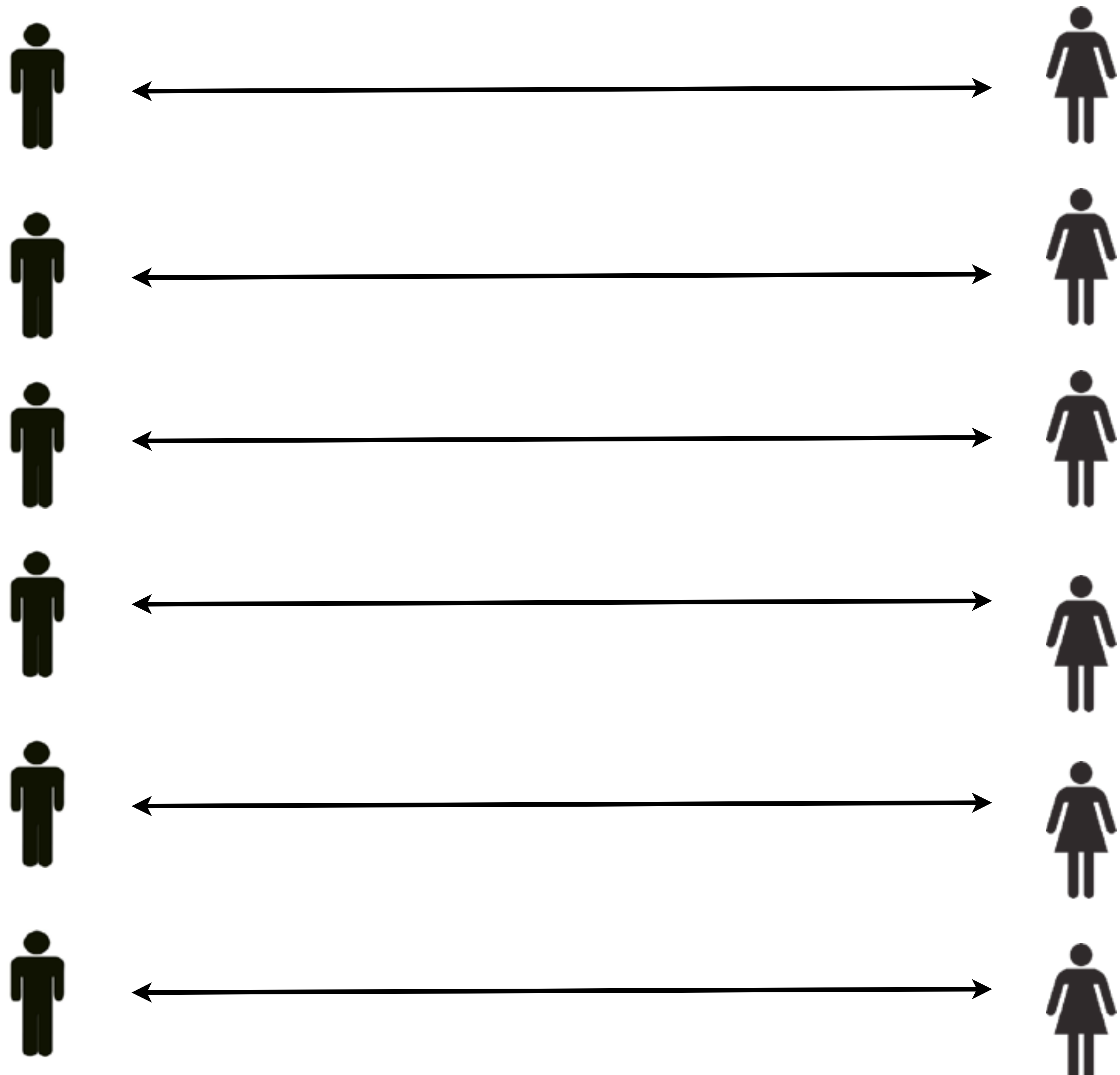

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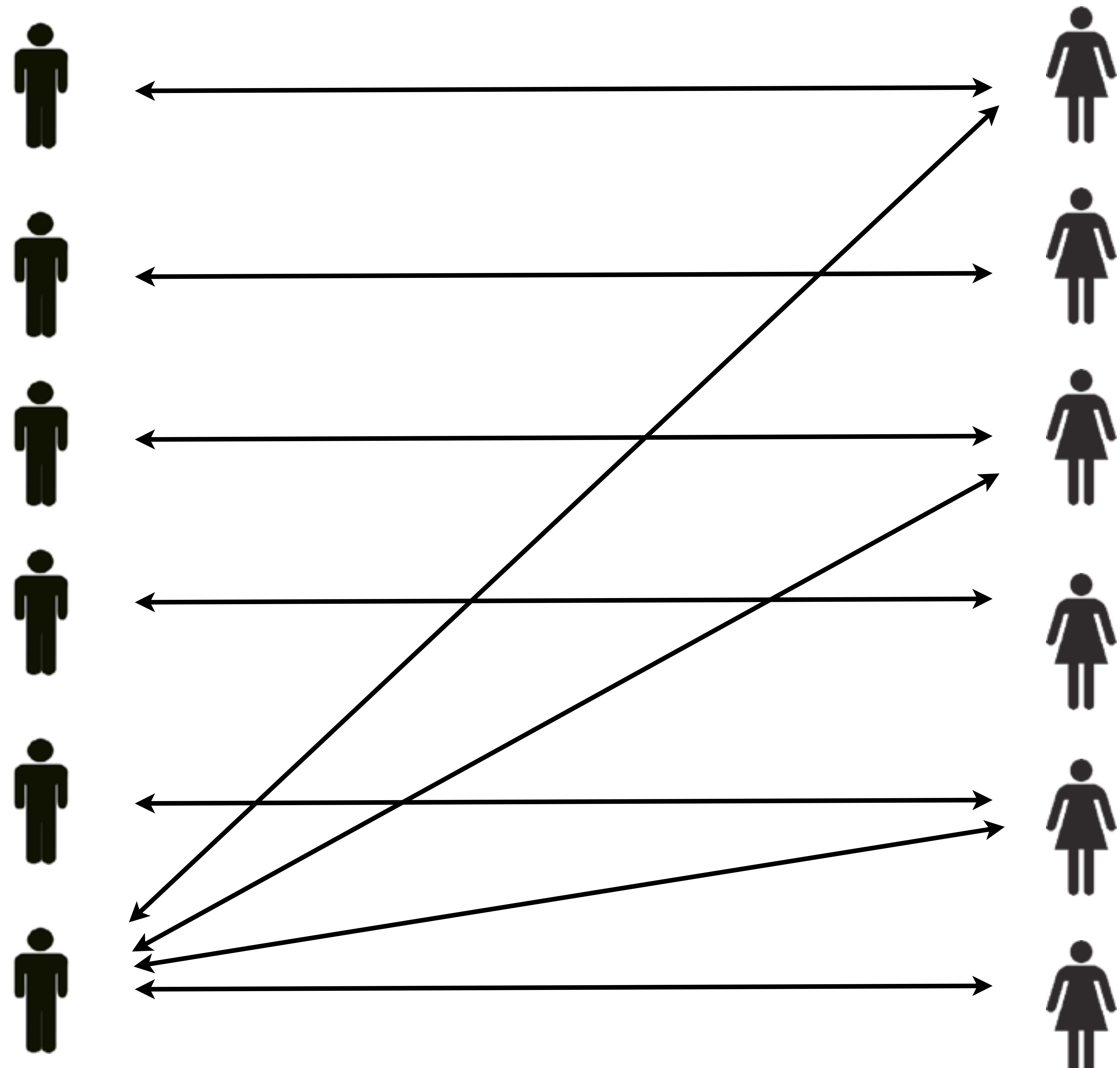
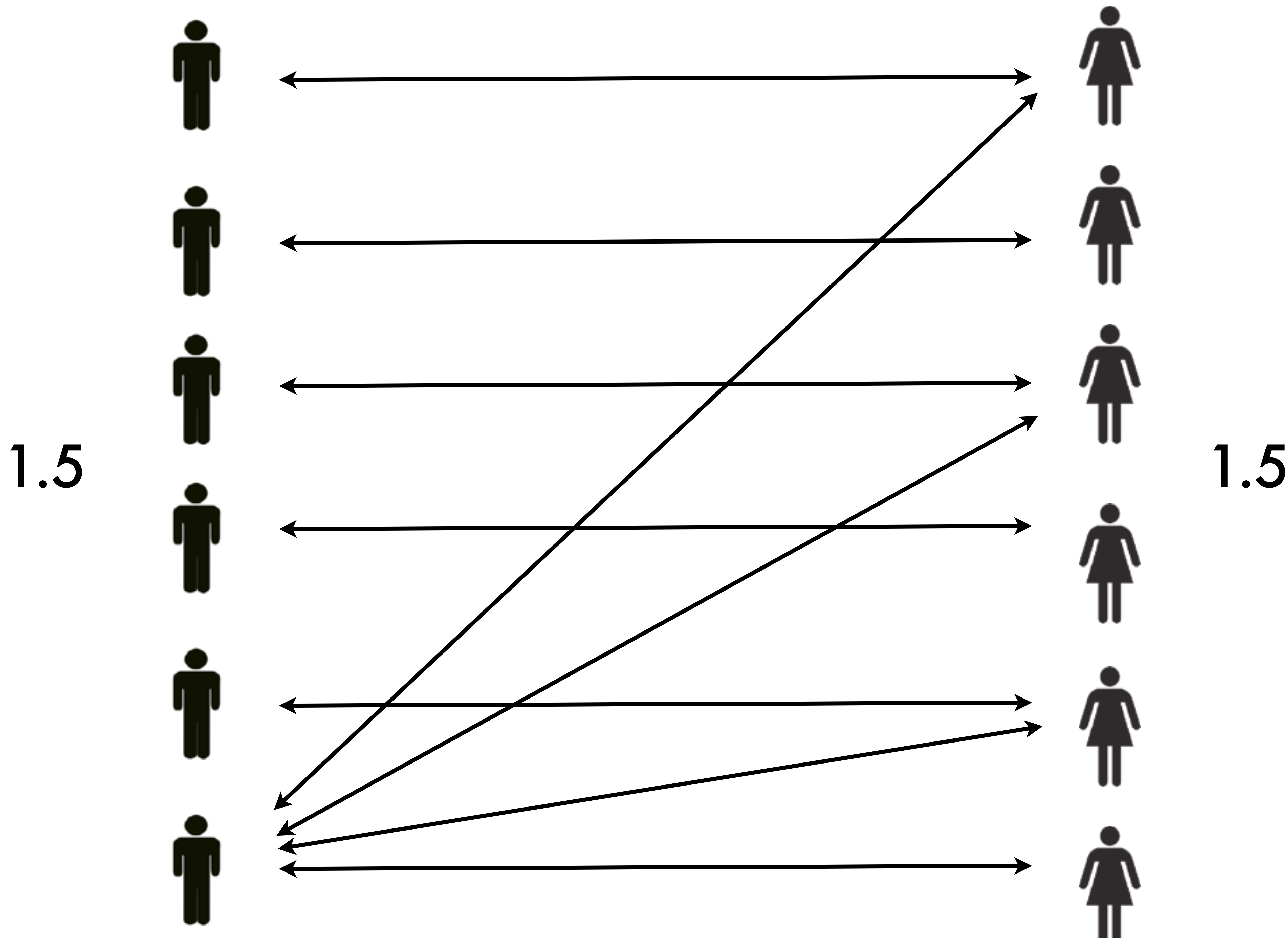
1.5

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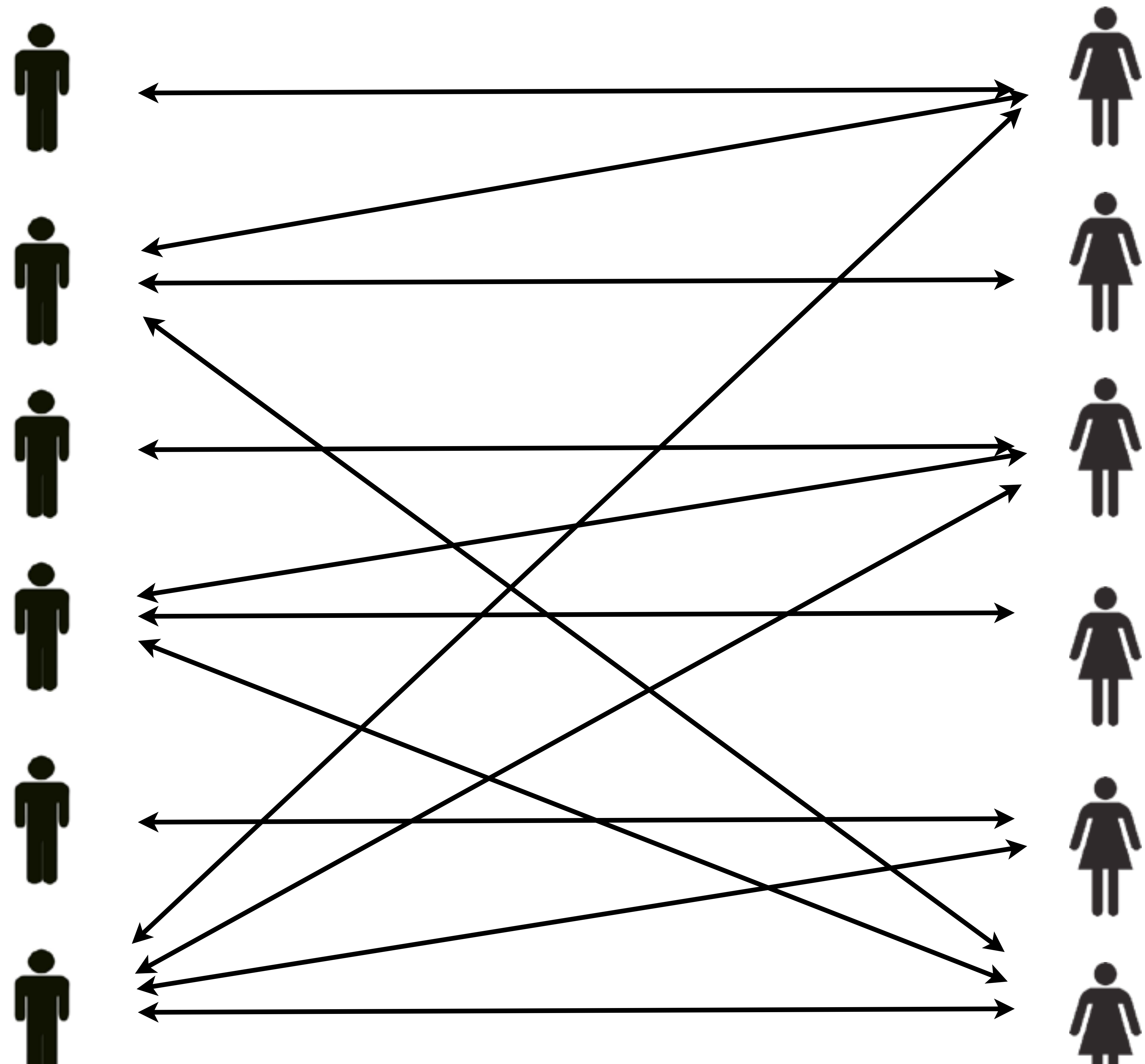

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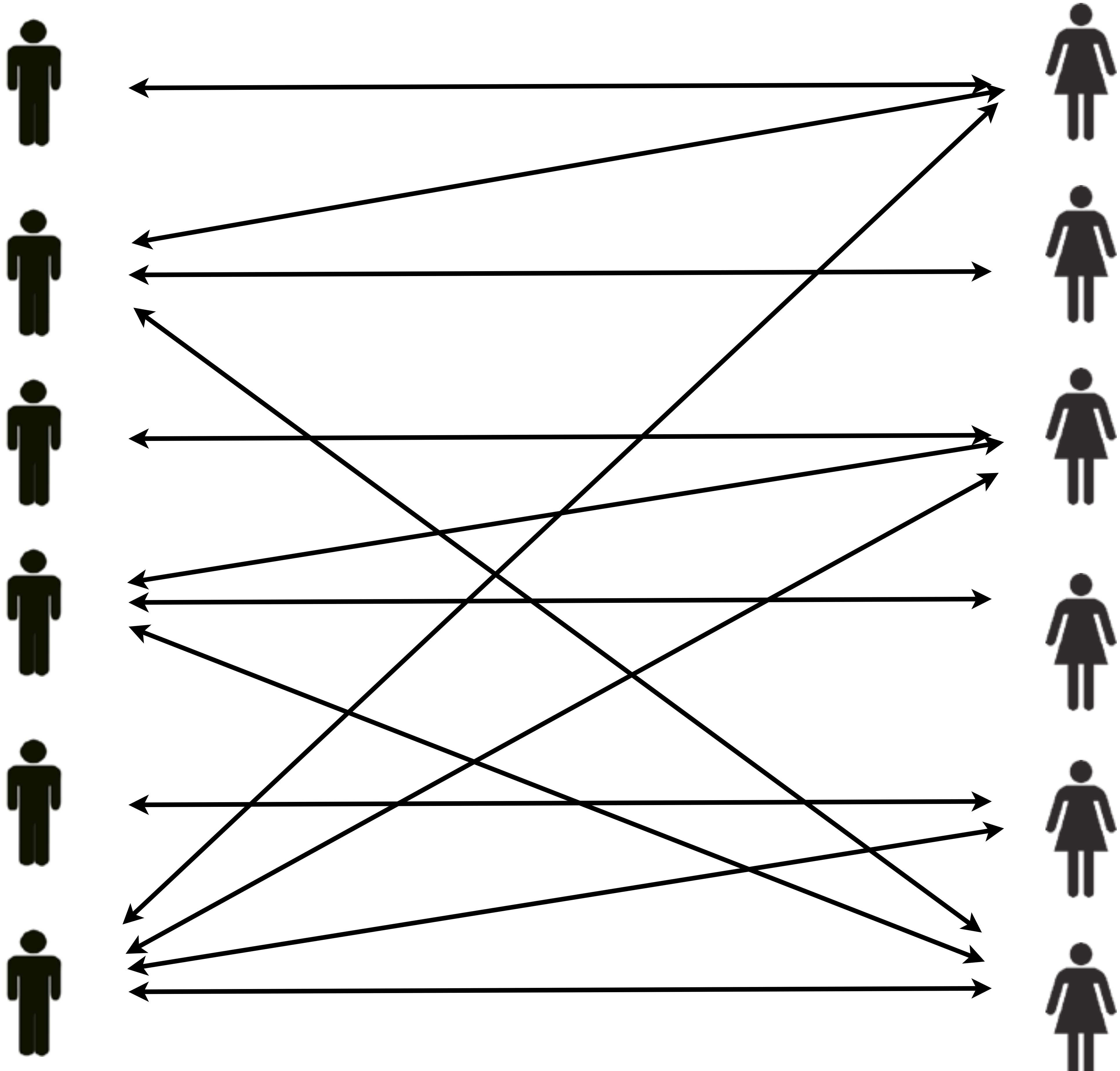

2.167

Why model?

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- There are always several alternative models that vie for explanation of data, and we must select between them
- Model selection rests on both quantitative evaluation and intellectual and scholarly judgment
- Even seemingly intuitive verbal theories can turn out to be incoherent or ill-specified
- Only instantiation in a quantitative model ensures that all assumptions of a theory have been identified and tested

“Verbally expressed statements are sometimes flawed by internal inconsistencies, logical contradictions, theoretical weaknesses and gaps. A running computational model, on the other hand, can be considered as a sufficiency proof of the internal coherence and completeness of the ideas it is based upon...” (Fum, Del Misser, Stocco, 2007)

Some possible psychological theories a scientist might have:

- Attention is like a spotlight
- A child learning about the world is like a scientist theorizing
- Language influences thought
- Working memory is having 7 +/- 2 slots to store information
- Categorization happens by comparing novel instances to exemplars
- Categories influence perception

Theories benefit from formalization with a computational model.

Why model?

- Every researcher has a model, whether they like it or not. ex: somatic marker hypothesis, Craik and Lockhart (1972) “levels of processing”, recall versus recognition, remember/know, this bit of brain inhibits this bit of brain
- Advantages of a FORMAL model:
    - **Make predictions explicit**
    - Implications often **defy expectations**
    - **Aid communication** between scientists
    - Support **cumulative progress**

“To have one’s hunches about how a simple combination of processes will behave is a humbling experience that no experimental psychologist should miss. Surprises are likely when the model has properties that are inherently difficult to understand such as variability, parallelism, and non-linearity - all undoubtedly, properties of the brain” (Hintzman, 1990)

* thanks to Tom Palmeri for pointing these excellent quotes out

Why model?

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  ex: somatic marker hypothesis, recall versus recognition, remember/know, this bit of brain inhibits this bit of brain
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    - Support **cumulative progress**

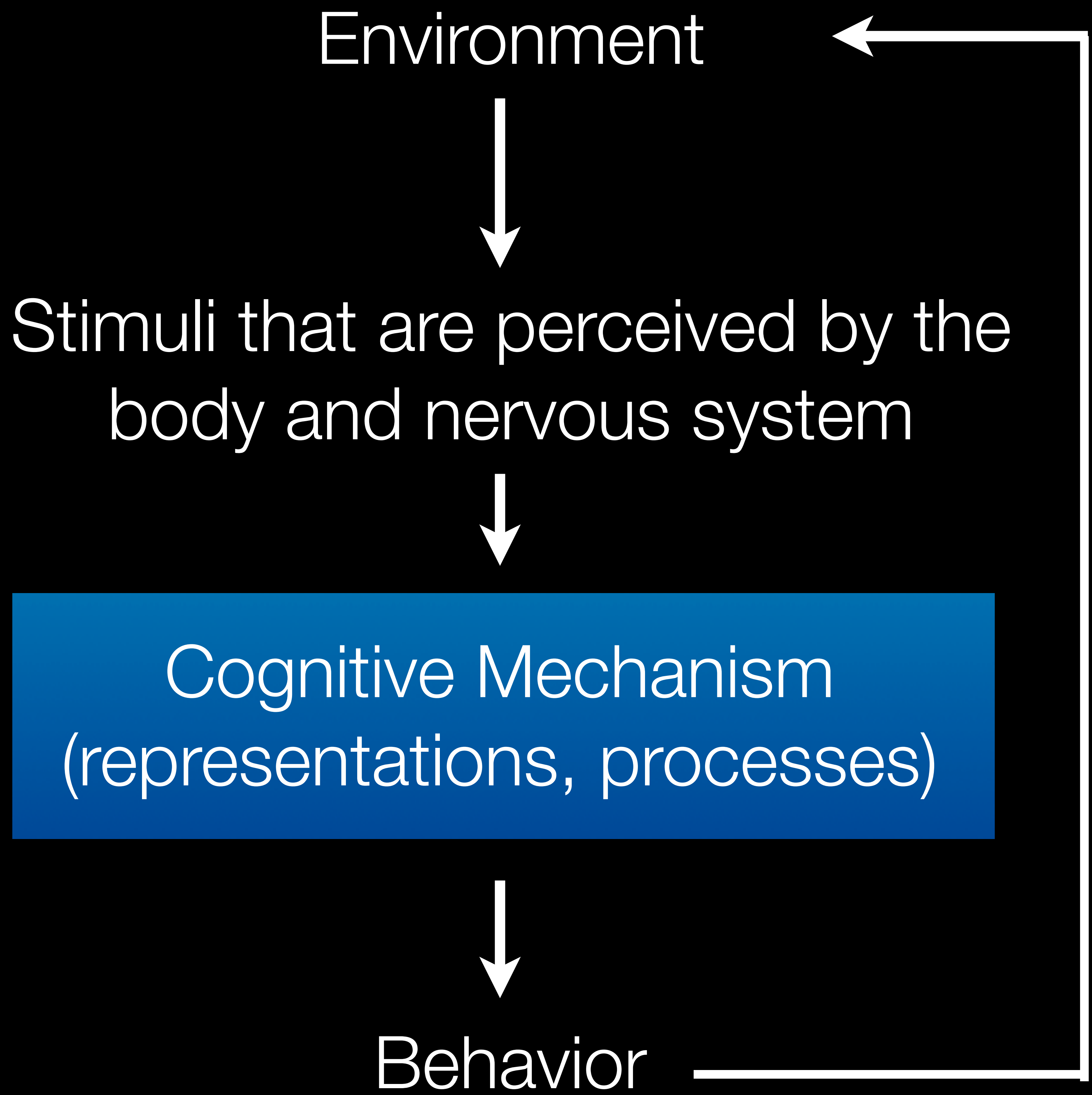
"Formal (i.e., mathematical or computation) theories have a number of advantages that psychologist often overlook. They force the theorist to be explicit, so that assumptions are publicly accessible and reliability of derivations can be confirmed..." (Hintzman, 1990)

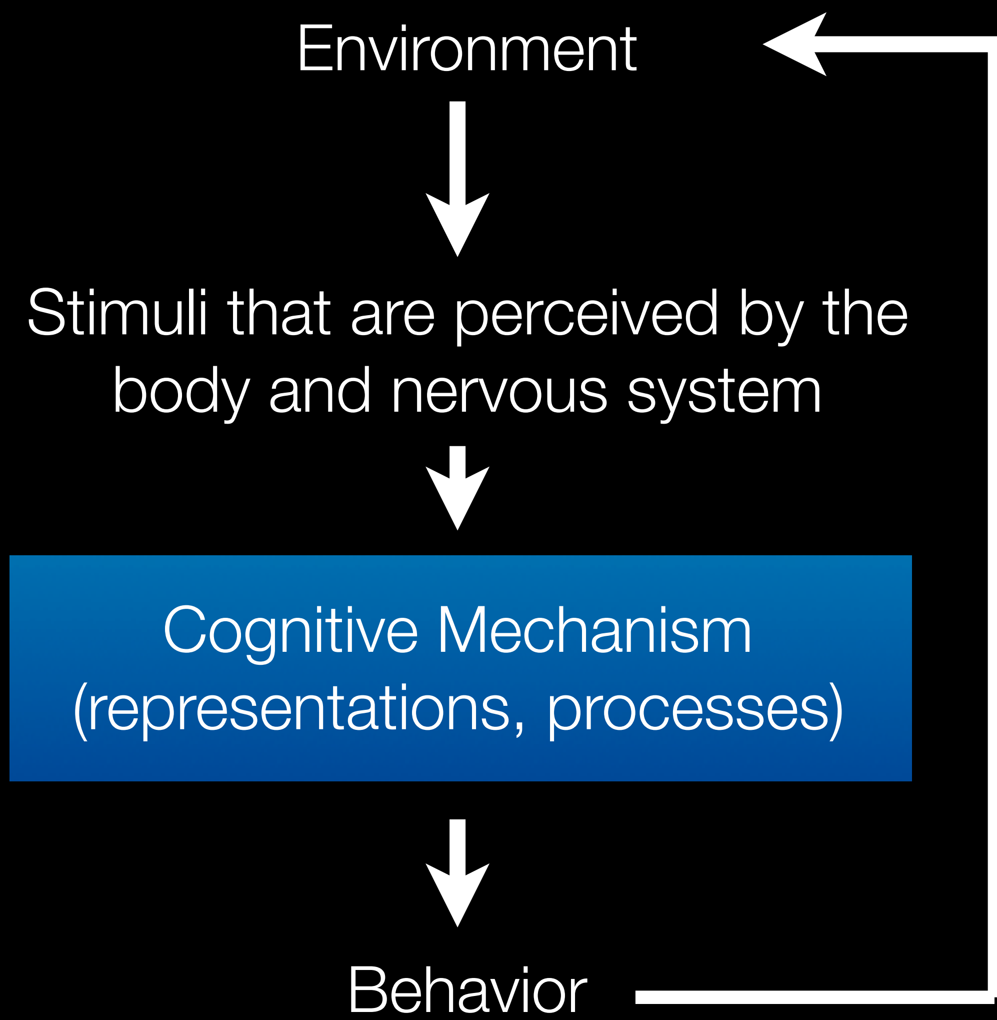
* thanks to Tom Palmeri for pointing these excellent quotes out

Environment

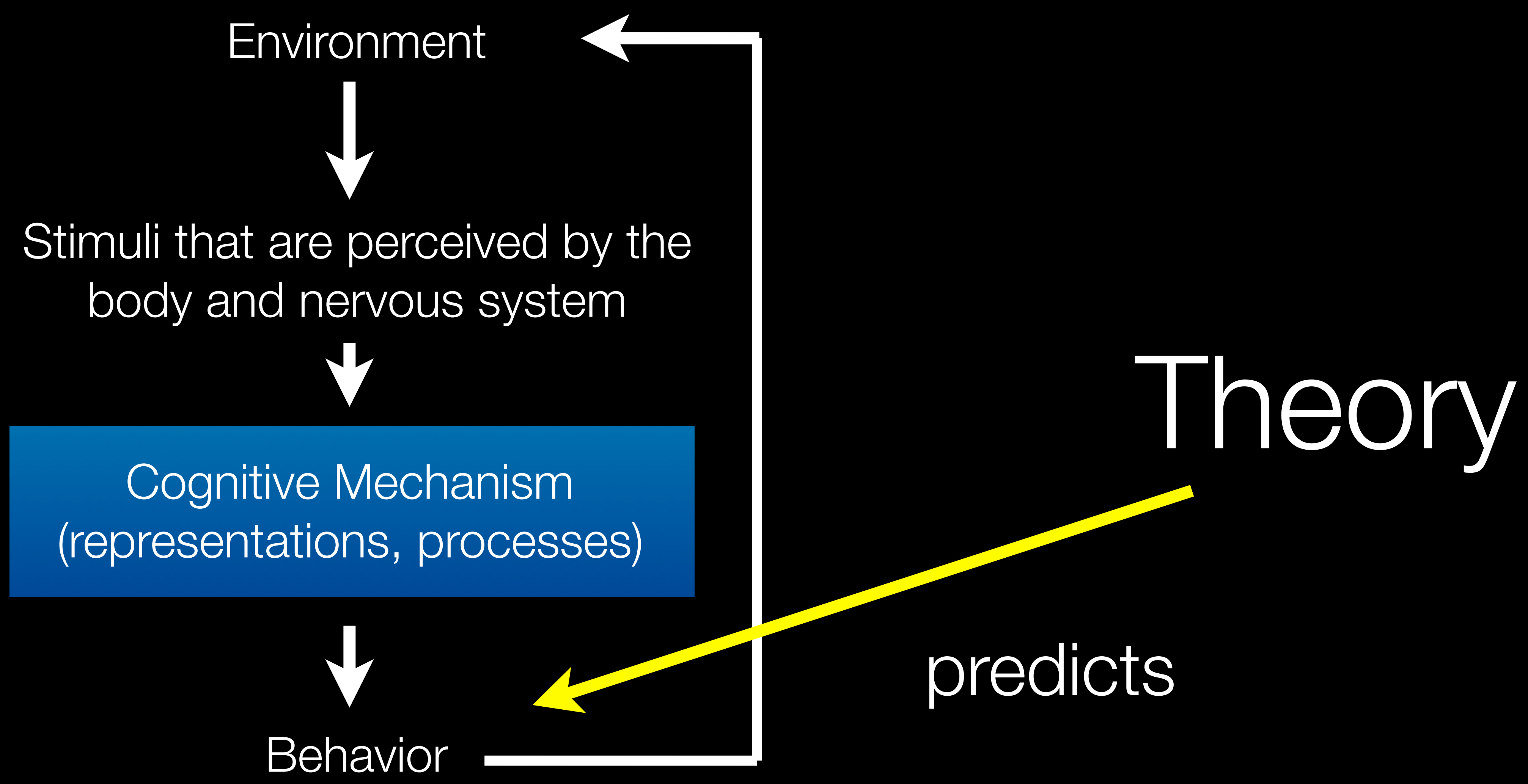
Stimuli that are perceived by the body and nervous system

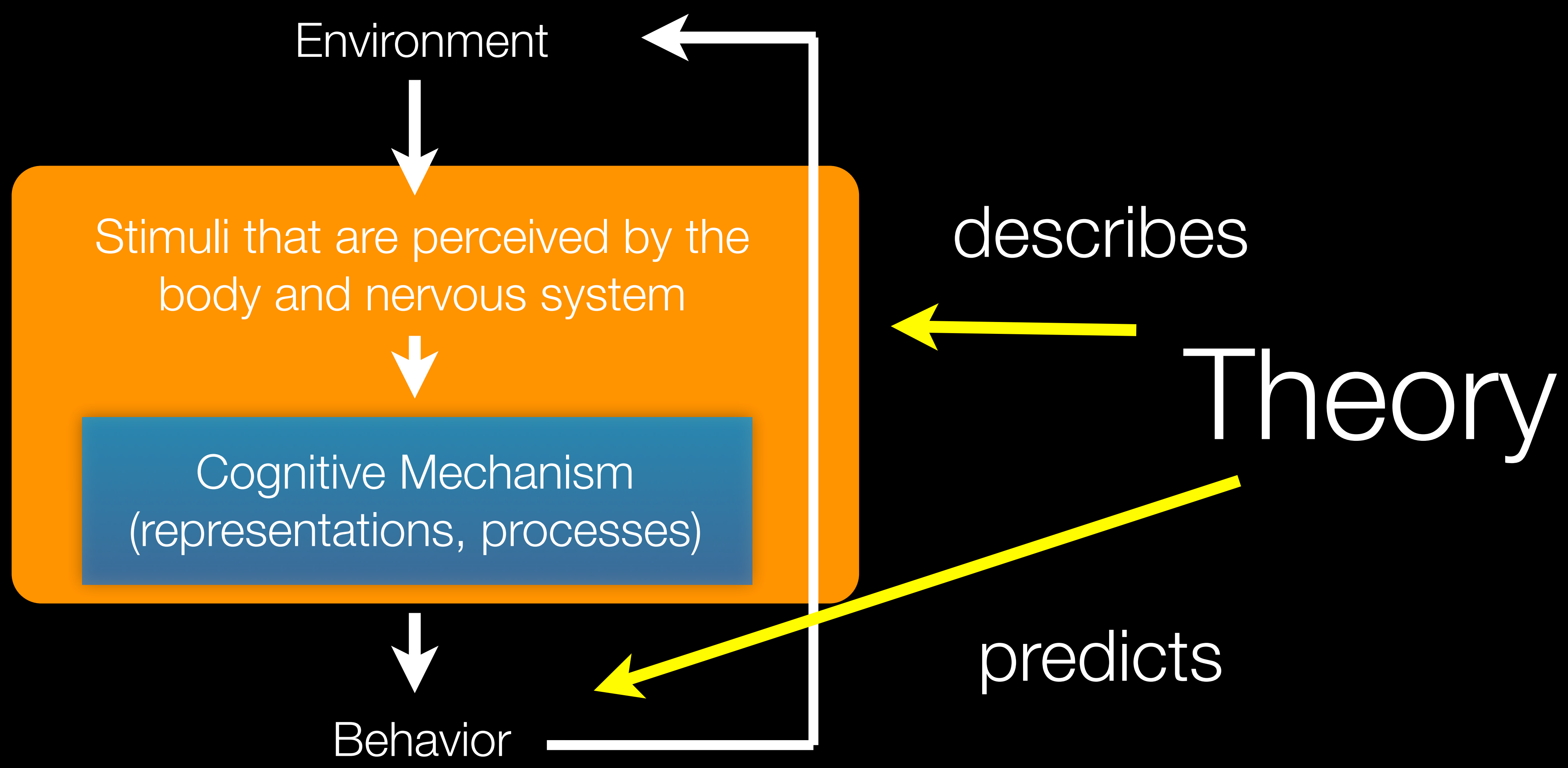
Behavior


Environment
Stimuli that are perceived by the body and nervous system
Cognitive Mechanism
(representations, processes)
Behavior


Environment
Stimuli that are perceived by the body and nervous system
Cognitive Mechanism
(representations, processes)
Behavior

Theory


Environment
Stimuli that are perceived by the body and nervous system
Cognitive Mechanism
(representations, processes)
Behavior
Theory
predicts


Environment
Stimuli that are perceived by the body and nervous system
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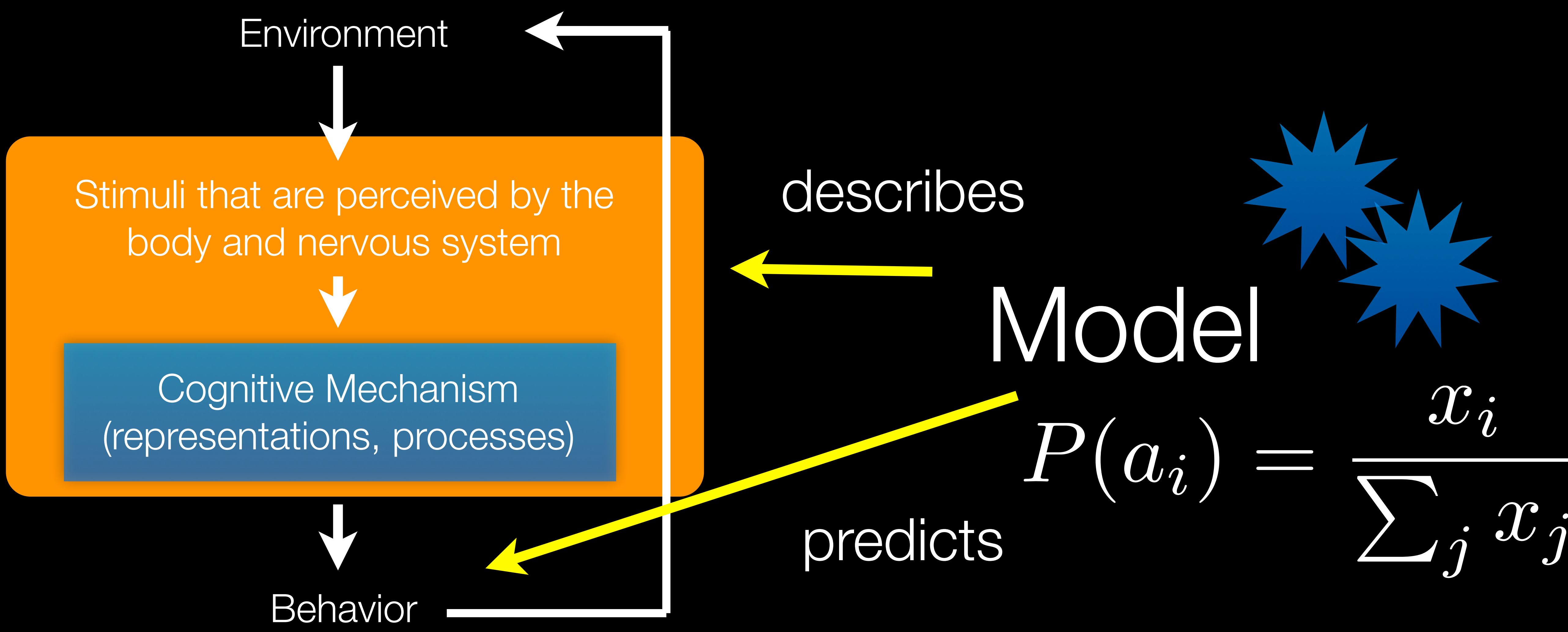
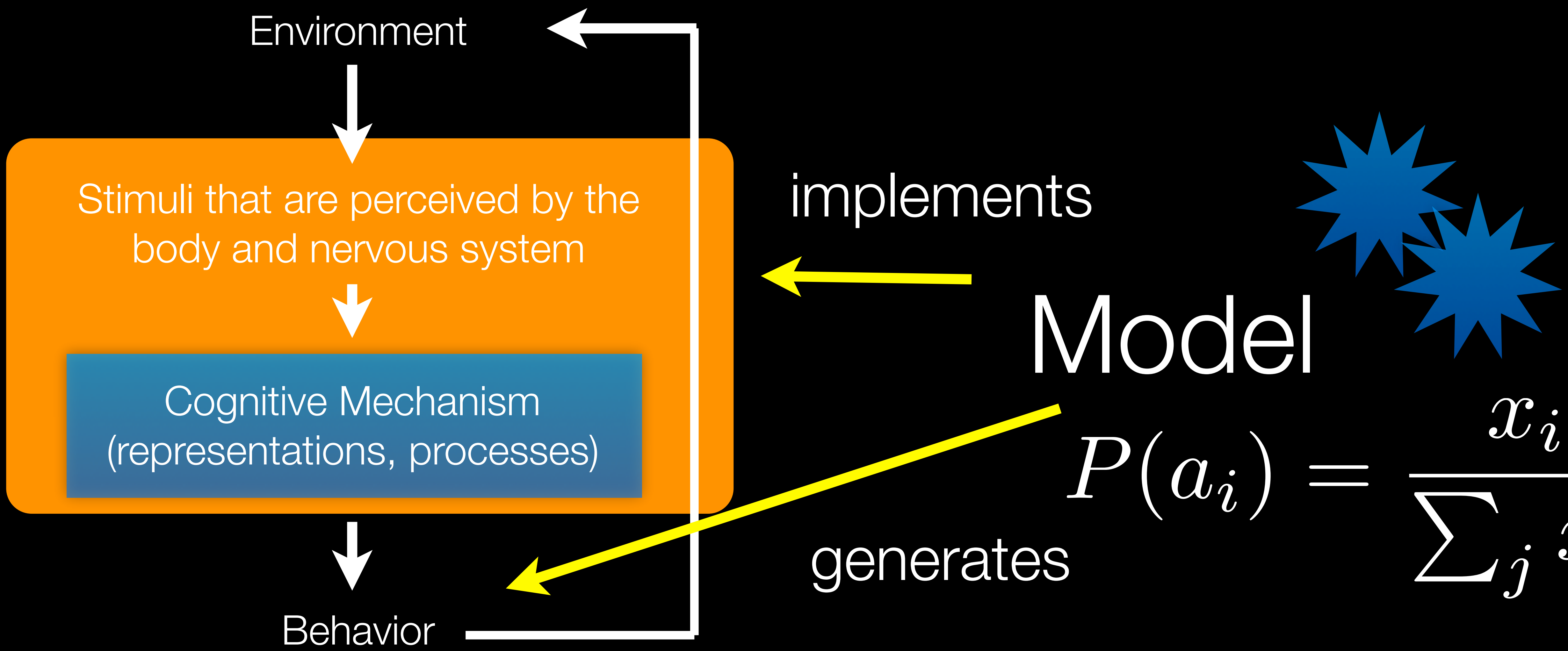
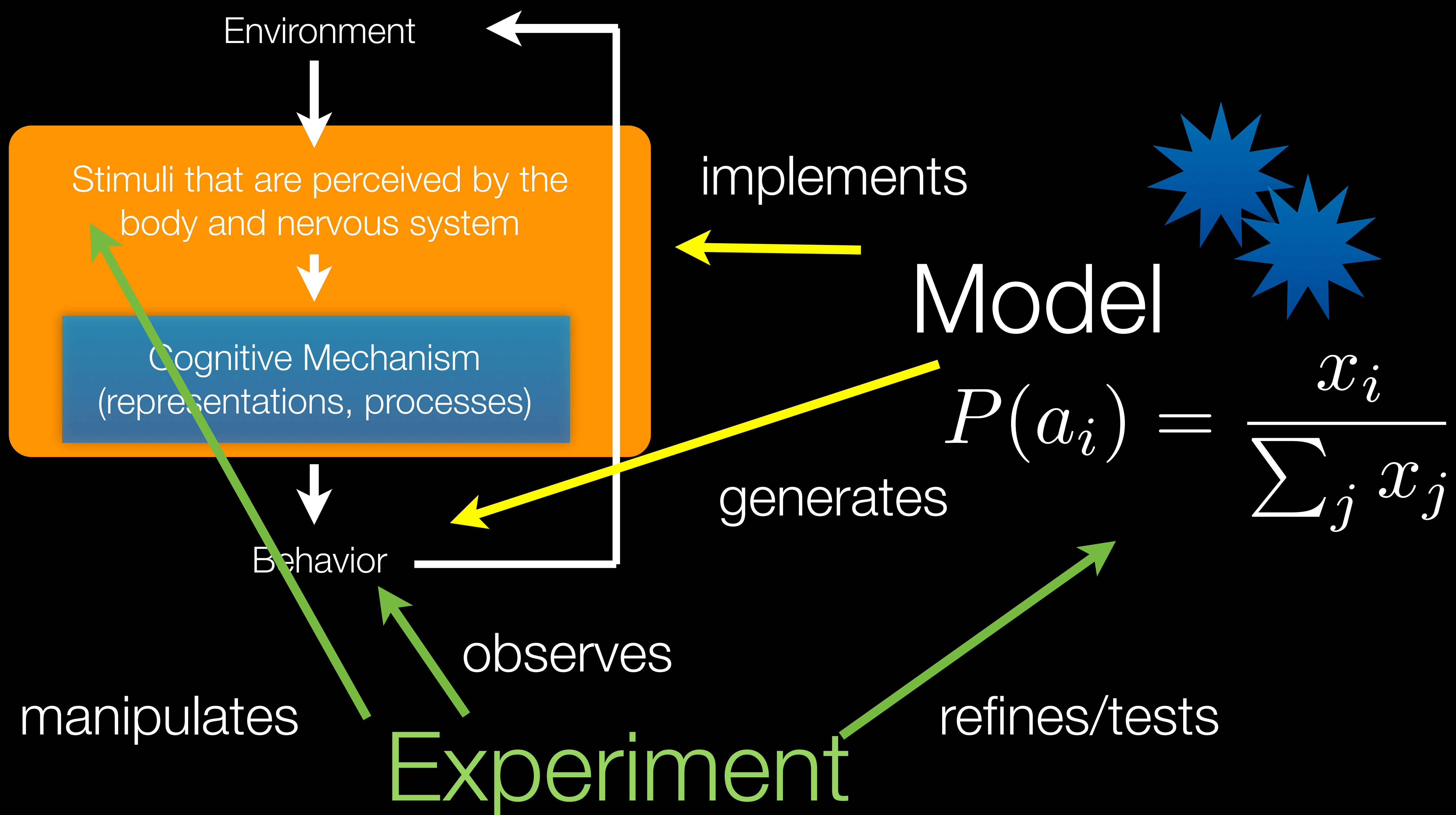
Behavior
describes
Theory
predicts

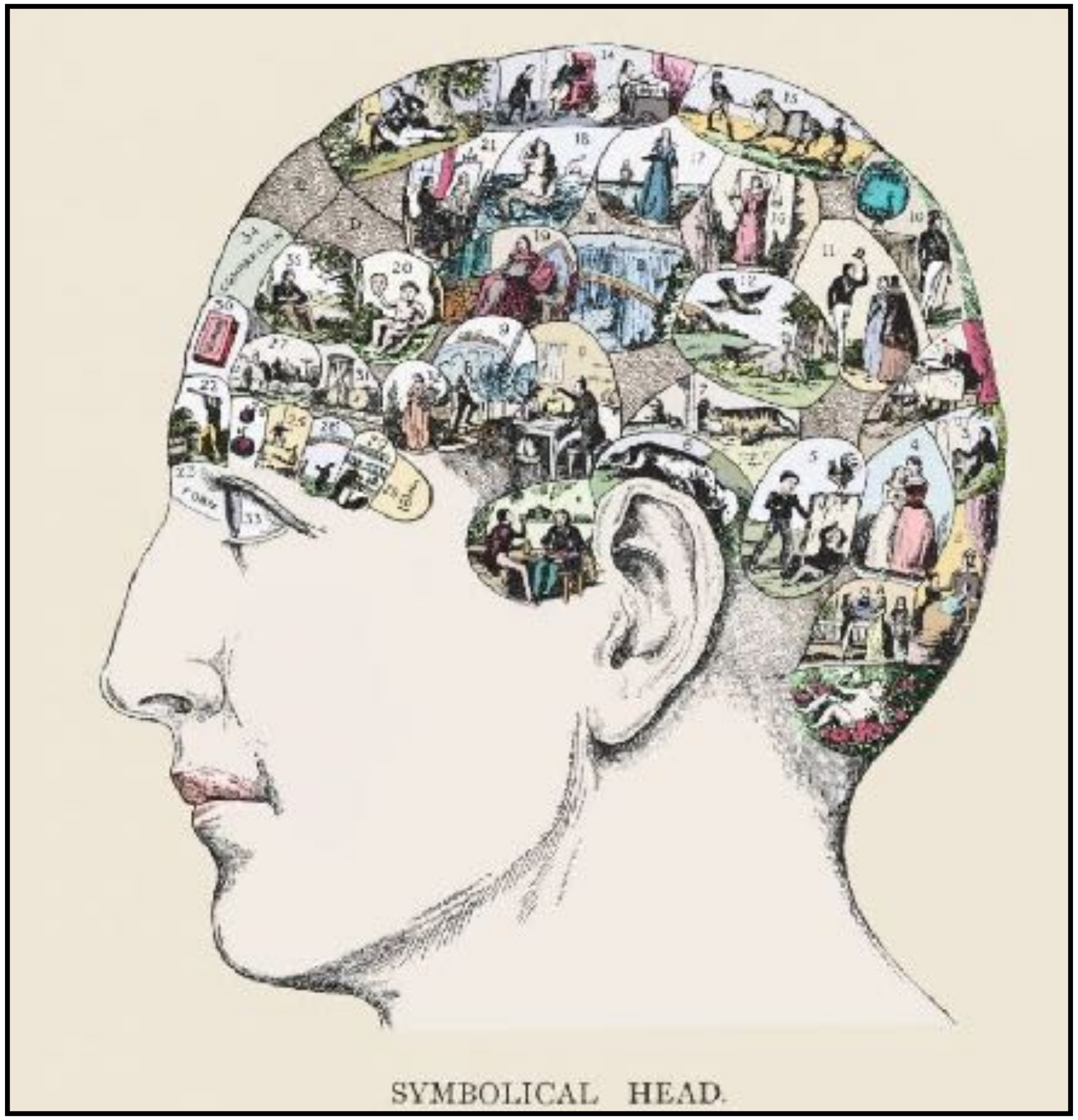

Environment
Stimuli that are perceived by the body and nervous system
Cognitive Mechanism (representations, processes)
Behavior
describes
Model
predicts
$P(a_i) = \frac{x_i}{\sum_j x_j}$



$$P(a_i) = \frac{x_i}{\sum_j x_j}$$

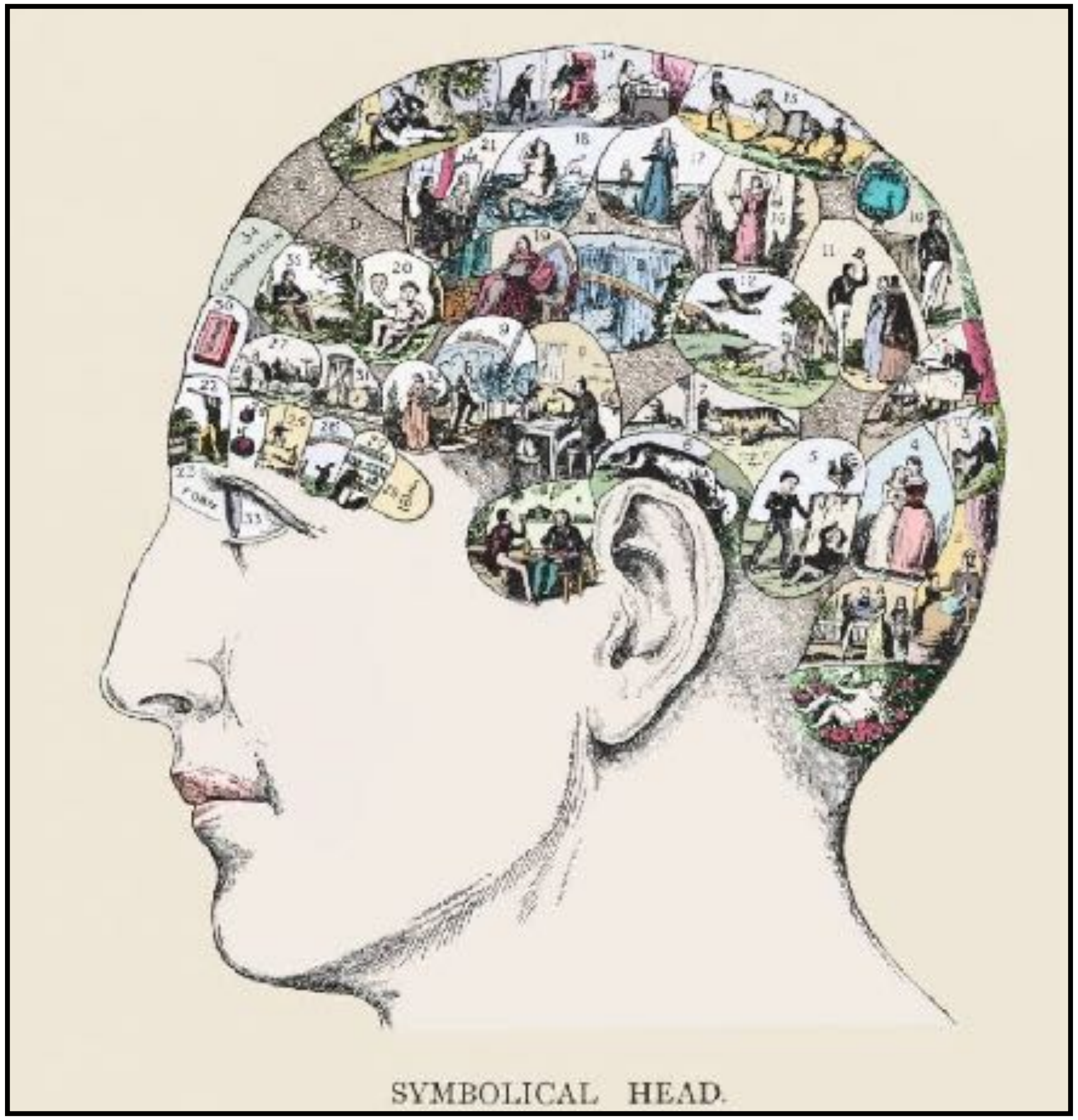

Environment
Stimuli that are perceived by the body and nervous system
Cognitive Mechanism
(representations, processes)
Behavior
implements
Model
$P(a_i) = \frac{x_i}{\sum_j x_j}$
generates
observes
manipulates
Experiment
refines/tests

What is a mind?



Debated for thousands of years. If you don't have an immediate answer, don't feel bad. Various proposals have been thrown around from by Plato, Buddha, Aristotle, Zoroaster, ancient Greek, Indian, and Islamic philosophers, and even a few folks at NYU.

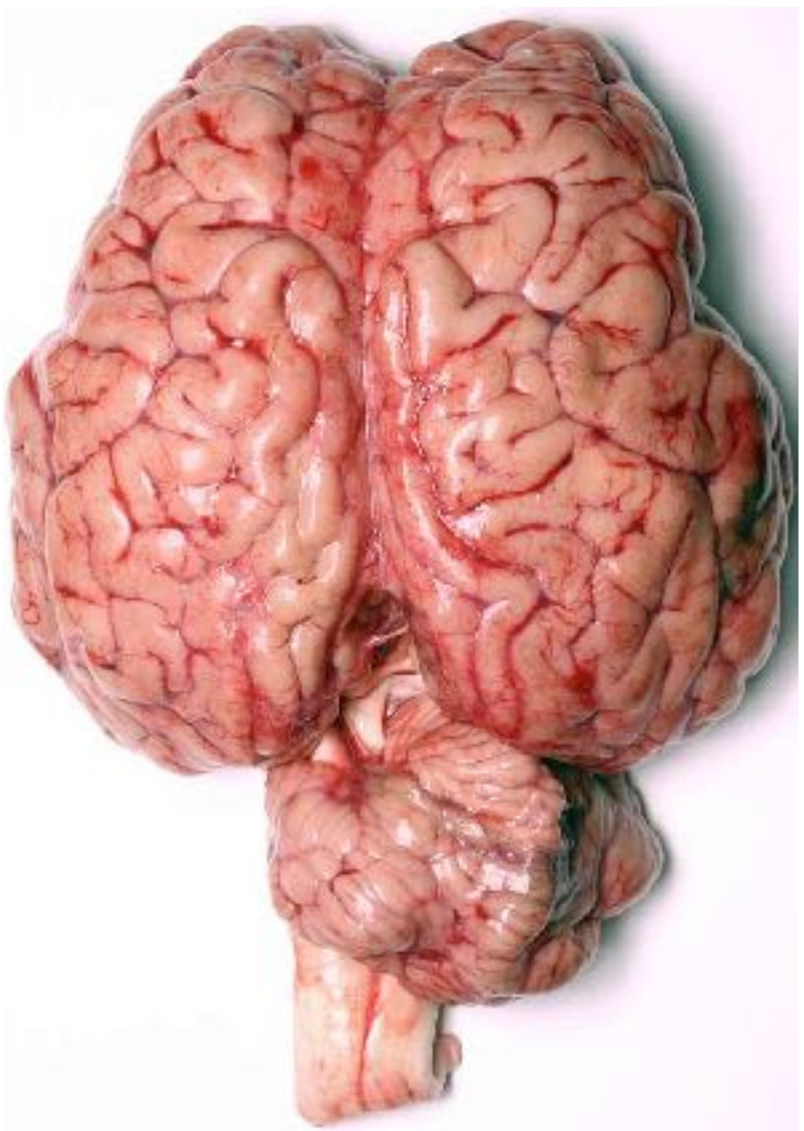
What is a mind?



What do they do?

Minds encompass our thoughts, which are the mental processes which allow us to deal with the world. These include not only explicit wishes, desires or intentions but unconscious processes as well.

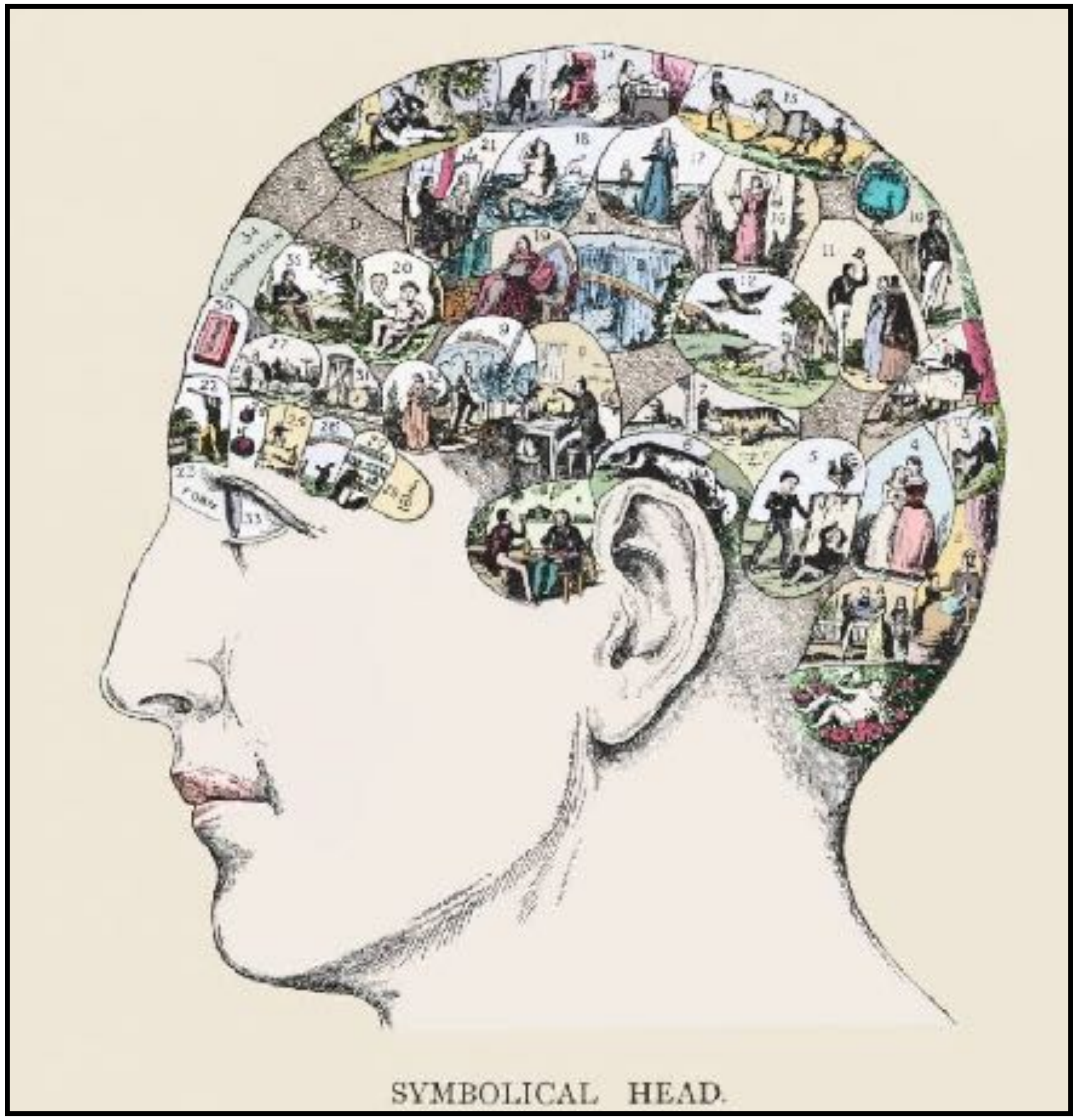
What is a mind?



Does MIND=BRAIN?

We know that we can’t have a mind or thoughts without a brain, but does that mean that minds and brain are synonymous?

What is a mind?



A common philosophical approach is the “slippery slope” argument to try to convince us that minds are not literally brains, but encompass anything that is organized as a set of represented mind states that accurately reflect aspect of the world.

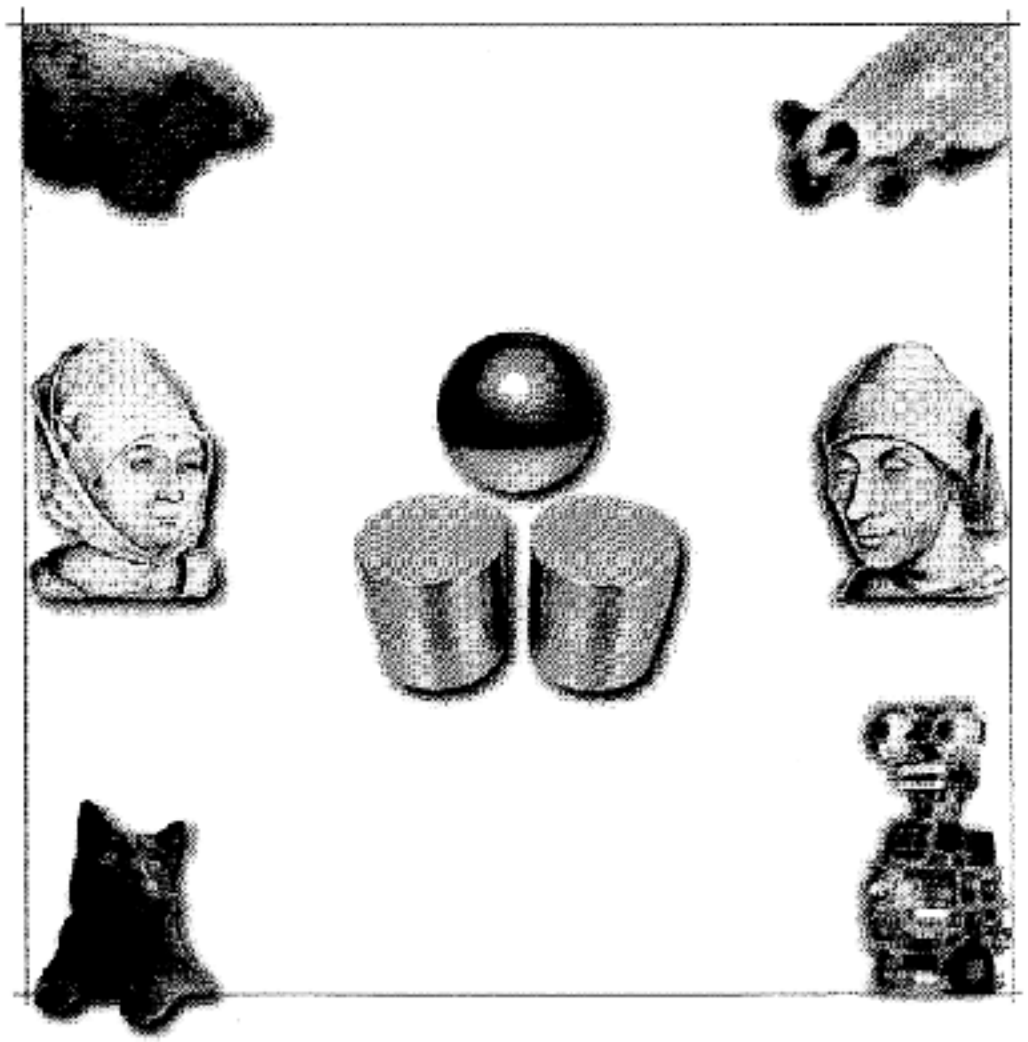


Figure 1.1 — The BRAIN/MIND RIDDLE. What is common to the minds of various sentient creatures that look at the scene in the center of this picture and see three objects? This question can be elaborated (by asking it about two cylinders and a sphere rather than "three objects"), or extended to other cognitive processes such as thought or discourse that need not involve vision or any other particular perceptual modality.

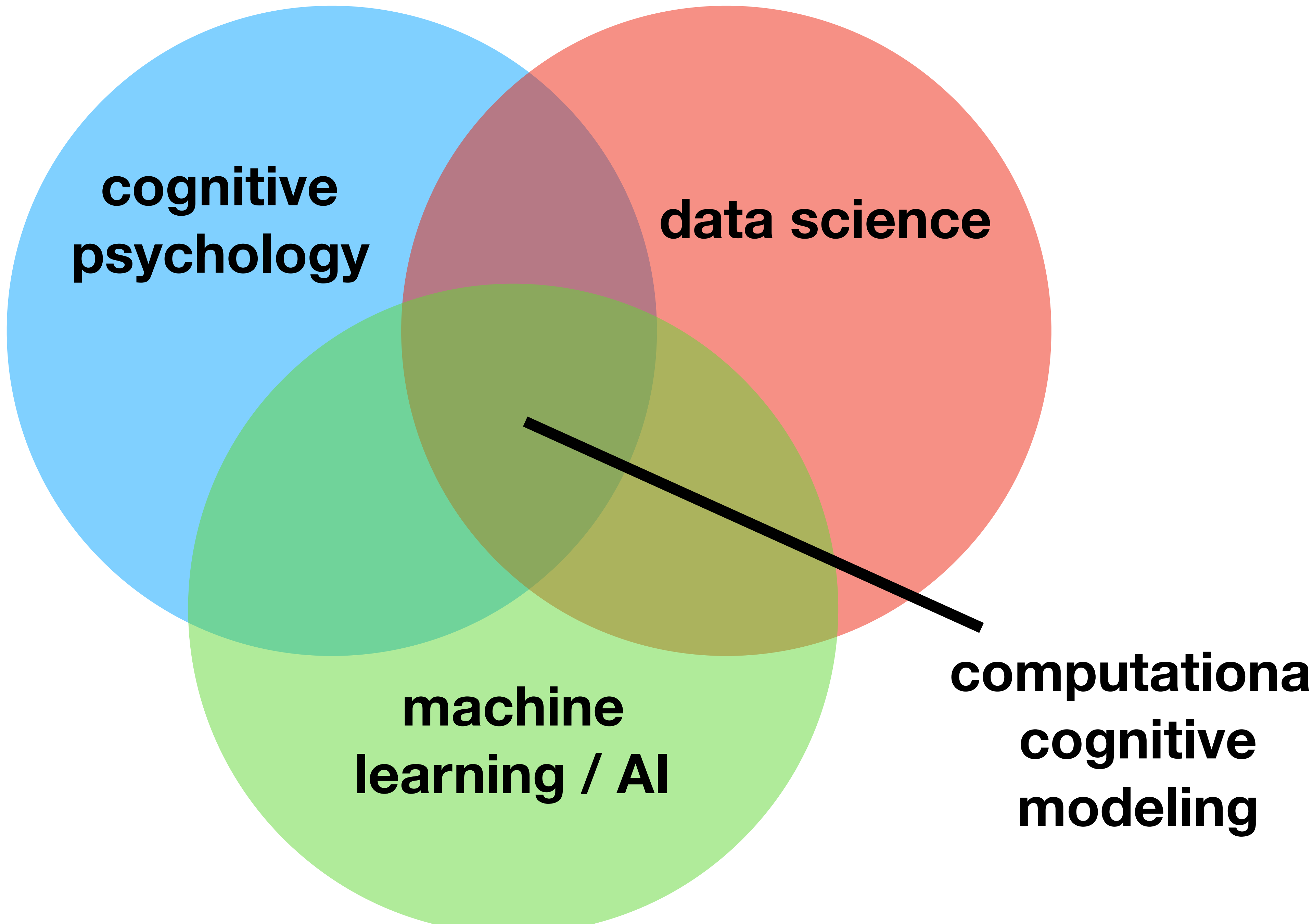
Edelman's argument

- What is common to all sober observers viewing the same scene and who are in agreement about what is viewed?
- Can't literally be neurons. My neurons are my own, and you can't borrow them to solve your own problems.
- Well maybe is the the literal organization of the human nervous system (up to the limit of correspondence). However, we know (or at least believe) that cats have a very similar visual system and view the world much like we do. Is it the mammalian visual system? What about other animals?
- What about artificial systems formed of computers and video cameras that can accurately recognize the scene as well?
- **The key to minds may be not the physical substrate in which they are embodied but the relations that various states of the system have to one another and to the environment/world.**

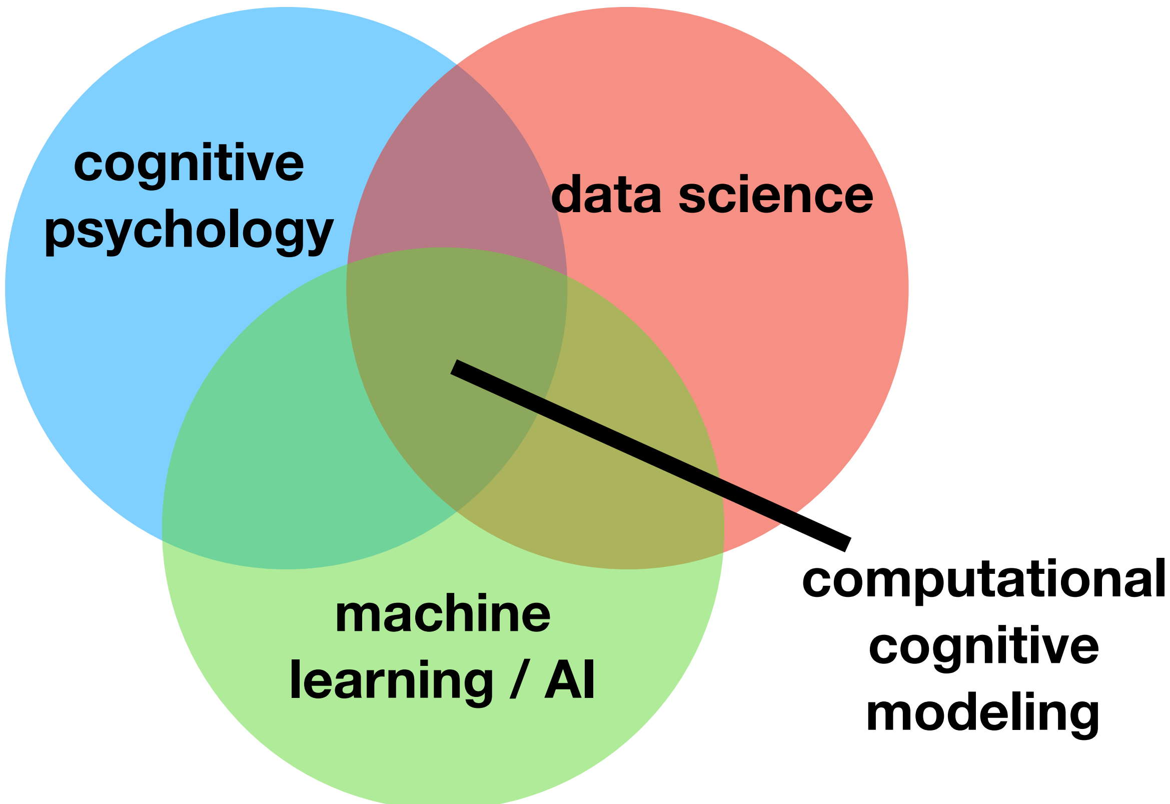
The “organizational” view of the mind

- Minds aren’t human neurons or cat neurons or robot parts, but the organization of dynamic, continually evolving systems that relate ongoing internal (i.e., mind) states and external (i.e., world) states
- **Correspondences can be made between the evolution of two systems to describe what they are doing independent of the exact things they operate on.**
- **Such correspondences are particularly well described in the language of computation, simply because the THEORY OF COMPUTATION offers use formal insight into how ostensibly dissimilar systems can be formally identical.**
- Everything that can be expressed in on system can be expressed in a different, but functionally identical system.

This course sits at the intersection of cognitive psychology and data science (hence cross-listing)



The connection between computational cognitive psychology and data science



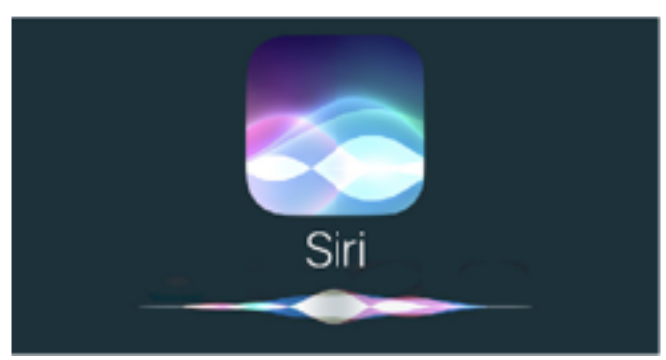
- **Similar goals**: often building computational models to explain or predict human behavioral data

- **Similar computational paradigms and techniques**: neural networks / deep learning, reinforcement learning, Bayesian modeling, probabilistic graphical models, program induction

- Data science is about **extracting knowledge from data**. The human mind is the best general system we know of for extracting knowledge from data.

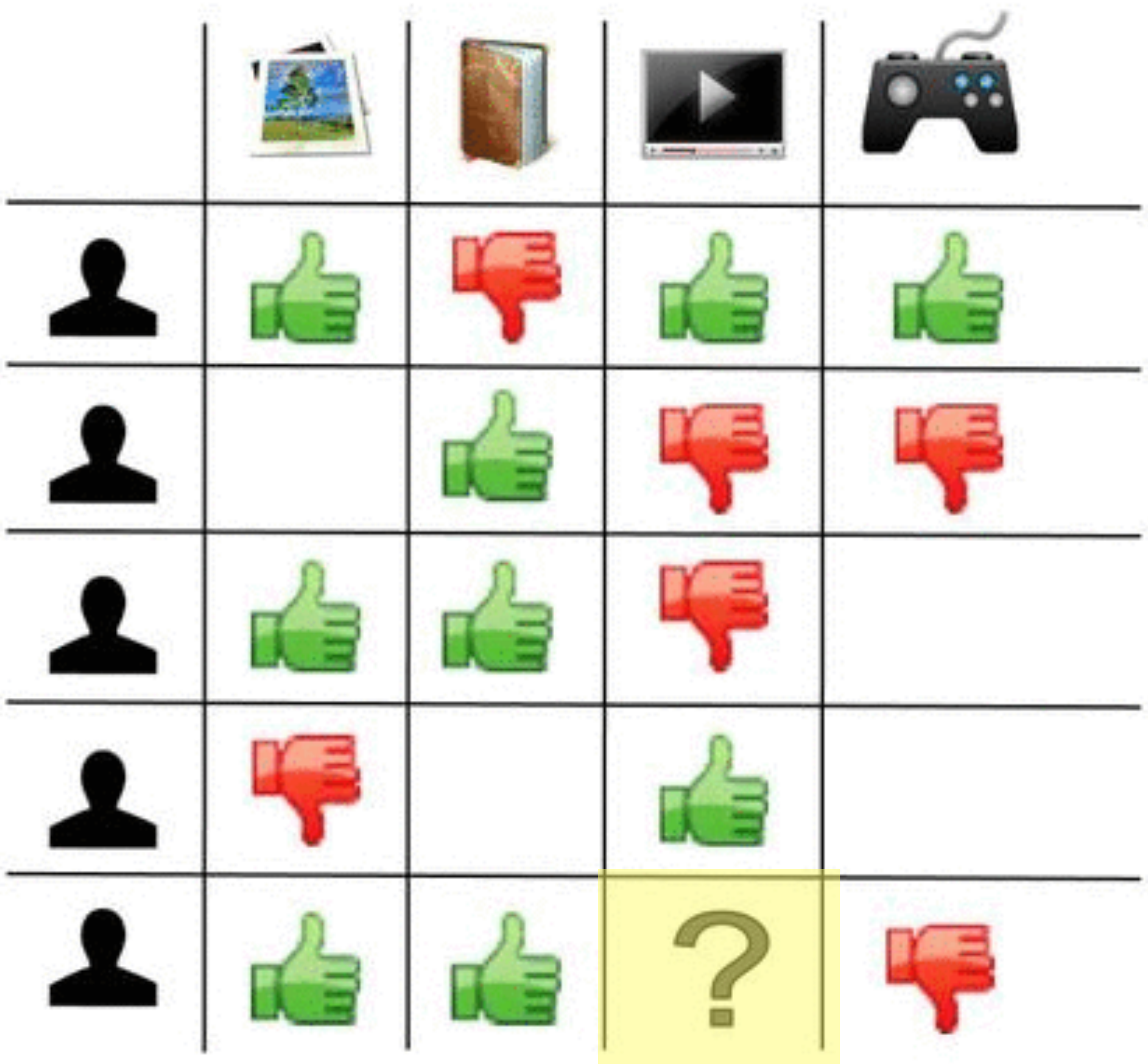
- There is ripe potential for even deeper connections. We hope that, by bringing together students from a variety of backgrounds, this class can help realize this potential.

In practice, data scientists deal with huge quantities of behavioral data



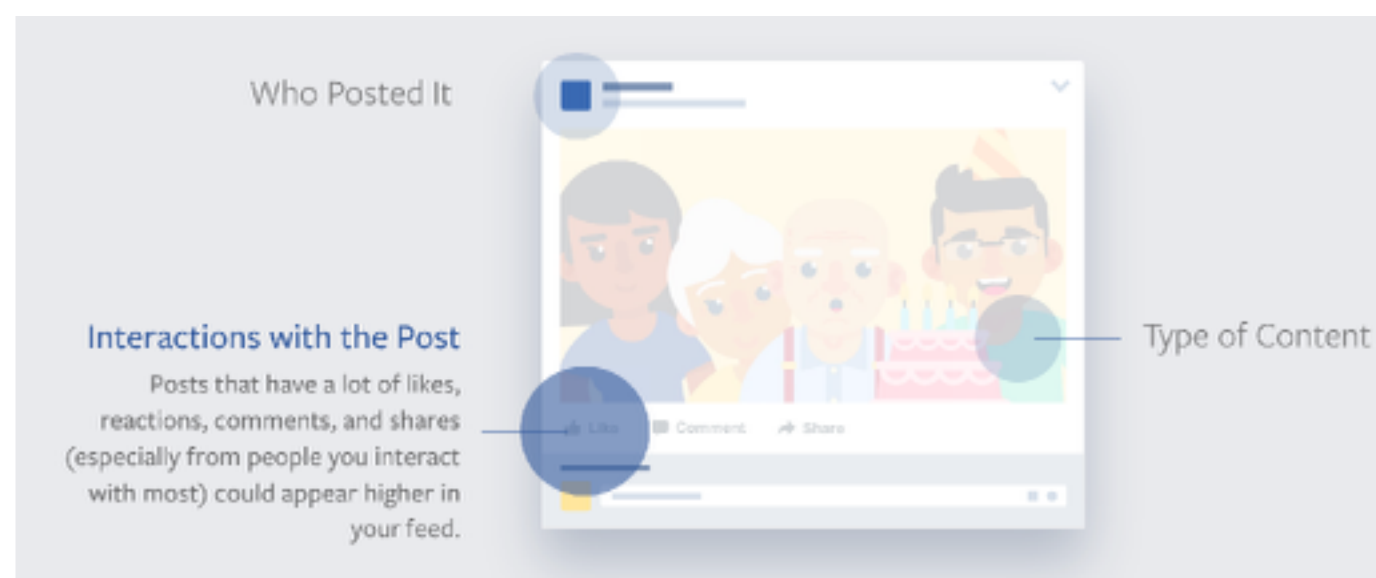
popular applications with behavioral data

collaborative filtering



churn modeling

adaptive content (e.g., news feed)

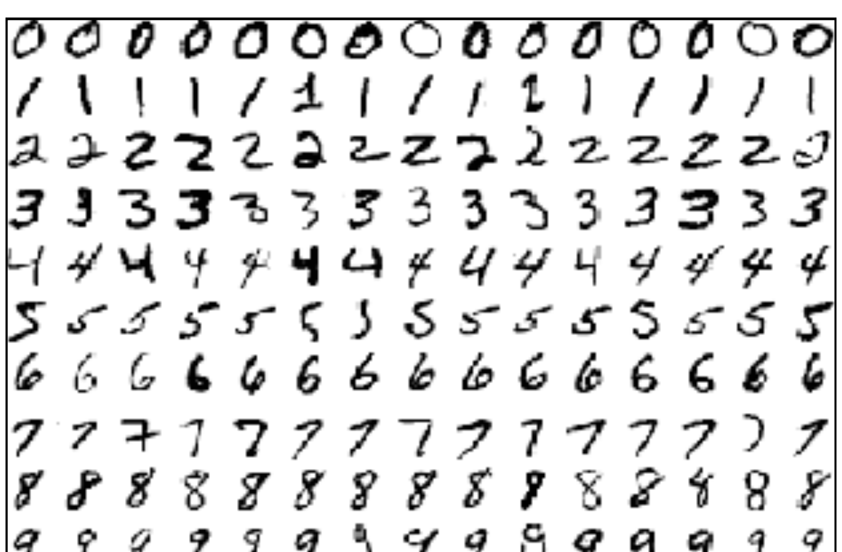


popular challenges for developing machine learning / AI algorithms

object recognition (ImageNet)

caption generation (MSCOCO)

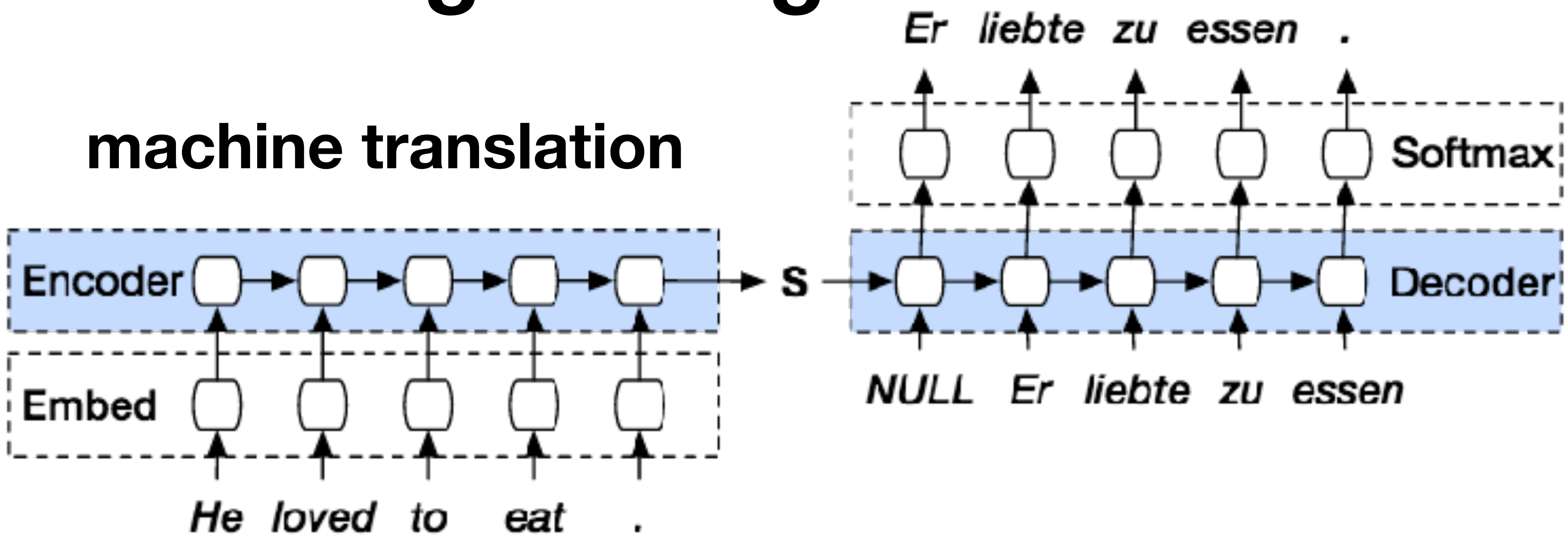
digit recognition (MNIST)



- Datasets consist of photos taken by PEOPLE, or of digits actually drawn by PEOPLE
- Task is to predict labels and sentences produced by PEOPLE, identifying objects and events that are meaningful to PEOPLE. In many cases the labels identify concepts invented by PEOPLE

popular challenges for developing machine learning / AI algorithms

machine translation



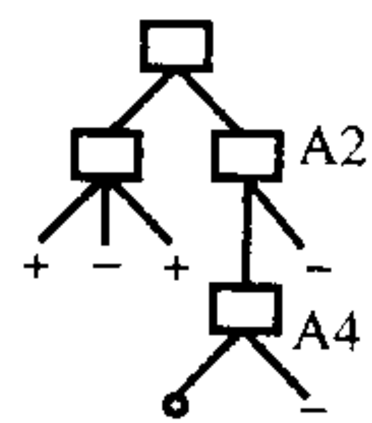
language modeling and natural language understanding

positing a mind to explain and predict behavior

x_0	x_2	x_3	x_4	x_5	x_6	x_7
0	0	0	1	0	0	0
0	1	0	0	1	0	1
1	0	0	1	0	0	0
1	1	1	1	0	1	1

rather than trying to predict clicks directly from browser history…

$p(y|x;\theta)$



y
0
0
1
1

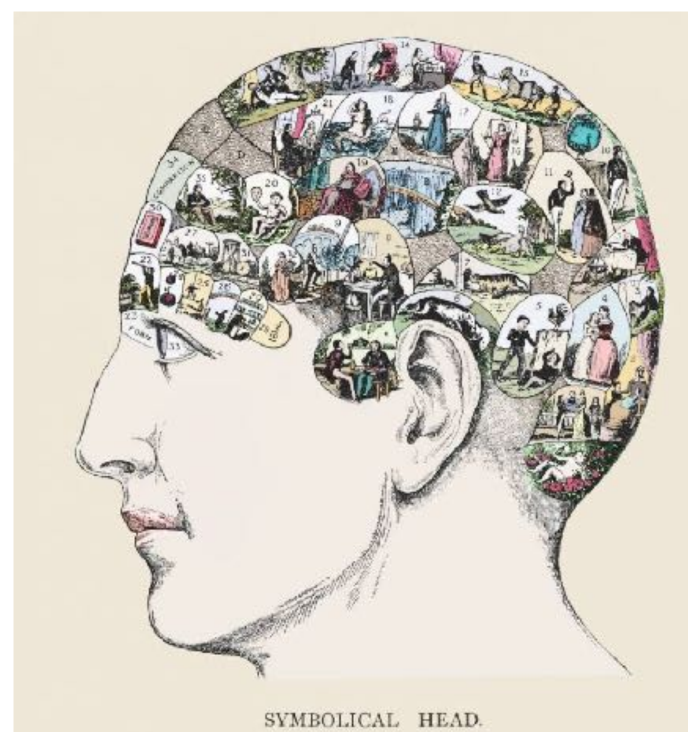
see Griffiths (2014). Manifesto for a new (computational) cognitive revolution.

positing a mind to explain and predict behavior

- This course aims to show the value of positing mental processes to explain and predict behavior, and that mental processes are readily modeled with familiar computational tools to a data scientist.
- This perspective is not yet mainstream practice in data science. We aim to teach you the right tools, but it will be up to you to make some of the connections to practice!

x_0	x_2	x_3	x_4	x_5	x_6	x_7
0	0	0	1	0	0	0
0	1	0	0	1	0	1
1	0	0	1	0	0	0
1	1	1	1	0	1	1

computational cognitive modeling



y
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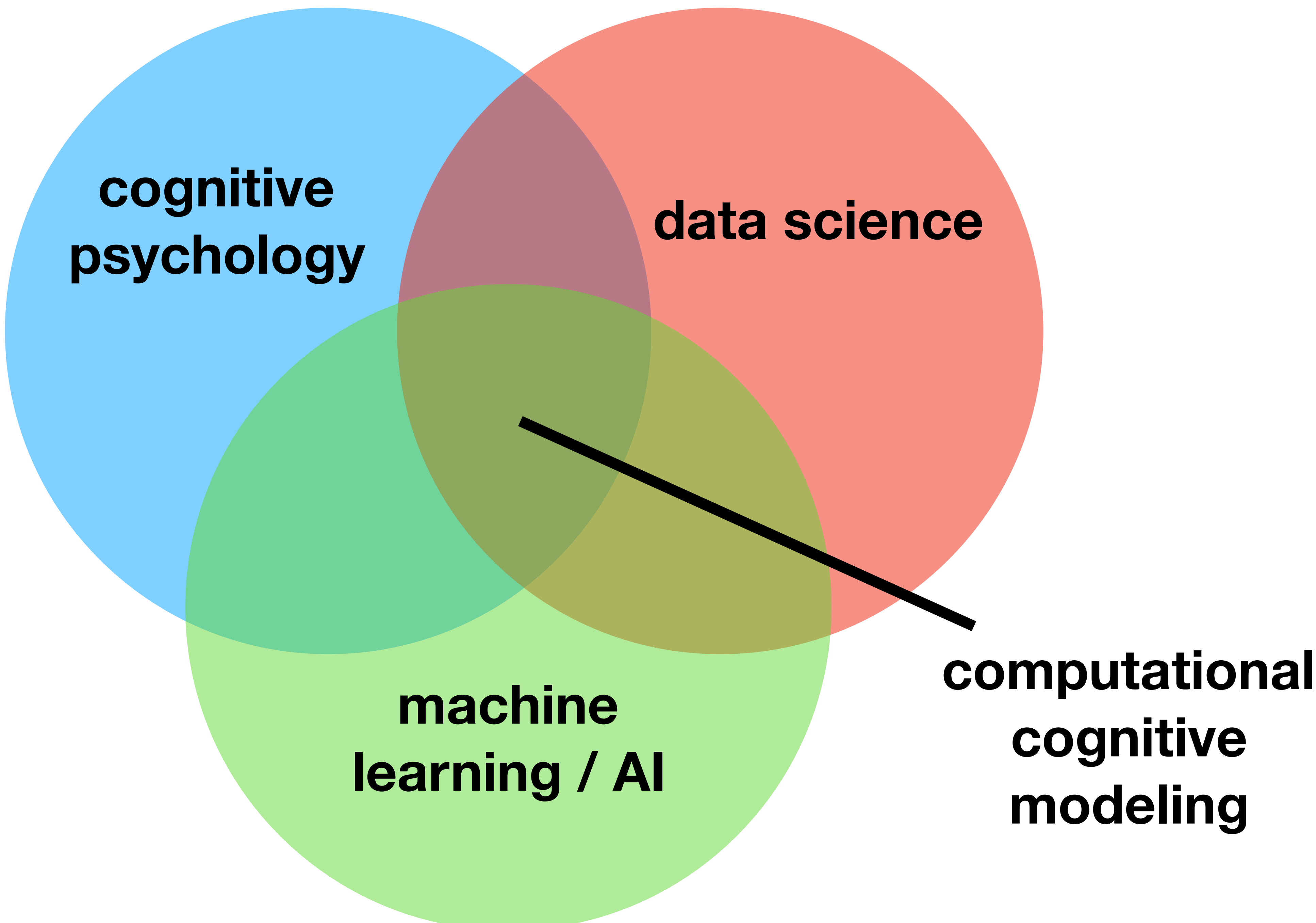


computational cognitive modeling can help make computers better...

question asking

one-shot learning

scene understanding

concept learning

transferring to new tasks

language acquisition

inventing new tasks

computational problems that are easier for people than machines

creativity

These abilities are especially good opportunities for improving machine learning and AI!

general purpose problem solving

language understanding

commonsense reasoning

self-assessment

curiosity and motivation

forming explanations

By understanding how people solve these challenging problems (computational cognitive modeling), there is great potential for building more powerful and more human-like machines

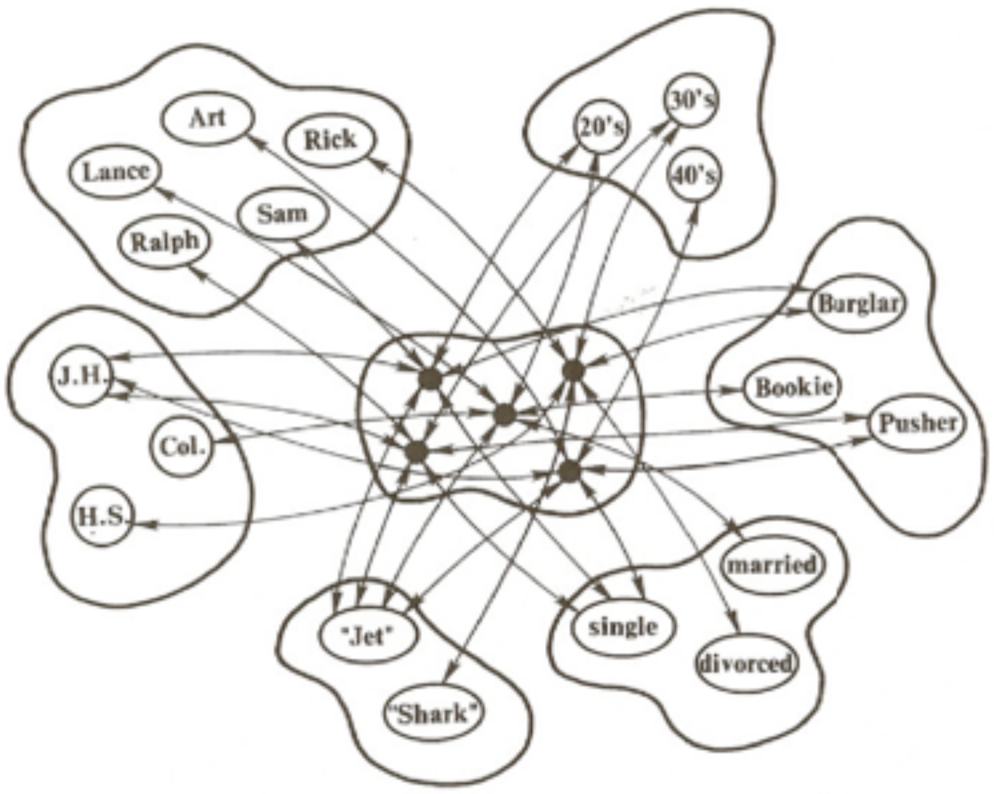
In this course, we are going to spend most of our time diving into various computational modeling paradigms

- neural networks / deep learning
- reinforcement learning
- Bayesian modeling
- probabilistic graphical models
- program induction and language of thought models

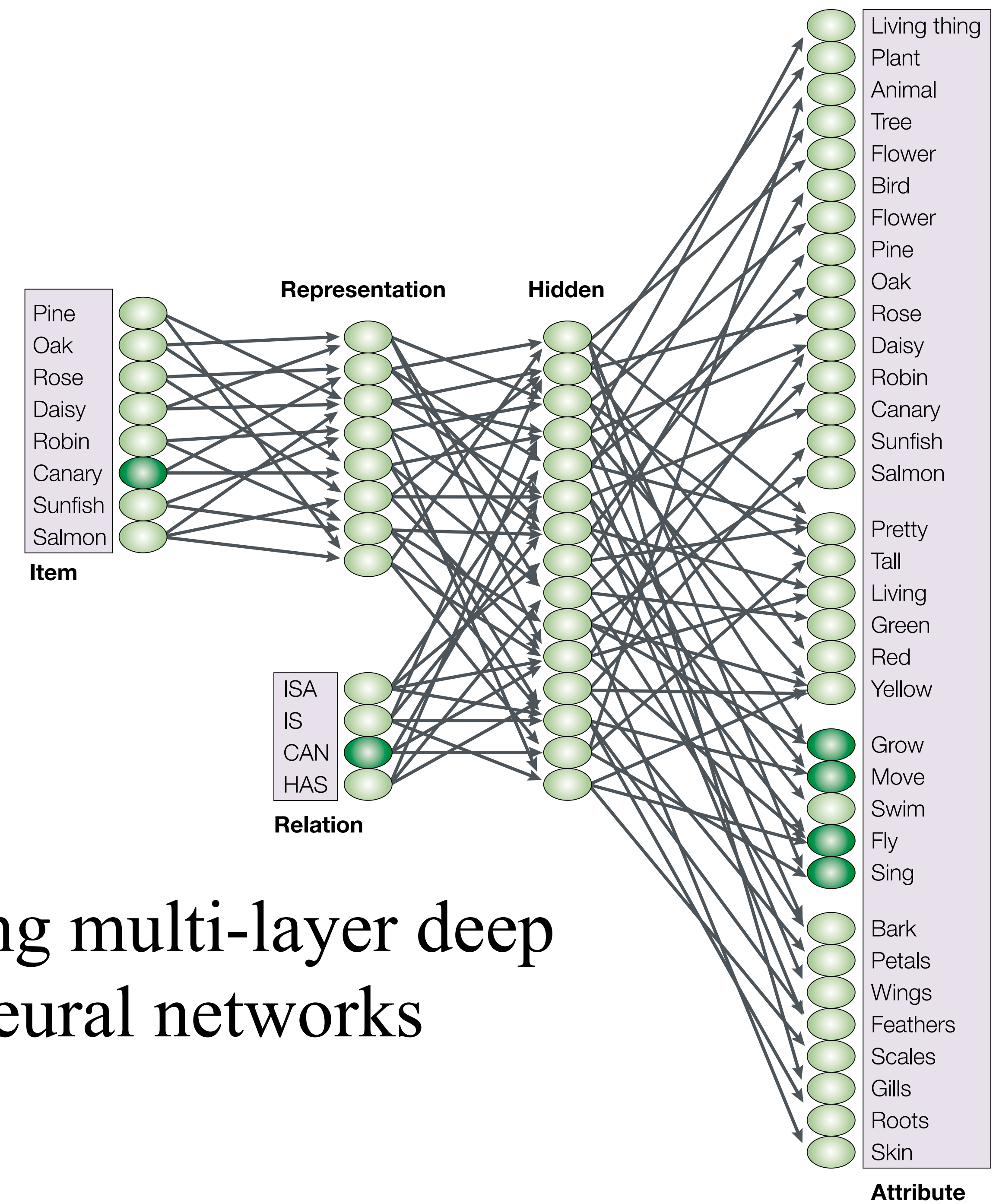
Notice overlap with contemporary machine learning!

neural networks / deep learning

Retrieving information from memory



building knowledge of objects and their properties

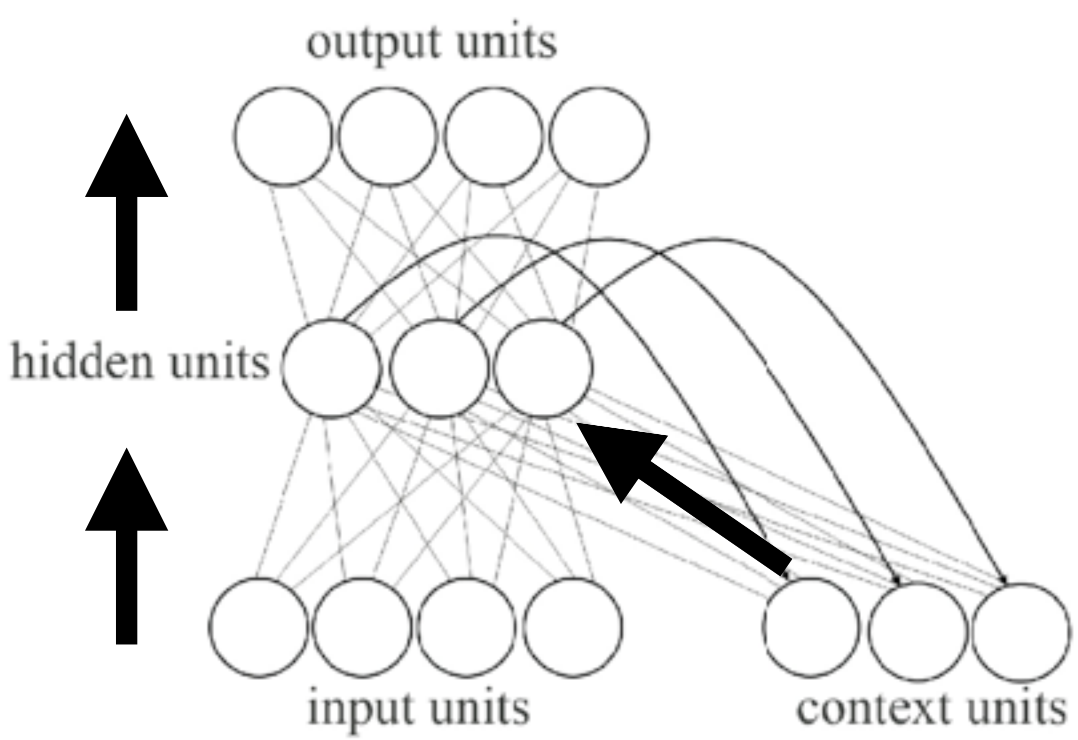


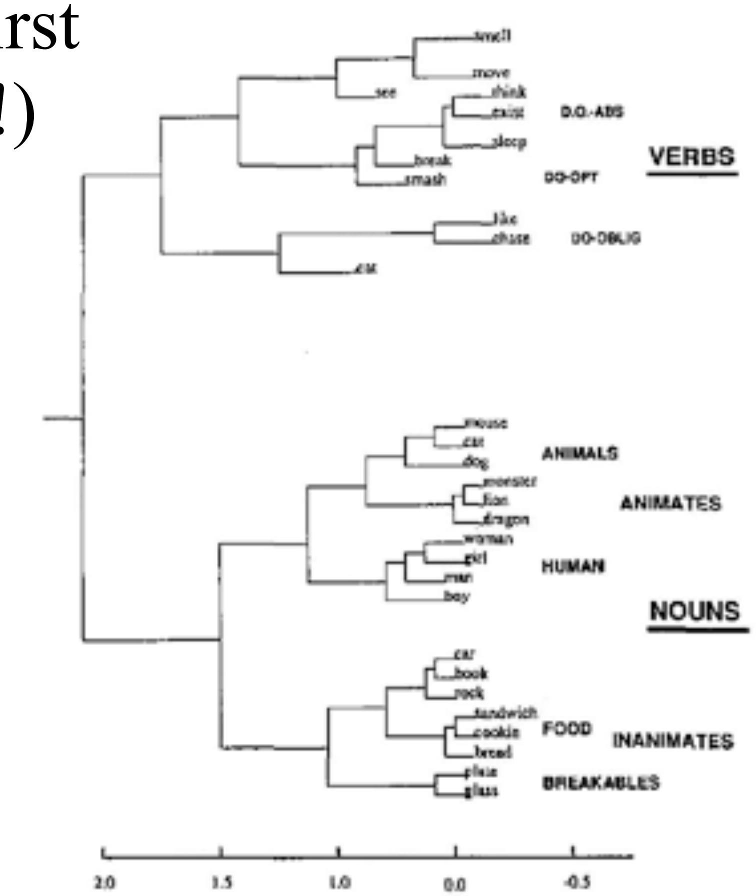
training multi-layer deep neural networks

neural networks / deep learning

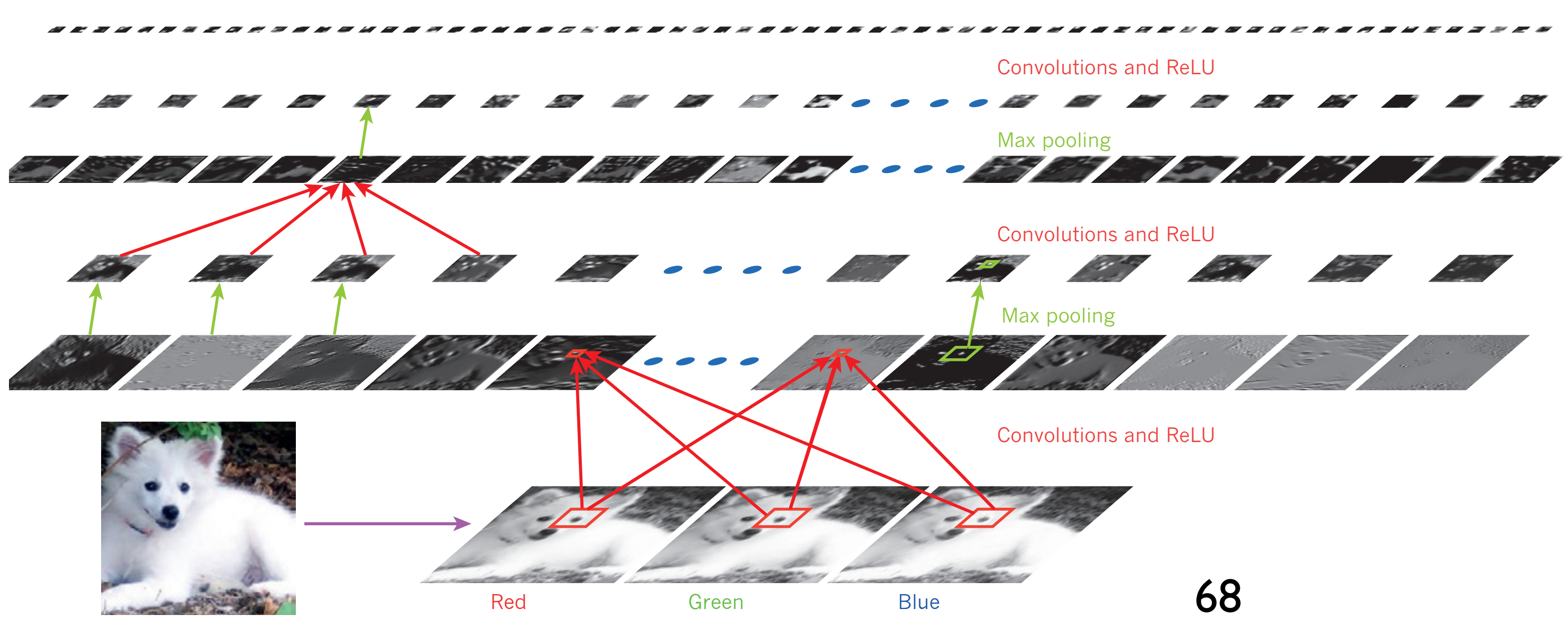
recurrent neural networks

(Training RNNs with backpropagation was first done for computational cognitive modeling!)

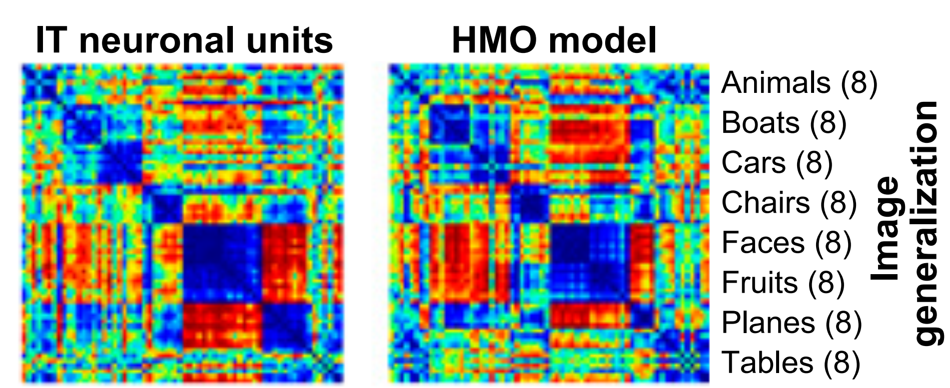




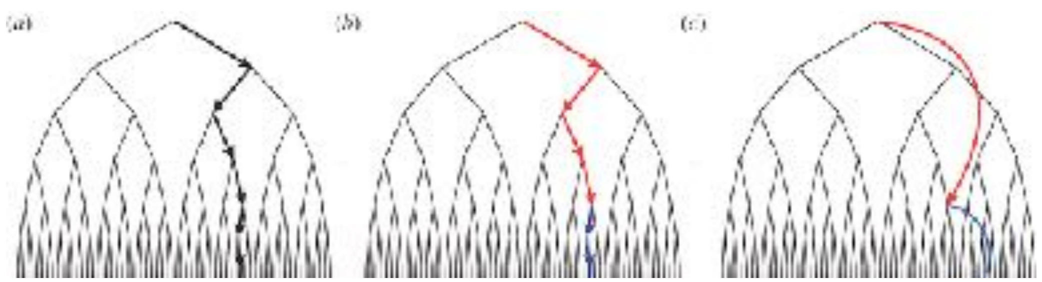
convolutional neural networks

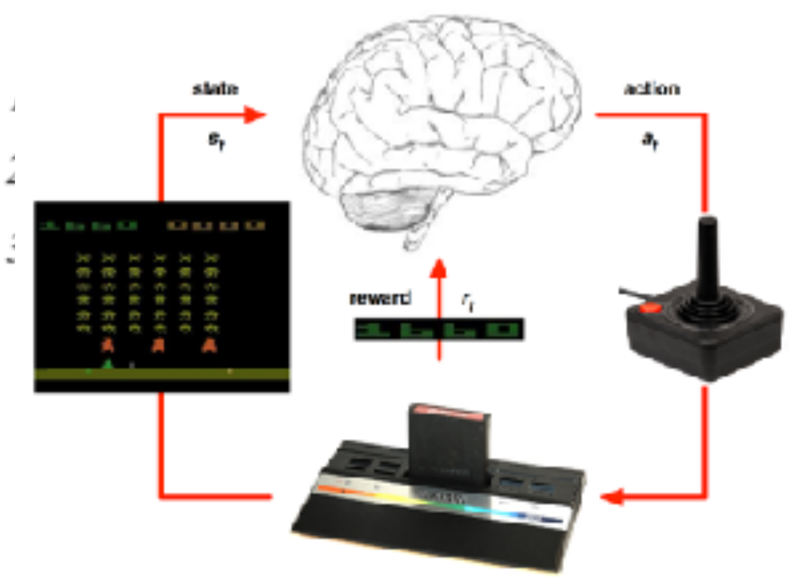


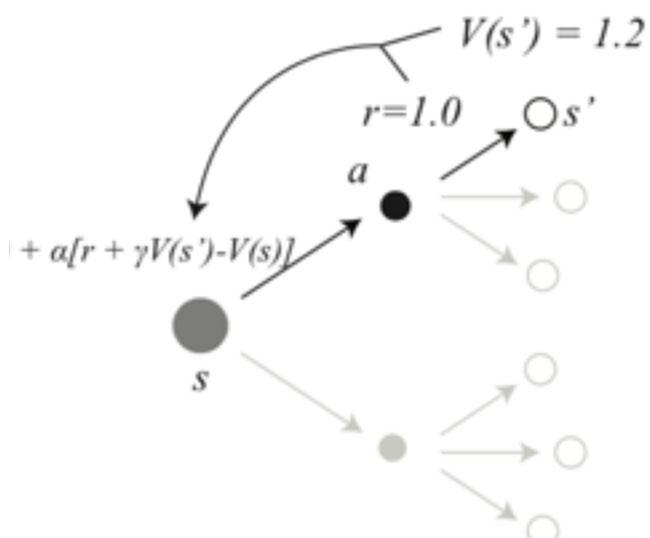
applications in neuroscience and cognitive science



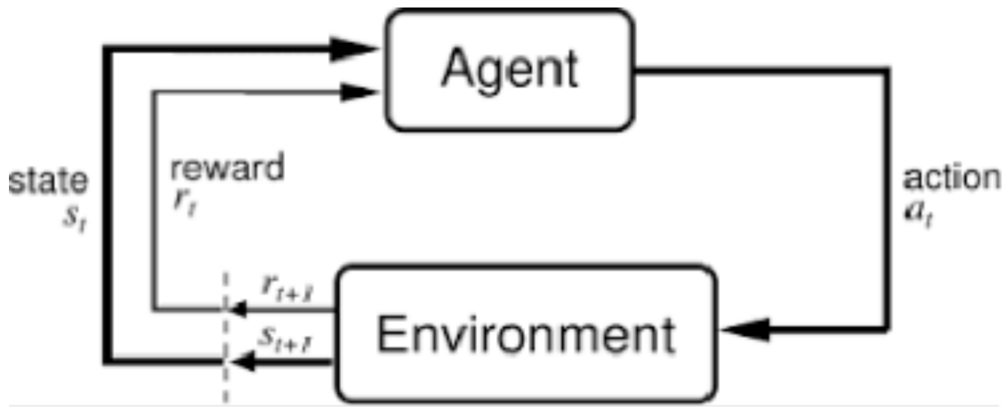
Reinforcement learning







"Recalculating ... recalculating ..."



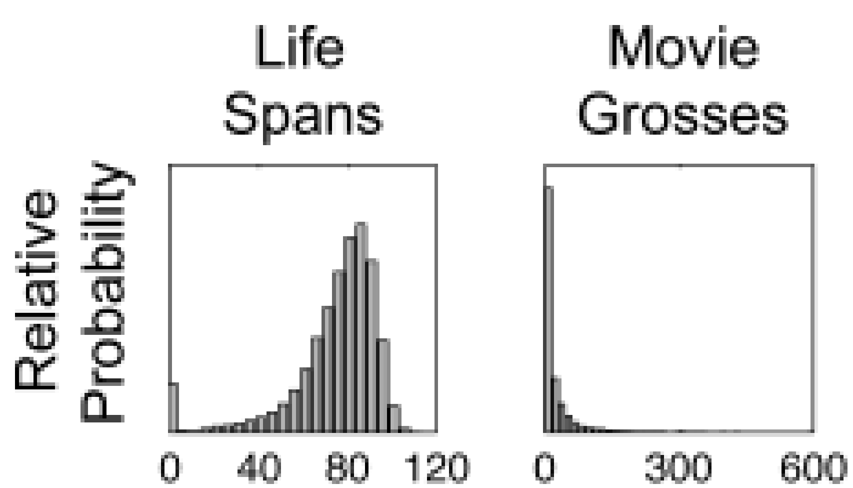
Bayesian modeling

$$P(h|D) = \frac{P(h)P(D|h)}{\sum_{h_i} P(h_i)P(D|h_i)}$$

$$h : \text{hypothesis} \quad D : \text{data}$$

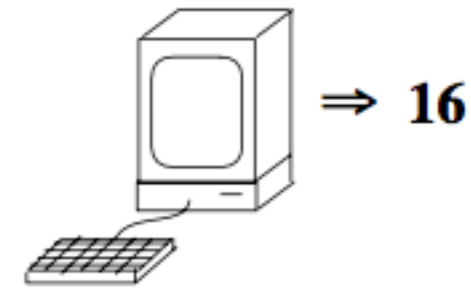
You meet a man who is 75 years old. How long will he live?

A movie has grossed 75 million dollars at the box office, but you don't know how long it's been running. How much will it gross total?



Bayesian modeling

1 random "yes" example:



$$P(h|D) = \frac{P(h)P(D|h)}{\sum_{h_i} P(h_i)P(D|h_i)}$$

h : hypothesis $\quad D$: data

Which numbers will be accepted by the same computer program?

15? 128?

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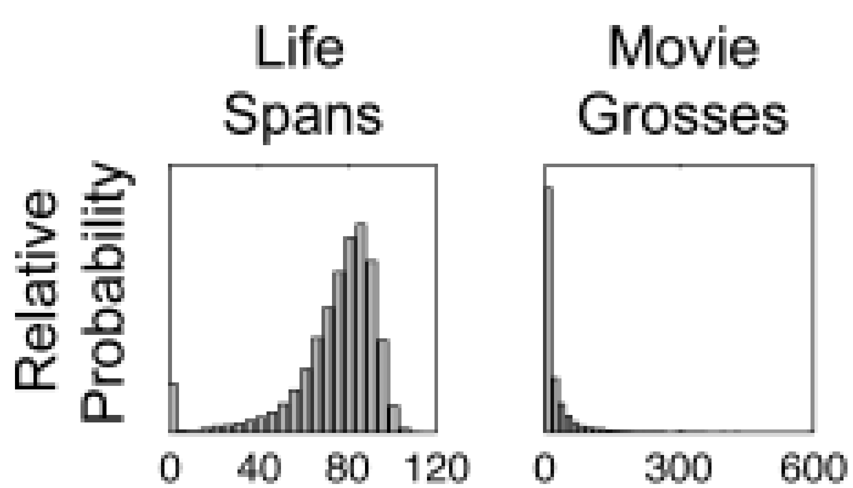

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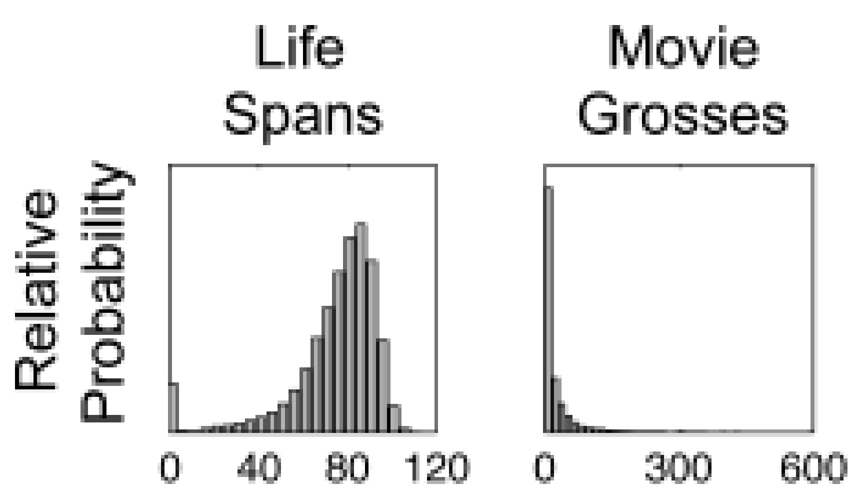

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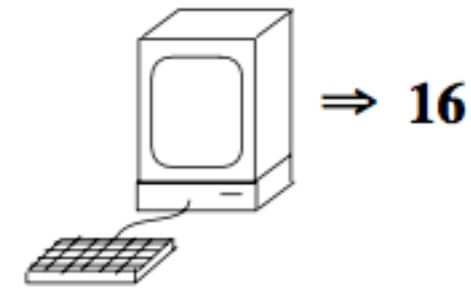
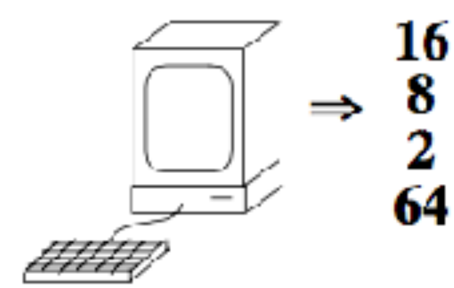


Which numbers will be accepted by the same computer program?

15? 128?

4 random "yes" examples:



Which numbers will be accepted by the same computer program?

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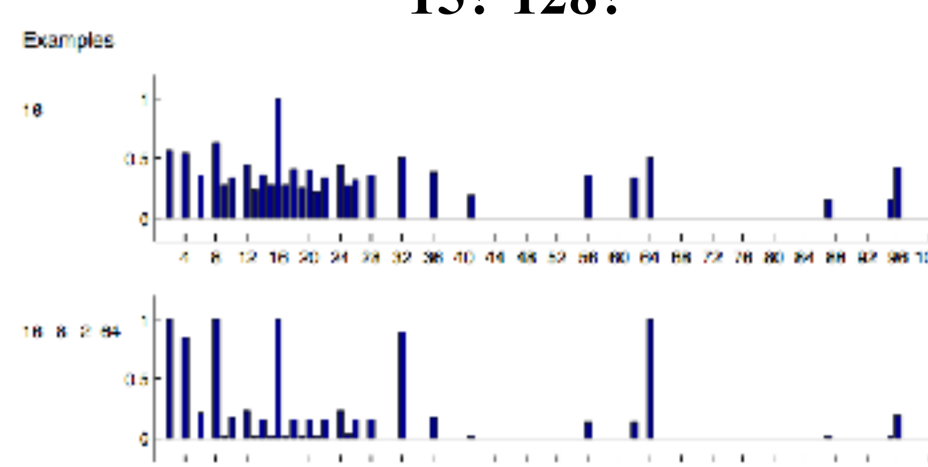
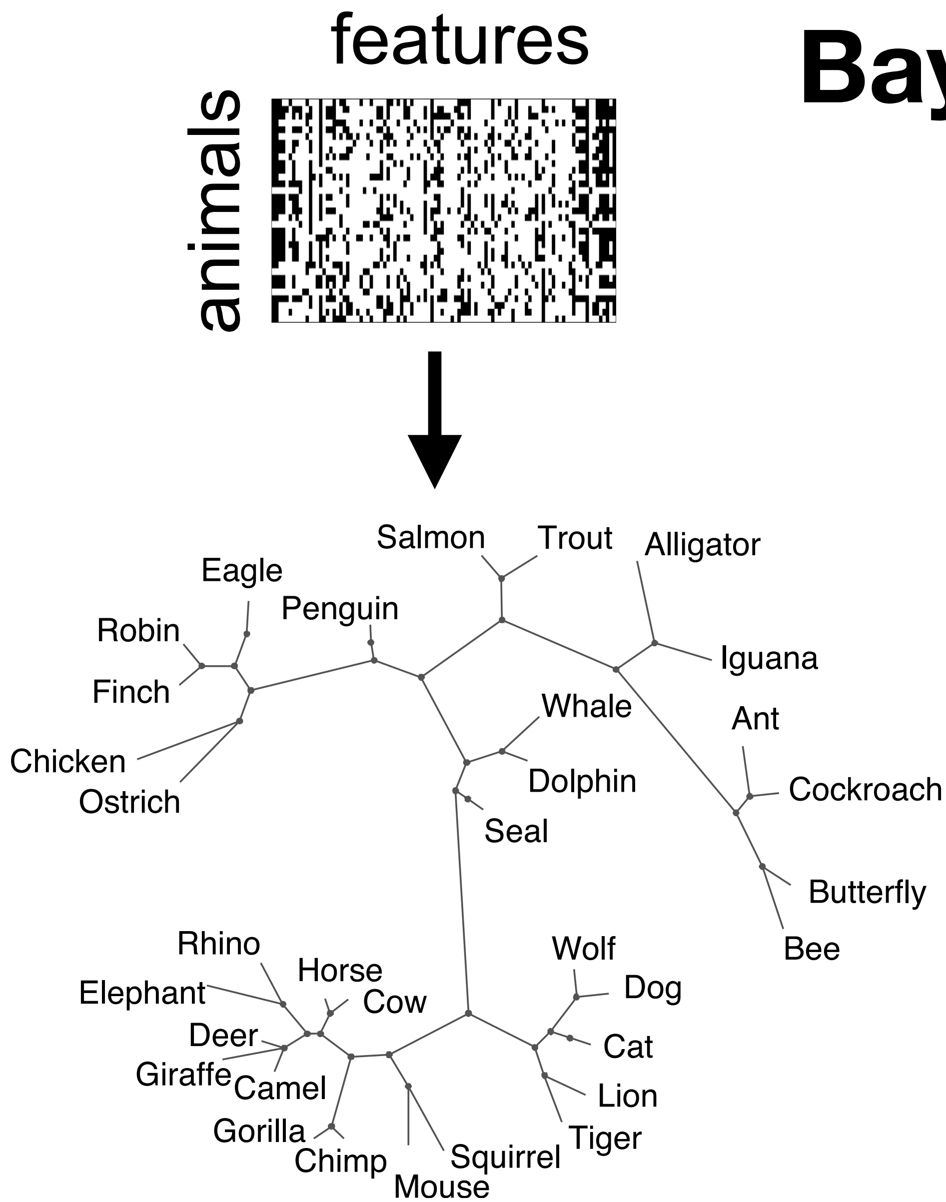
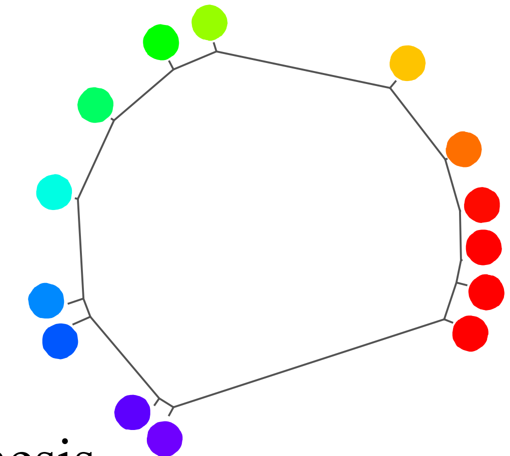


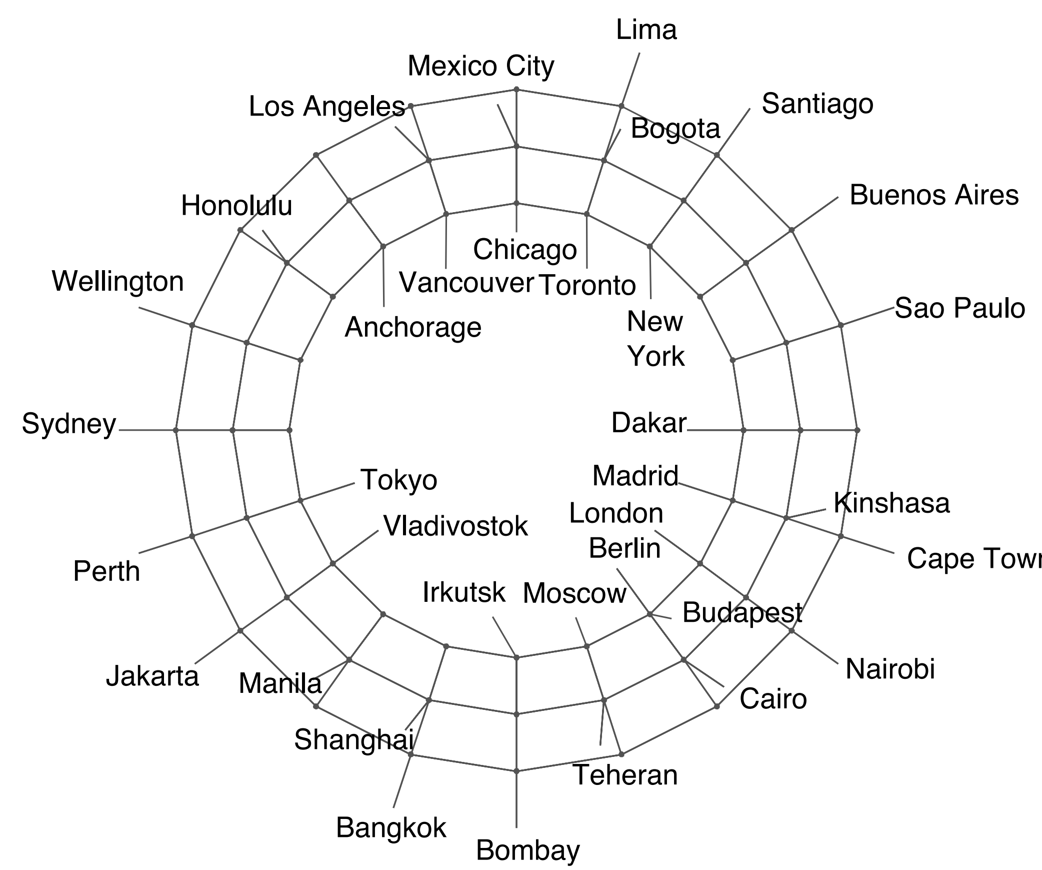
Bayesian modeling





Cows use biotin for hemoglobin synthesis
Seals use biotin for hemoglobin synthesis
—Therefore—
All mammals use biotin for hemoglobin synthesis

How strong is this inductive argument?

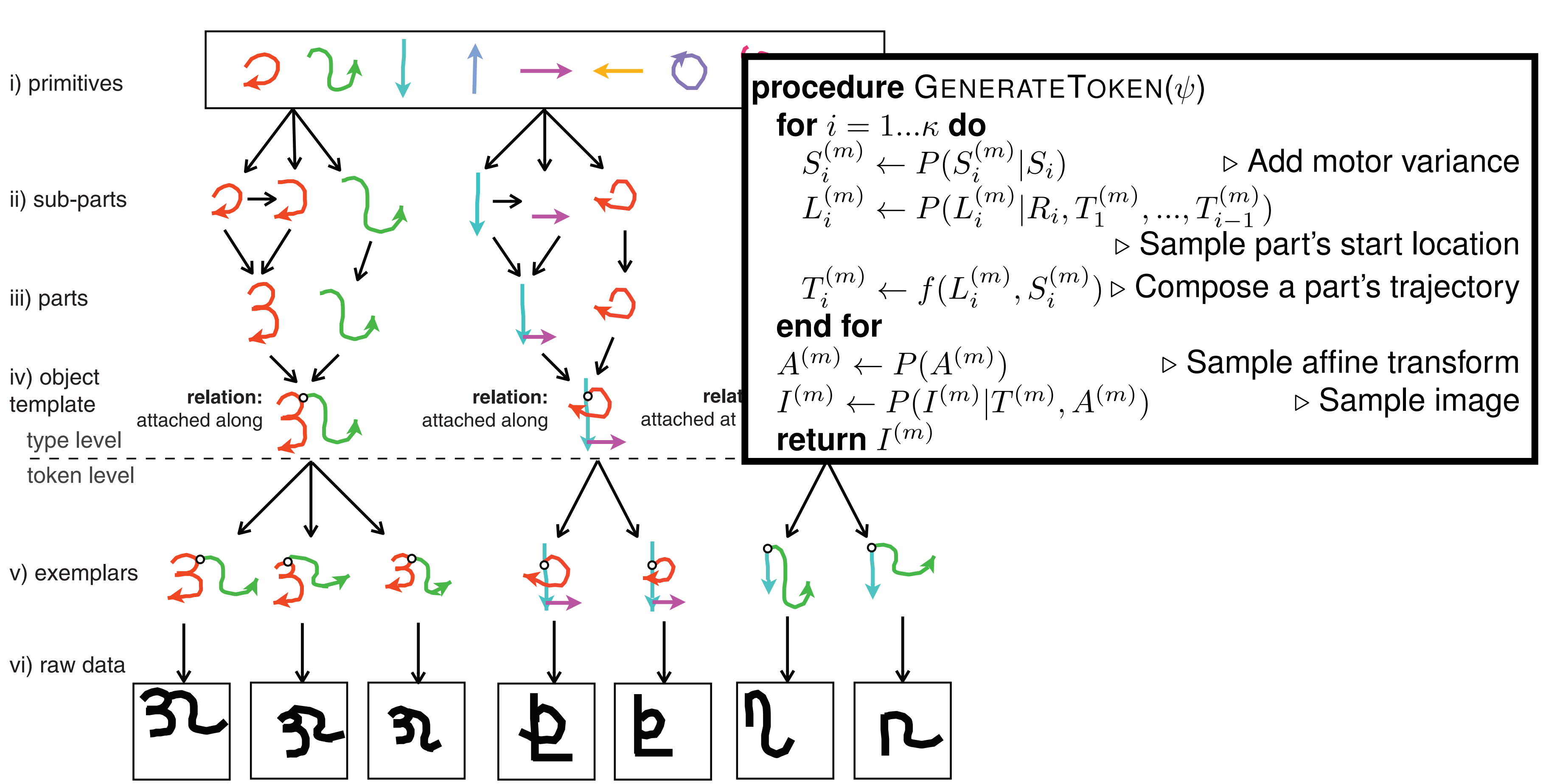


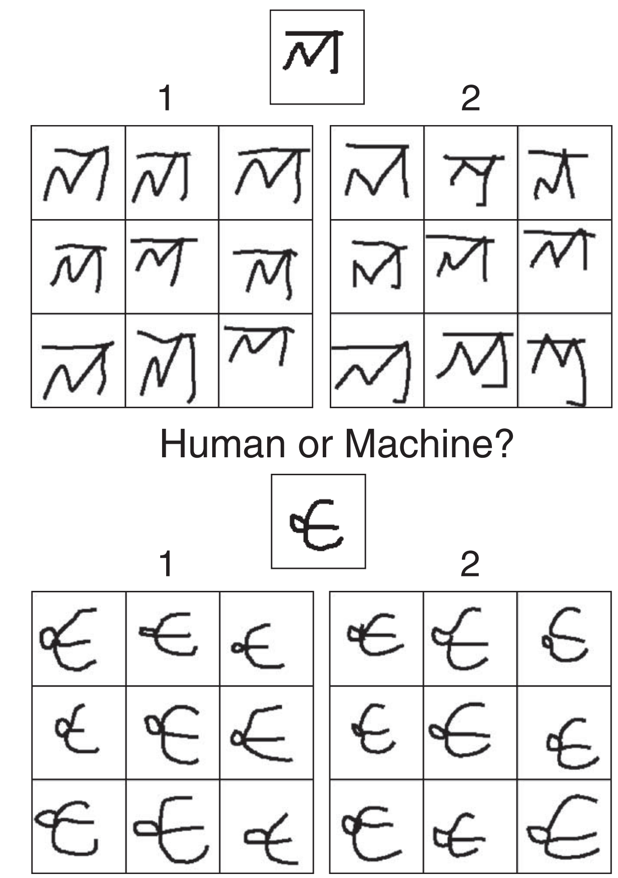
Native American artifact X has been found near San Diego
Native American artifact X has been found near Phoenix
—Therefore—-
Native American artifact X has been found near Boston

How strong is this inductive argument?

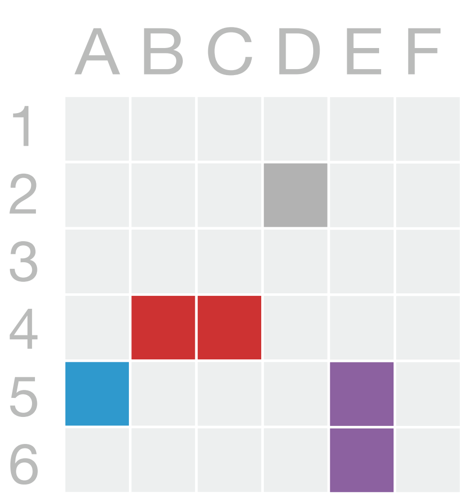
Program induction and language of thought models

one-shot concept learning





question asking



What is the top left of all the ship tiles?

```
(topleft (setDifference (set 1A ... 6F) (coloredTiles Water)))
```

Are all the ships horizontal?

```
(all (map (lambda x (== H (orient x))) (set Blue Red Purple)))
```

Are blue and purple ships touching and red and purple not touching (or vice versa)?

```
(== (touch Blue Purple) (not (touch Red Purple)))
```

Background

- Currently enrolled in what type of program:
  - Psychology Ph.D.? Psychology Masters? Data Science Masters? DS Ph.D.?

- Previous coursework:
  - Cognitive Psychology? Programming? Probability, statistics, MathTools? Machine learning? AI?

- Who knows about:
  - priming?
  - prototype vs. exemplar models?
  - categorical perception?
  - semantic networks?
  -logistic regression?
  - backpropagation algorithm?
  - simple recurrent network?
  - Model-based vs. model-free reinforcement learning?
  - Bayes' rule?
  - Conjugate prior?
  - MCMC?
  - Probabilistic graphical model?
  - program induction?

What you will come away with…

1. How to build computational models to test and evaluate psychological theories

2. How to build computational cognitive models to better understand behavioral data, by modeling the cognitive processes that produce that data

3. An introduction to key technical tools (in Python and Jupyter notebooks):

- neural networks / deep learning (in PyTorch)
- reinforcement learning
- Bayesian modeling
- Model comparison and fitting
- Probabilistic graphical models
- program induction and language of thought models

4. Ideally, students will leave the course with a richer understanding of how computational modeling advances cognitive science, and how computational cognitive modeling can inform research in data science, machine learning, and artificial intelligence

For next time....

Readings (available on NYU Classes; "Resources" folder)

- Marr, D. (1982) "Vision" (Chapter 1)
- Love, B.C., Medin, D.L, & Gureckis, T.M (2004). SUSTAIN: A Network Model of Category Learning. Psychological Review, 111, 309-332.
- Sanborn, A. N., Griffiths, T. L., & Navarro, D. J. (2010). Rational approximations to rational models: Alternative algorithms for category learning. Psychological Review, 117 (4), 1144-1167.

Homework (link on course webpage):

- Homework 1a and 1b (due in two weeks 2/6).
- Homework 1a is an introduction to Jupyter Notebook and Python
- Homework 1b is an exploration of complexity and emergence in simple systems

Questions?