Computational Cognitive Modeling

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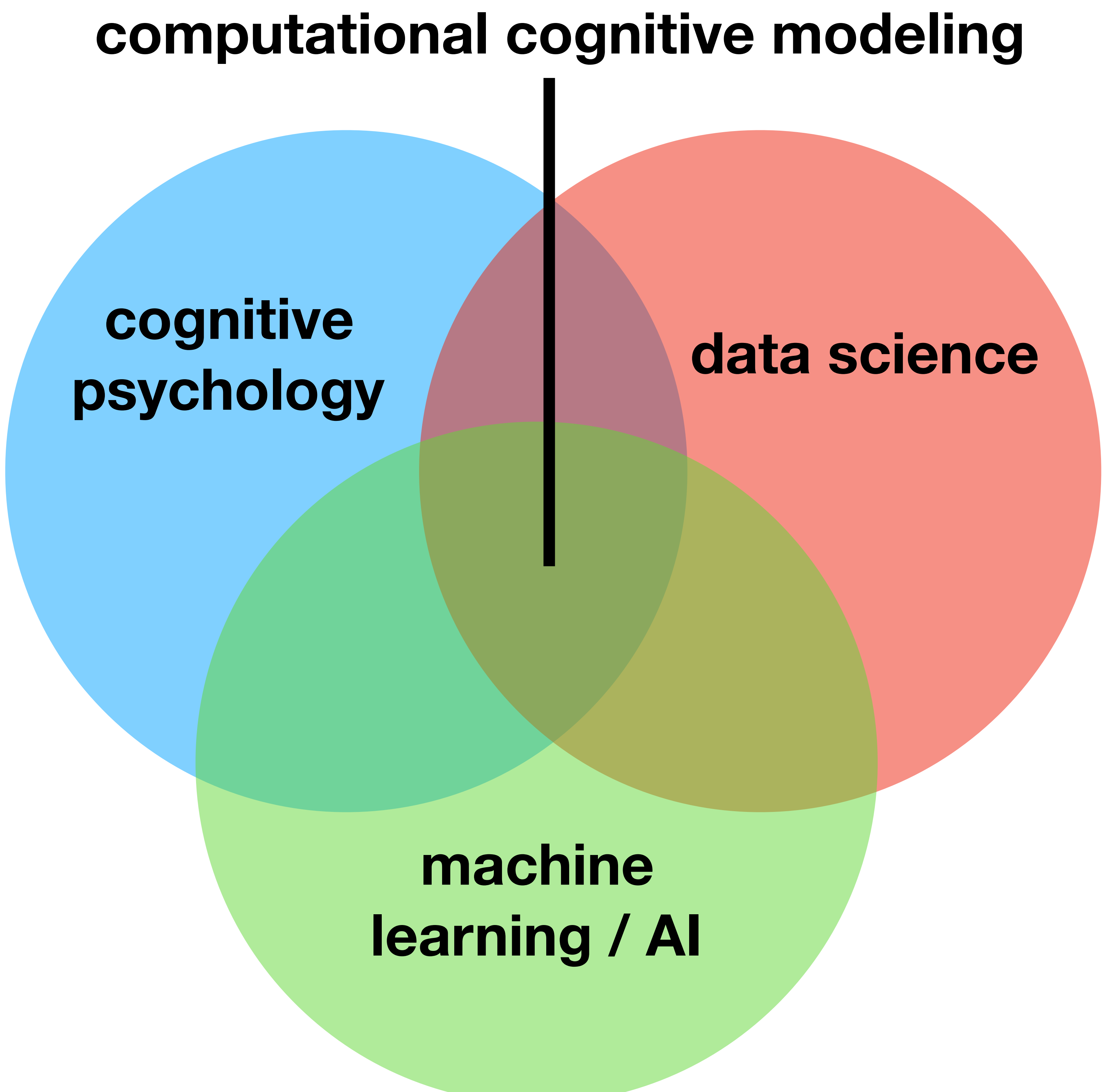
What is Computational Cognitive Modeling?

- Computational Cognitive Modeling is devoted to unlocking the mystery of the human mind and brain, in terms of their underlying computational processes.
- A core goal is to build computer simulations that *mimic* the intelligent behavior of humans, and to use simulations to predict and explain human behavior.

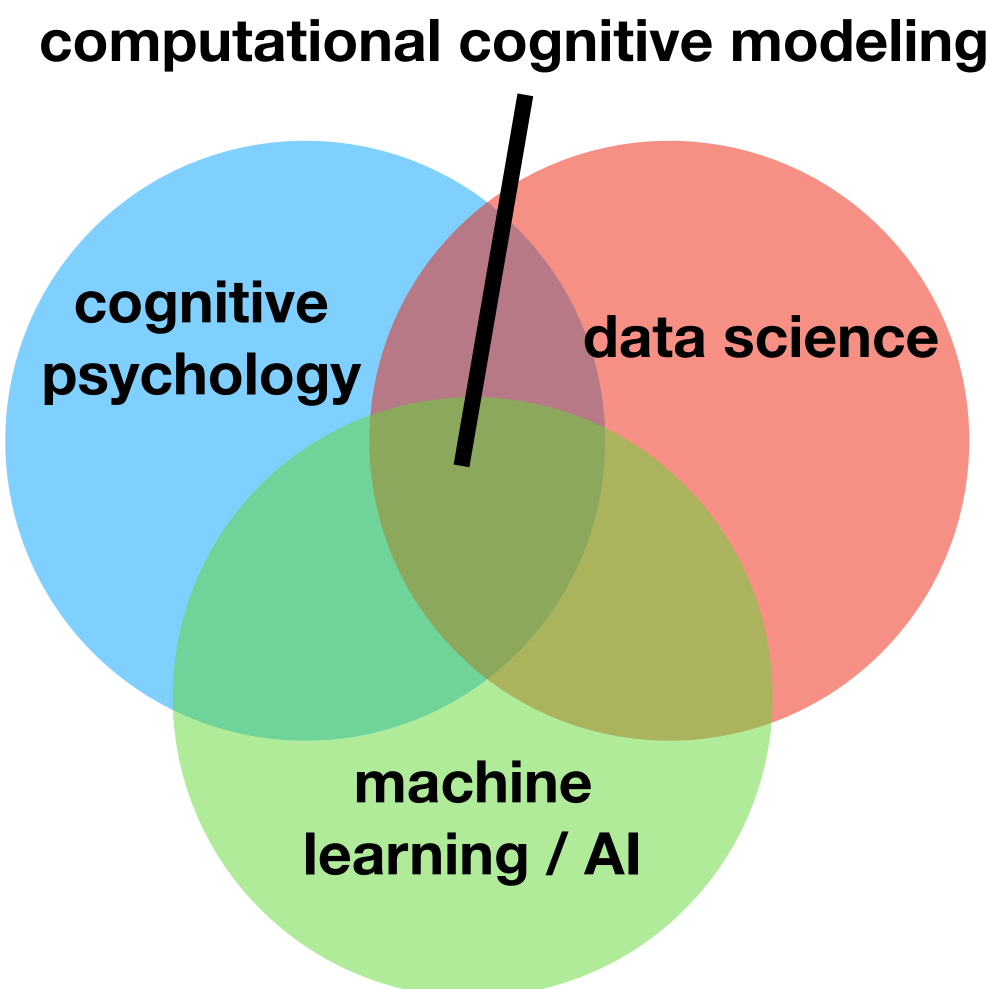
Key questions for this course

- What is intelligence?
- What kind of computer is the mind and brain?
- Can we better understand the mind/brain by building computational cognitive models?
- Can we better understand behavioral data by building computational cognitive models?
- Can we improve machine intelligence by incorporating insights from human intelligence?

At the intersection of cognitive psychology and data science

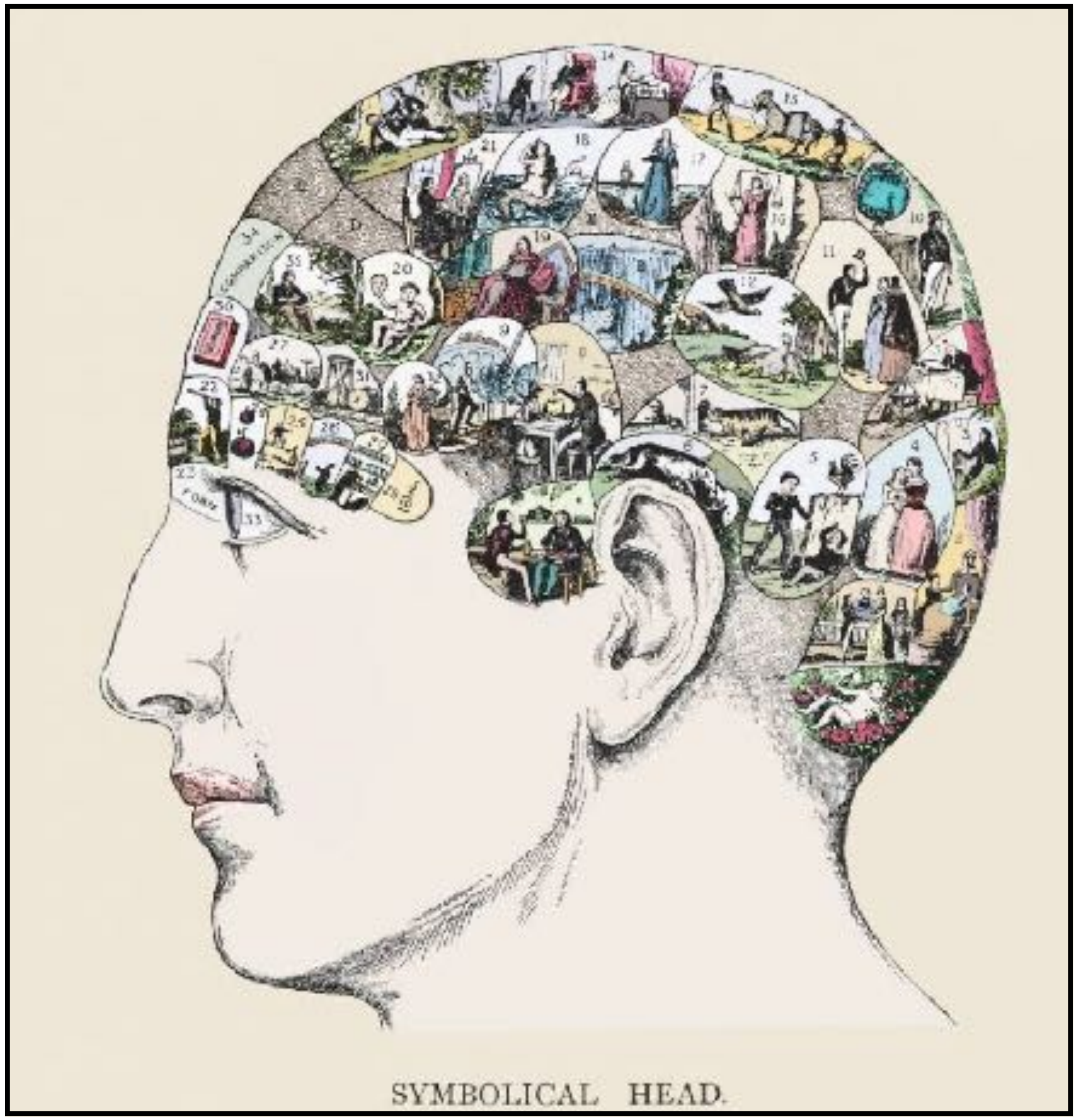


Connections between cognitive modeling and data science



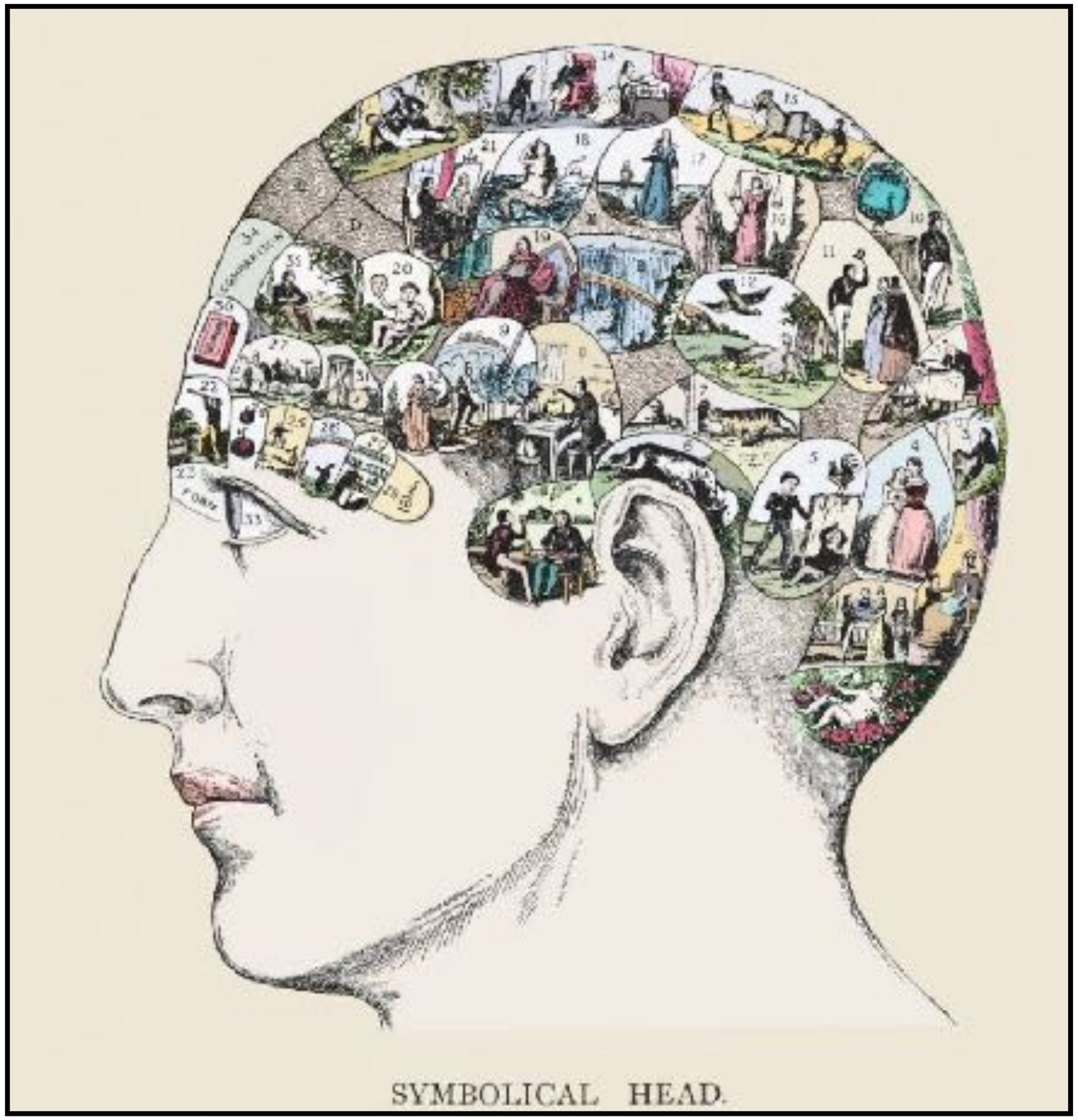
- **Similar goals**: building computational models to explain or predict behavioral data
- **Similar computational paradigms and techniques**: neural networks / deep learning, reinforcement learning, Bayesian modeling, probabilistic graphical models, program induction
- Data science is about **extracting 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.

What is a mind?



This has been 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 several folks at NYU.

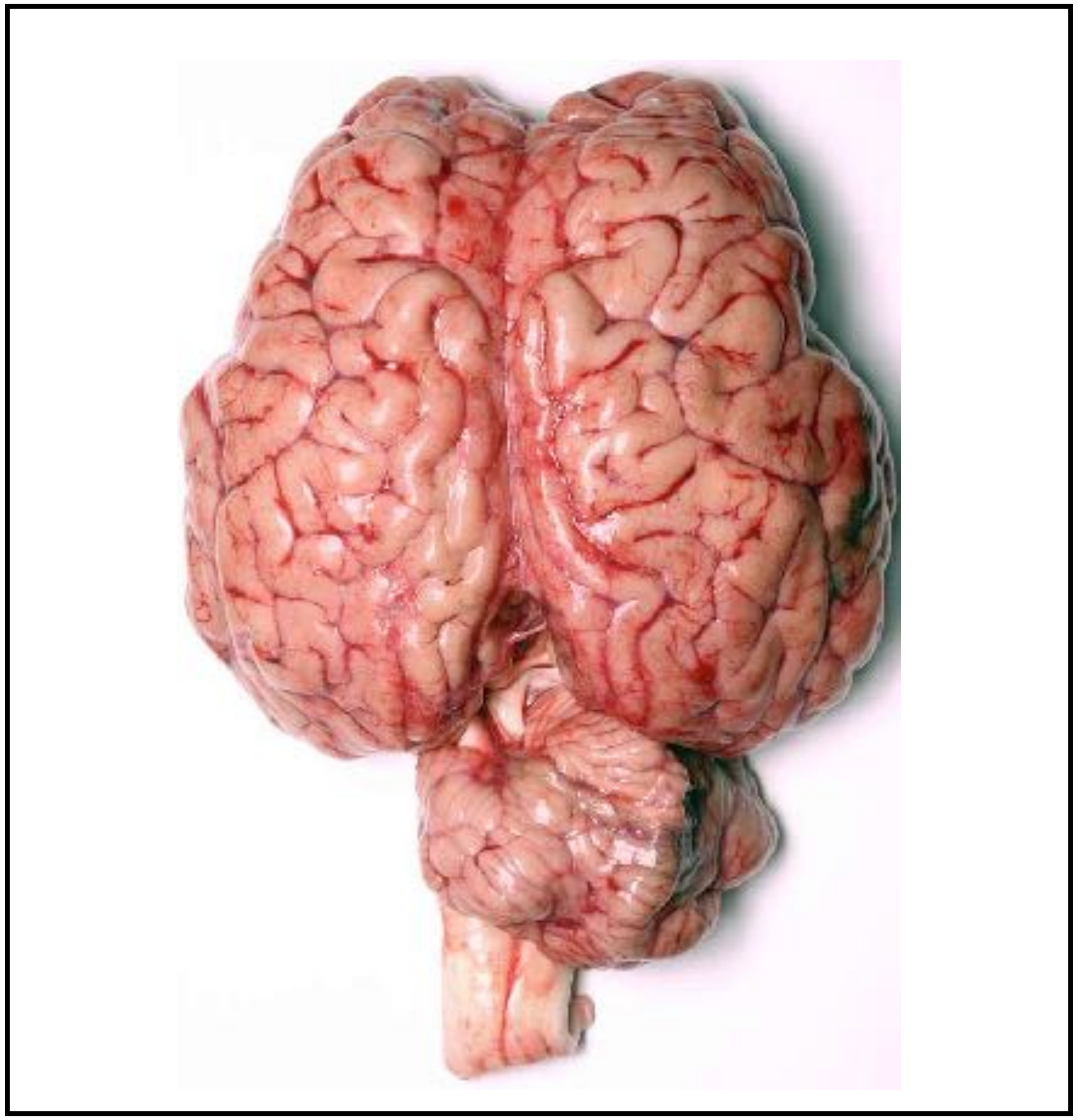
What is a mind?



What do minds do?

Minds encompass our thoughts, which are mental processes that allow us to deal with the world. These include not only explicit wishes, desires, and intentions, but also unconscious processes too.

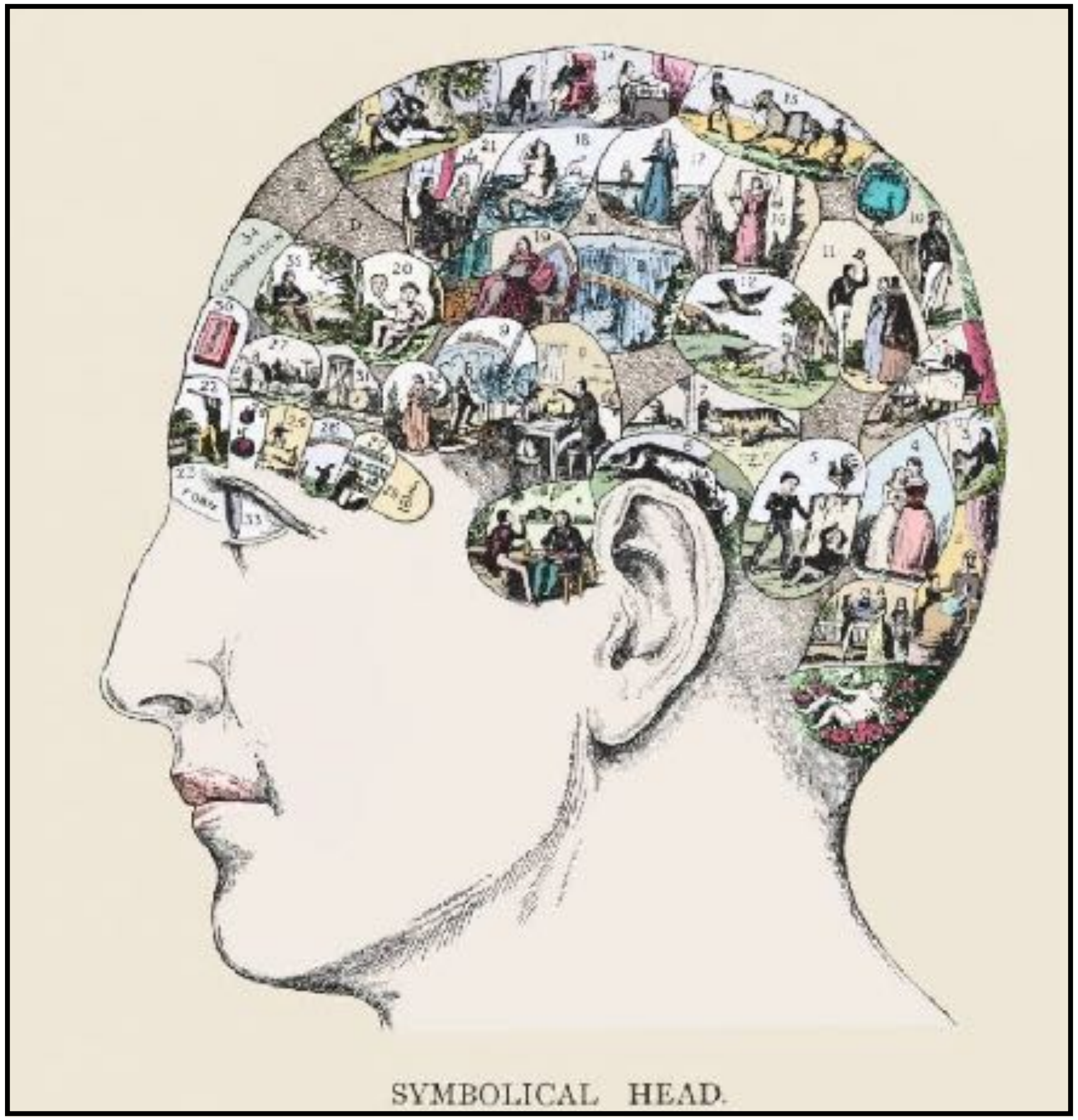
What is a mind?



Does MIND=BRAIN?

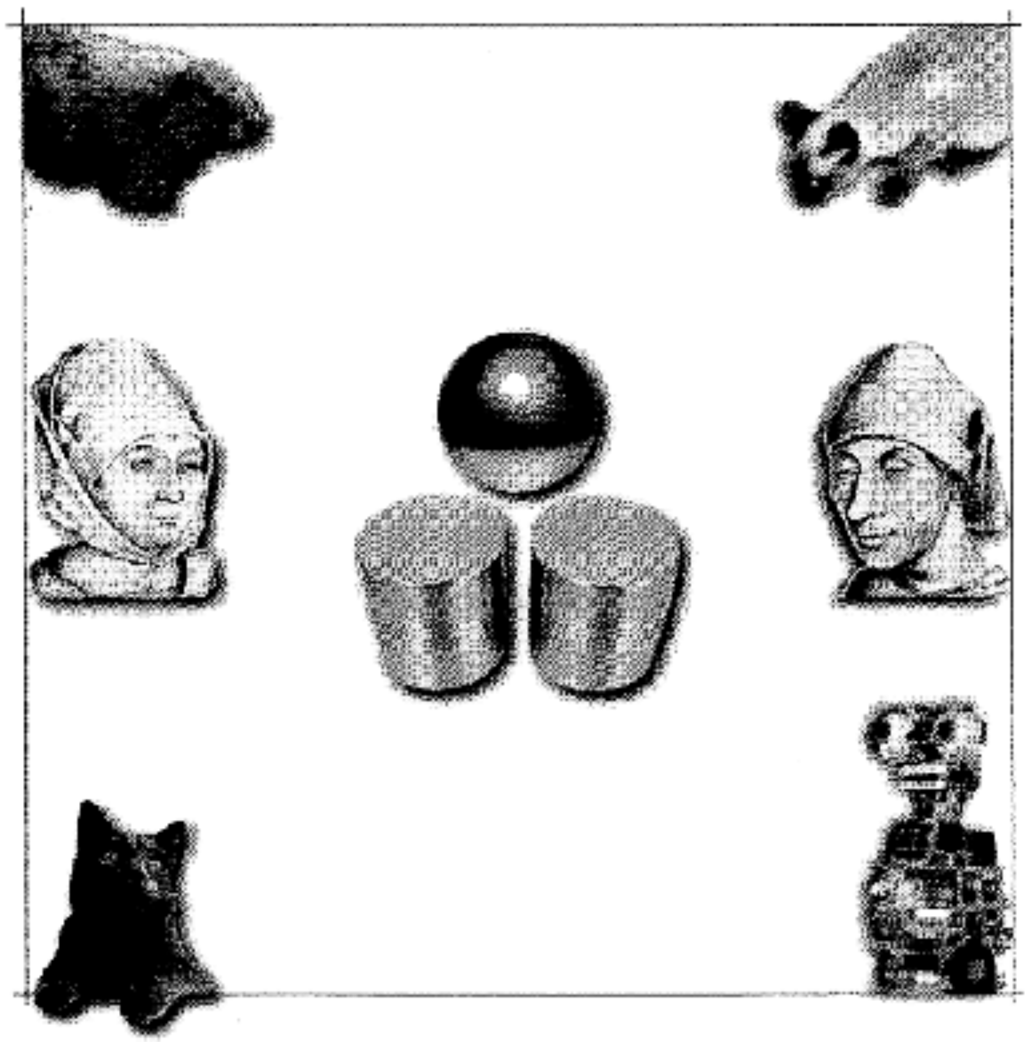
We know that we can't have a mind or thoughts without a brain, but does that mean that minds and brain are synonymous?

What is a mind?



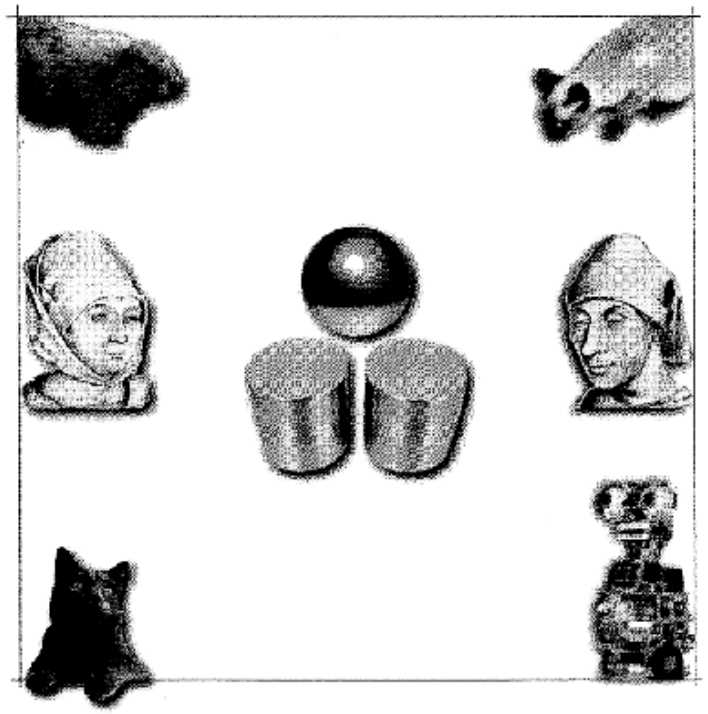
A “slippery slope” argument can convince us that minds are not literally brains, but encompass anything that is organized as representational states that accurately reflect aspects of the world.

The Brain/Mind Riddle



What is common to the various entities (person 1, person 2, cat 1, cat 2, robot, etc.) that look at this scene of two cylinders and a sphere?

Shimon Edelman's argument



The question: What is common to observers viewing the same scene and who agree upon what is viewed?

- Can't literally be neurons. My neurons are my own, and you can't borrow them to solve your own problems.
- Is it the literal organization of the human nervous system? 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 is not their physical substrate, but the relations that states of the system have to one another, and to the external environment.**

Minds as computers

- Minds aren't human neurons or cat neurons or robot parts. They are dynamic, continually evolving systems that relate ongoing internal (i.e., mind) states and external (i.e., world) states

- Correspondences can be made between two systems by describing what they do, independent of their exact physical substrate.

- **We can describe these correspondences through the language of computation, simply because the THEORY OF COMPUTATION offers use formal insight into how ostensibly dissimilar systems can be formally identical.**

Why build computational cognitive models? (As a psychologist)

"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 Missier, & Stocco, 2007)

Some famous psychological theories…

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

Each of these theories benefits from formalization with a computational model to…

- **Make predictions explicit**
- Implications often **defy expectations**
- **Aid communication** between scientists
- Support **cumulative progress**

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

Rich history of connections between fields

cognitive science / psychology

machine learning / AI / data science

Bi-directional exchanges of computational methods and paradigms

cognitive science / psychology ⇄ **machine learning / AI / data science**

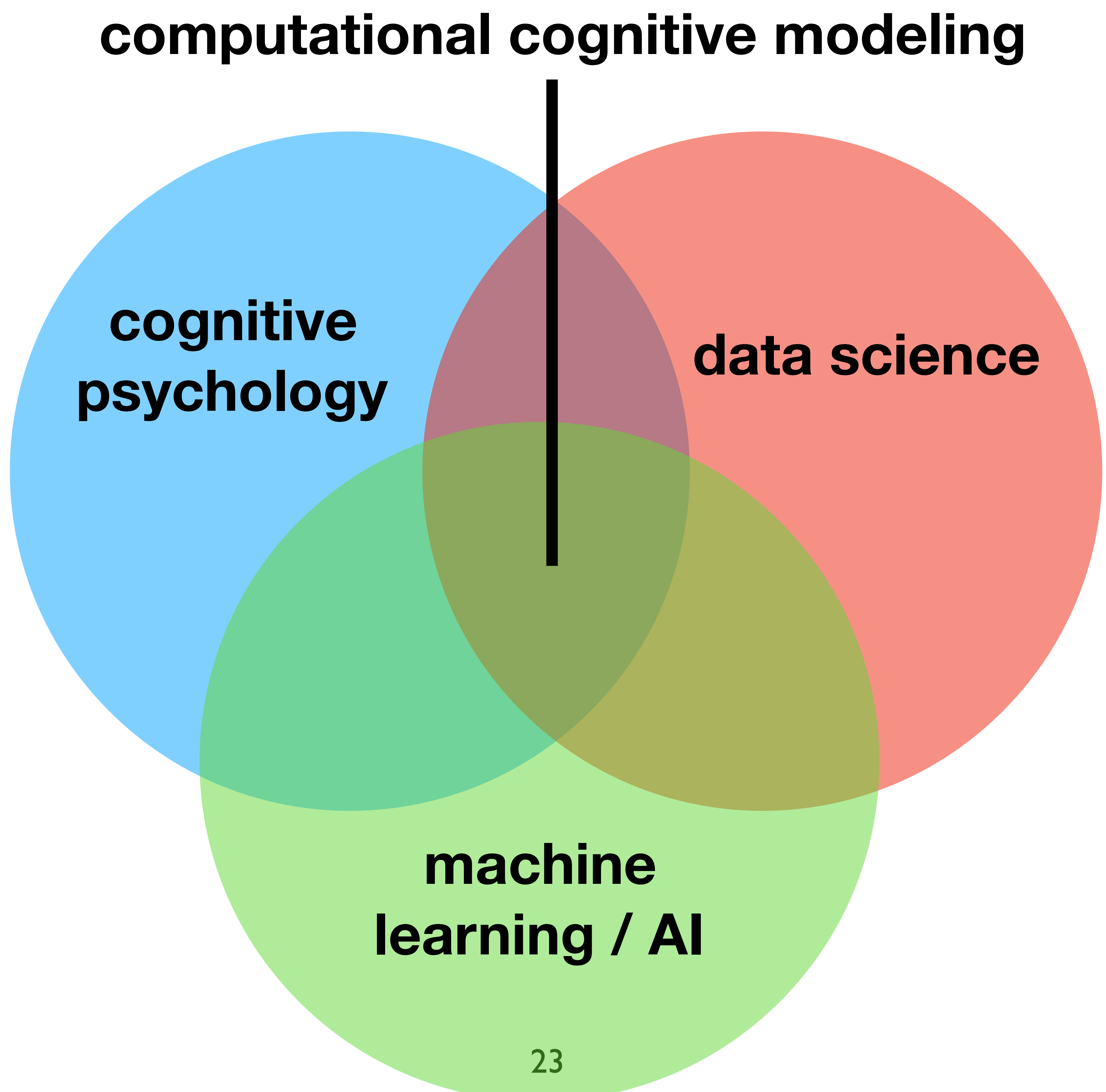
- Artificial neural networks
- Temporal difference learning
- Factor analysis
- Multi-dimensional scaling
- Probabilistic graphical models
- Structured Bayesian models
- Bayesian non-parametric models
- Probabilistic programming
- Recurrent neural networks
- …

Computational cognitive modeling can help make more powerful machines with more human-like learning capabilities

cognitive science / psychology

machine learning / AI / data science

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



question asking

one-shot learning

scene understanding

concept learning

transferring to new tasks

inventing new tasks

language acquisition

computational problems that are easier for people than for machines

creativity

Special opportunities for improving machine learning and AI through both engineering and REVERSE engineering.

language understanding

general purpose problem solving

commonsense reasoning

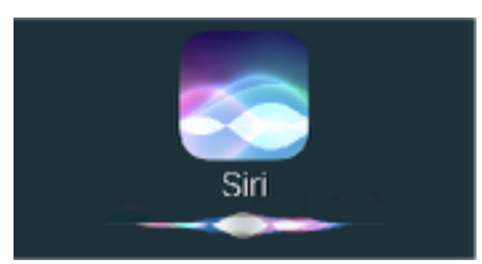
self-assessment

forming explanations

curiosity and motivation

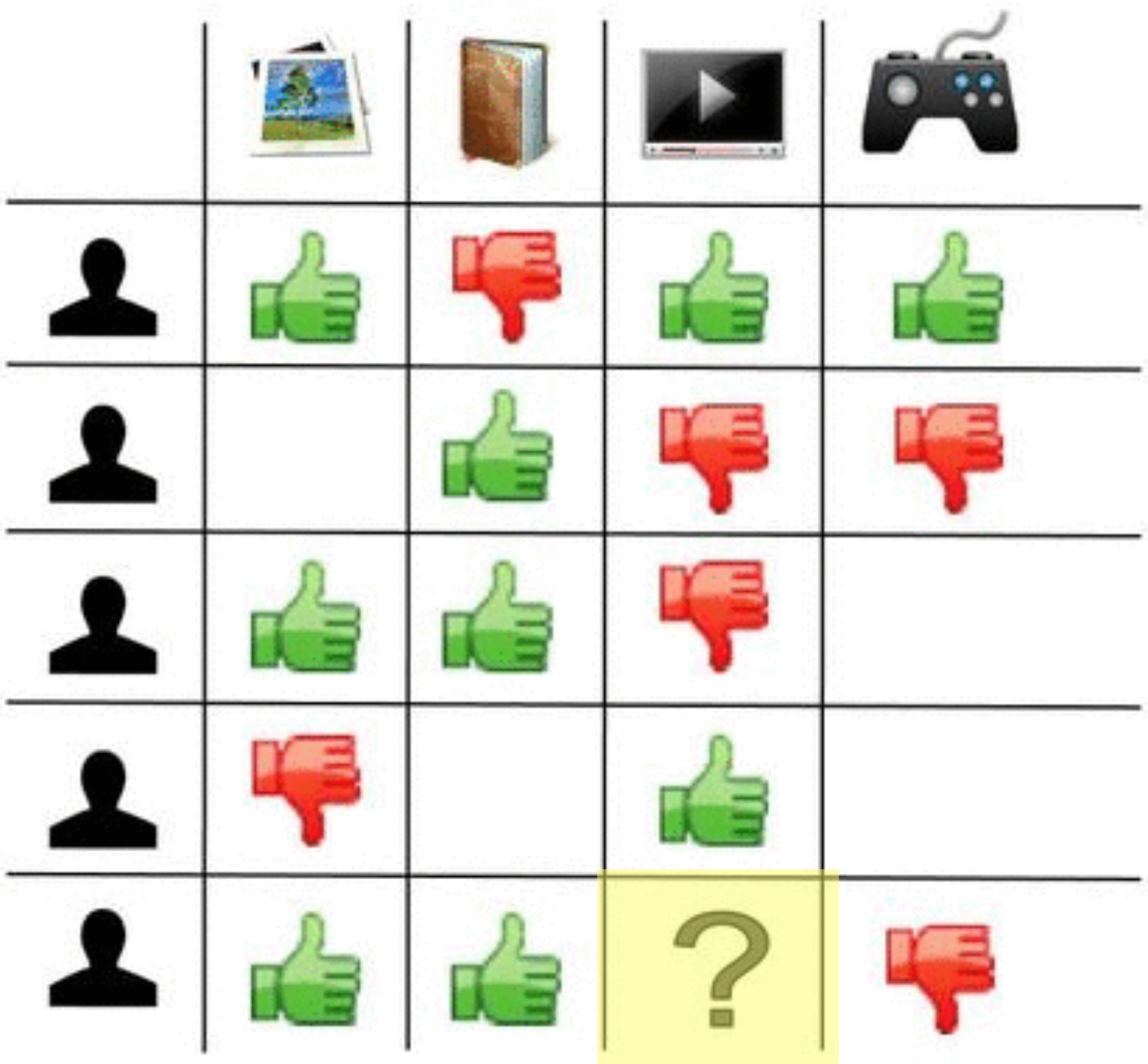
Can we better understand behavioral data by building computational cognitive models?

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



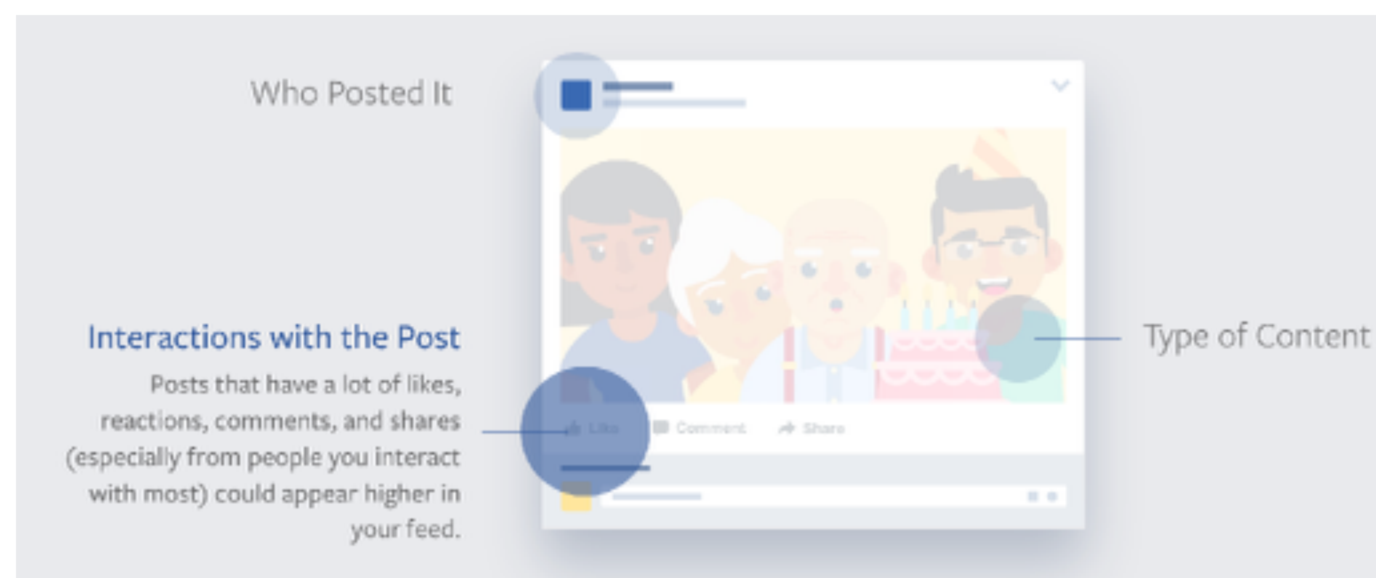
popular applications with behavioral data

collaborative filtering



churn modeling

adaptive content (e.g., news feed)



popular challenges for developing machine learning / AI algorithms

object recognition (ImageNet)

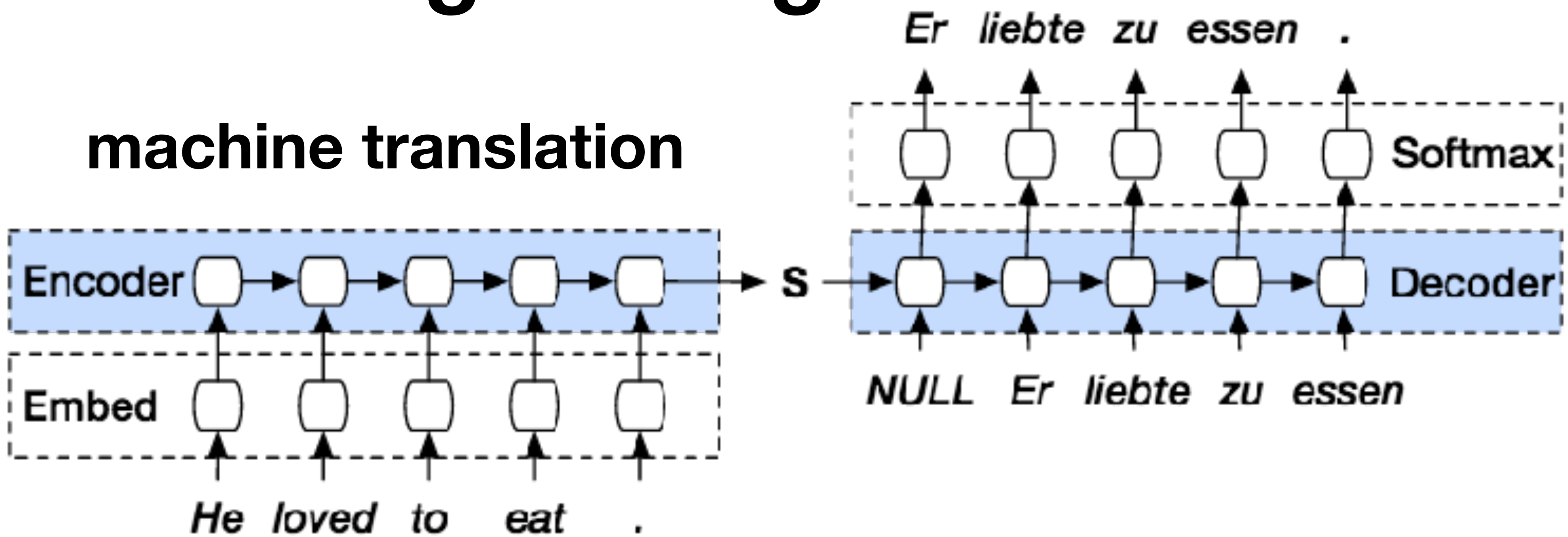
caption generation (MSCOCO)

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

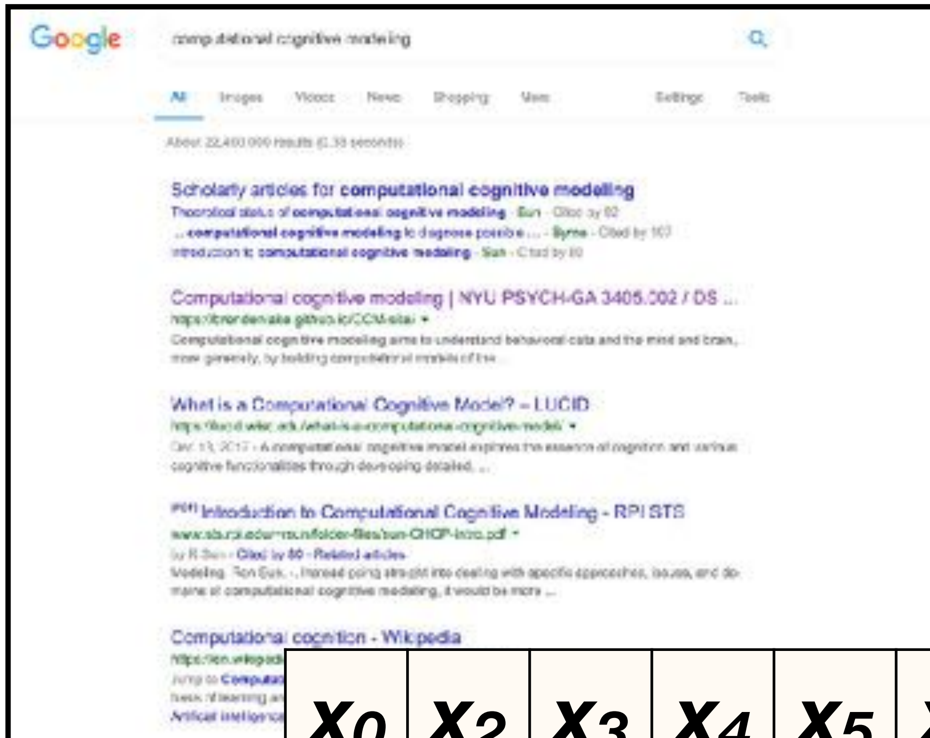
popular challenges for developing machine learning / AI algorithms

machine translation



language modeling and natural language understanding

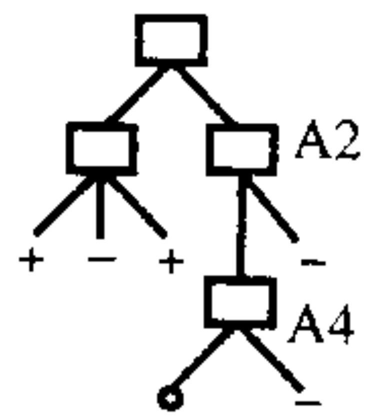
positing a mind to explain and predict behavior



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…

$p(y|x;\theta)$

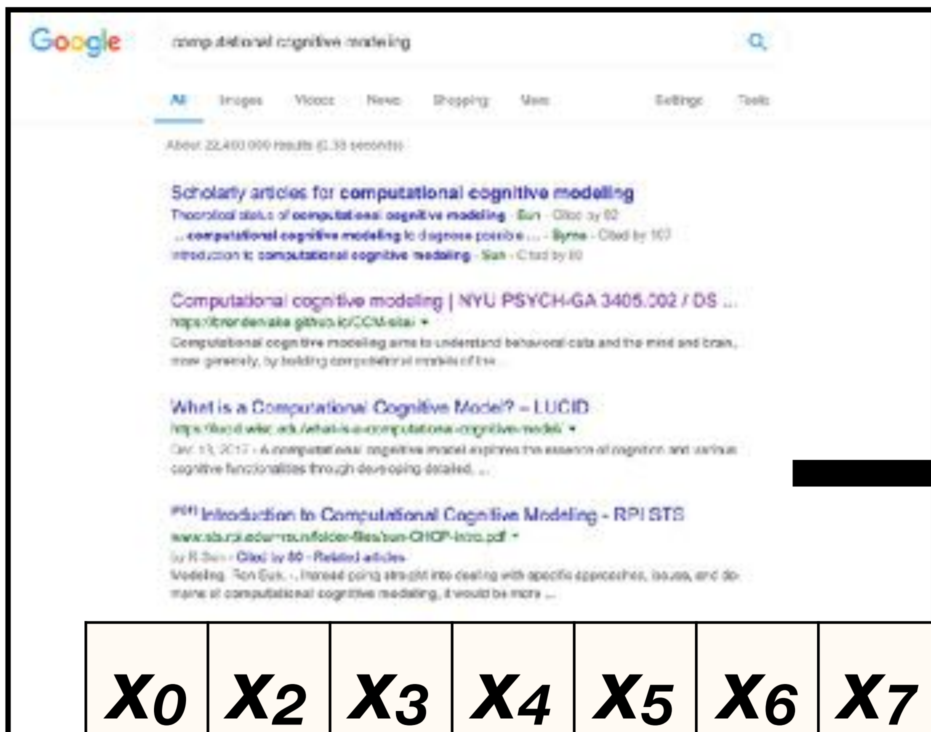


y
0
0
1
1

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

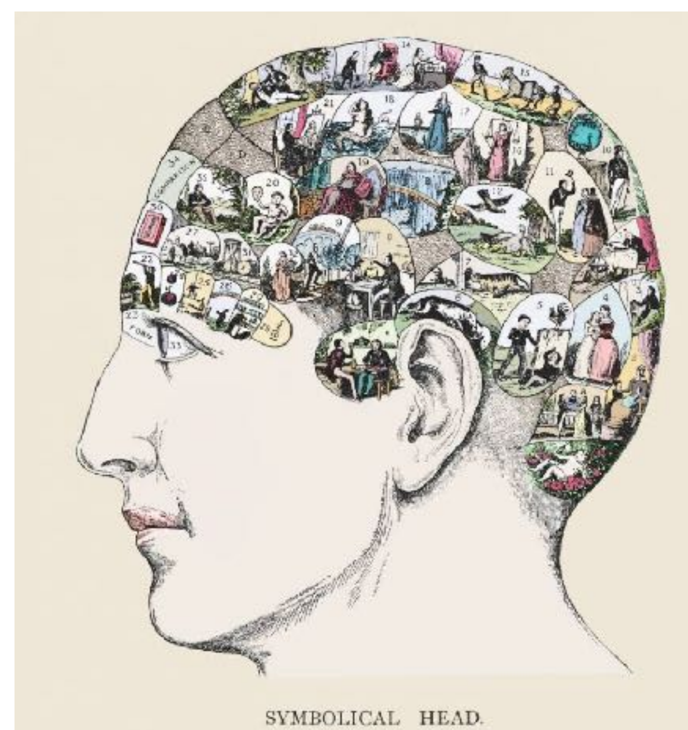
positing a mind to explain and predict behavior

- 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.
- **Important qualifier: This perspective is not yet mainstream in data science. This course is will teach you the right tools, but it's up to you to make 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
0
0
1
1

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

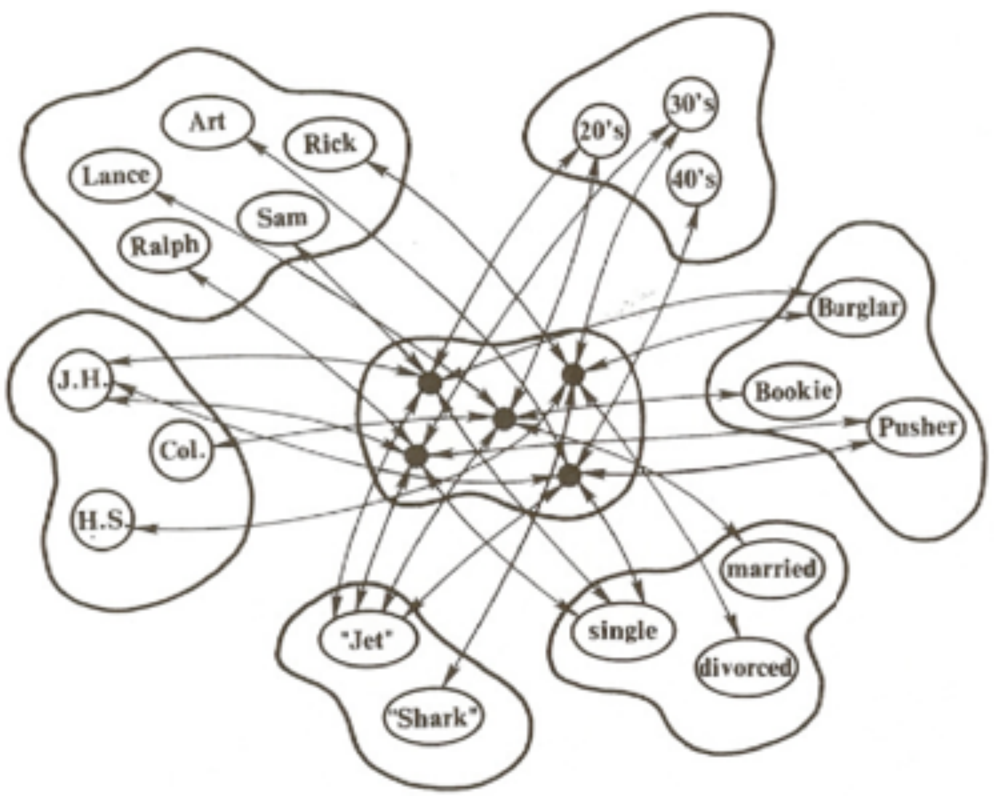
We will spend most of our time diving into various computational modeling paradigms

- Neural networks / deep learning
- Reinforcement learning
- Bayesian modeling
- Classification/categorization
- Probabilistic graphical models
- Program induction and language of thought models

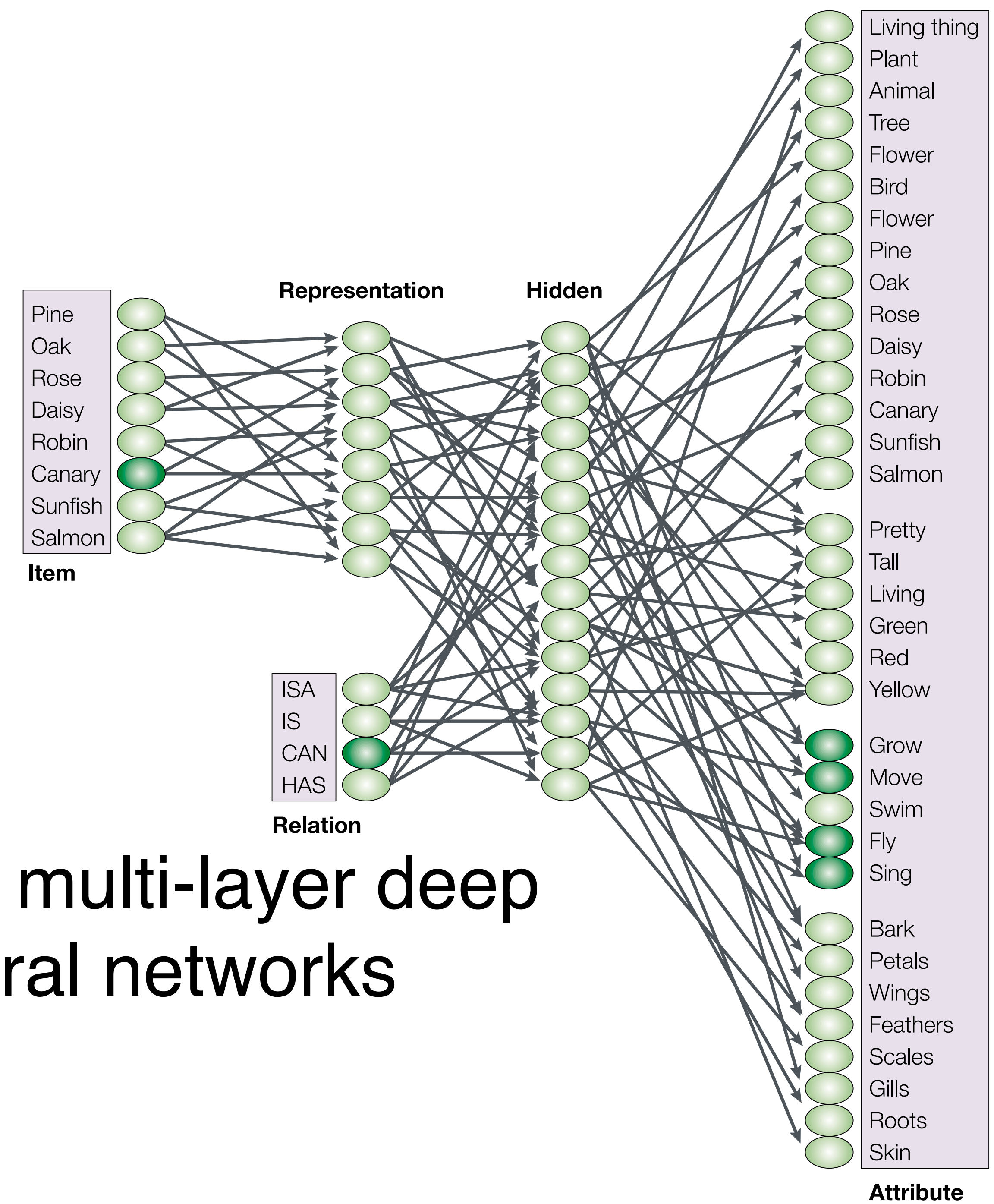
Notice synergy with contemporary machine learning!

Neural networks / deep learning

Retrieving information from memory



Learning about objects and their properties; modeling cognitive development

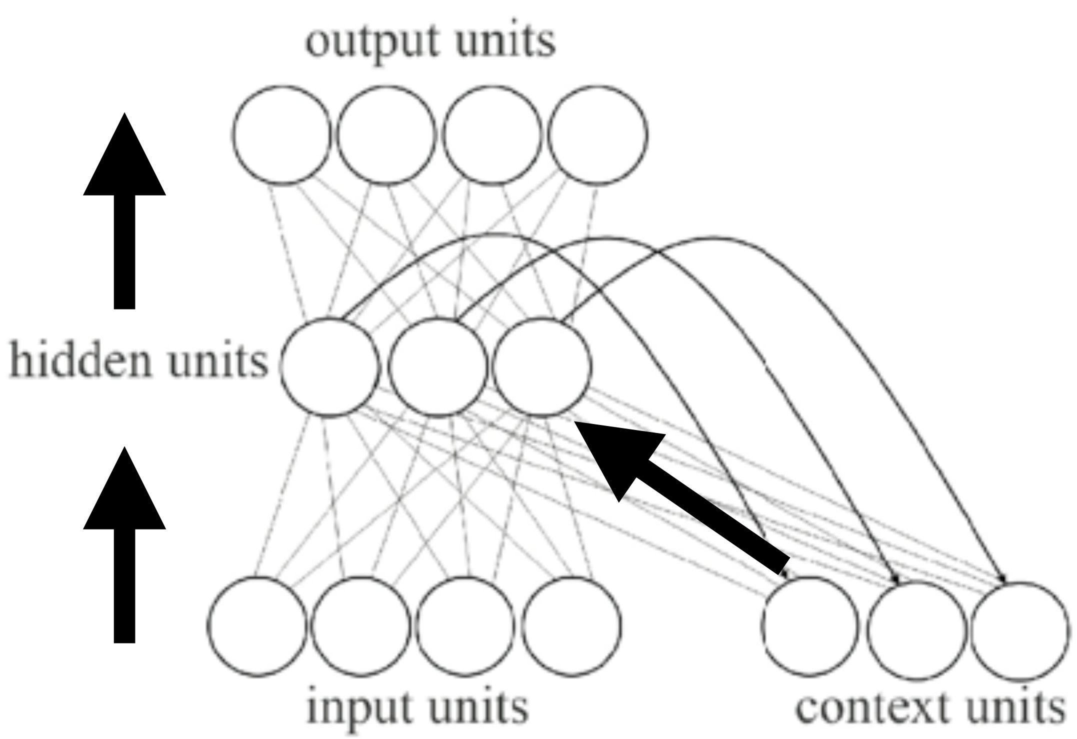


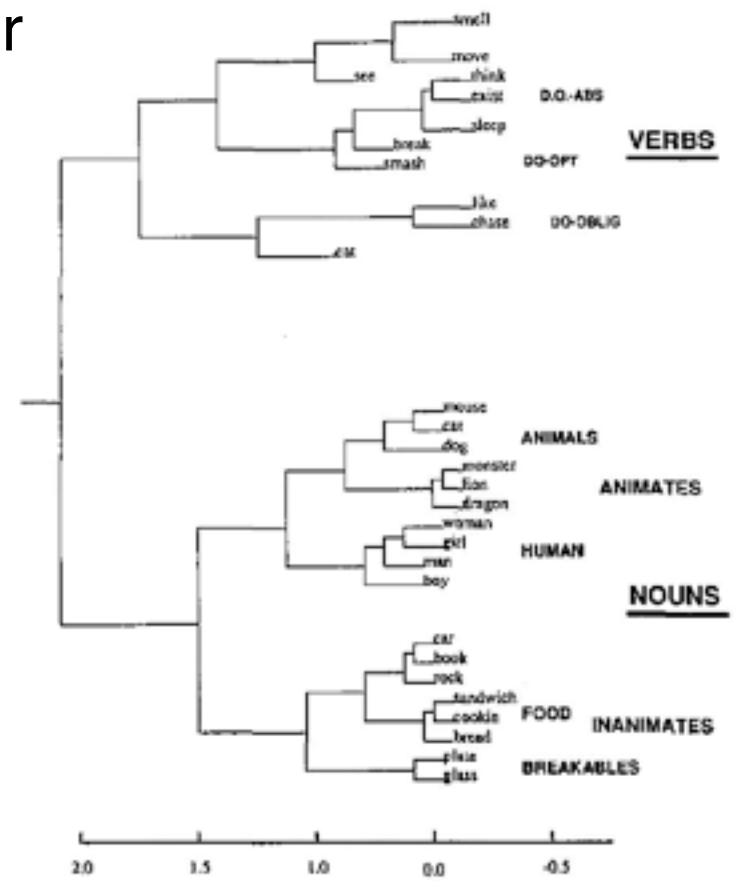
Training multi-layer deep neural networks

Neural networks / deep learning

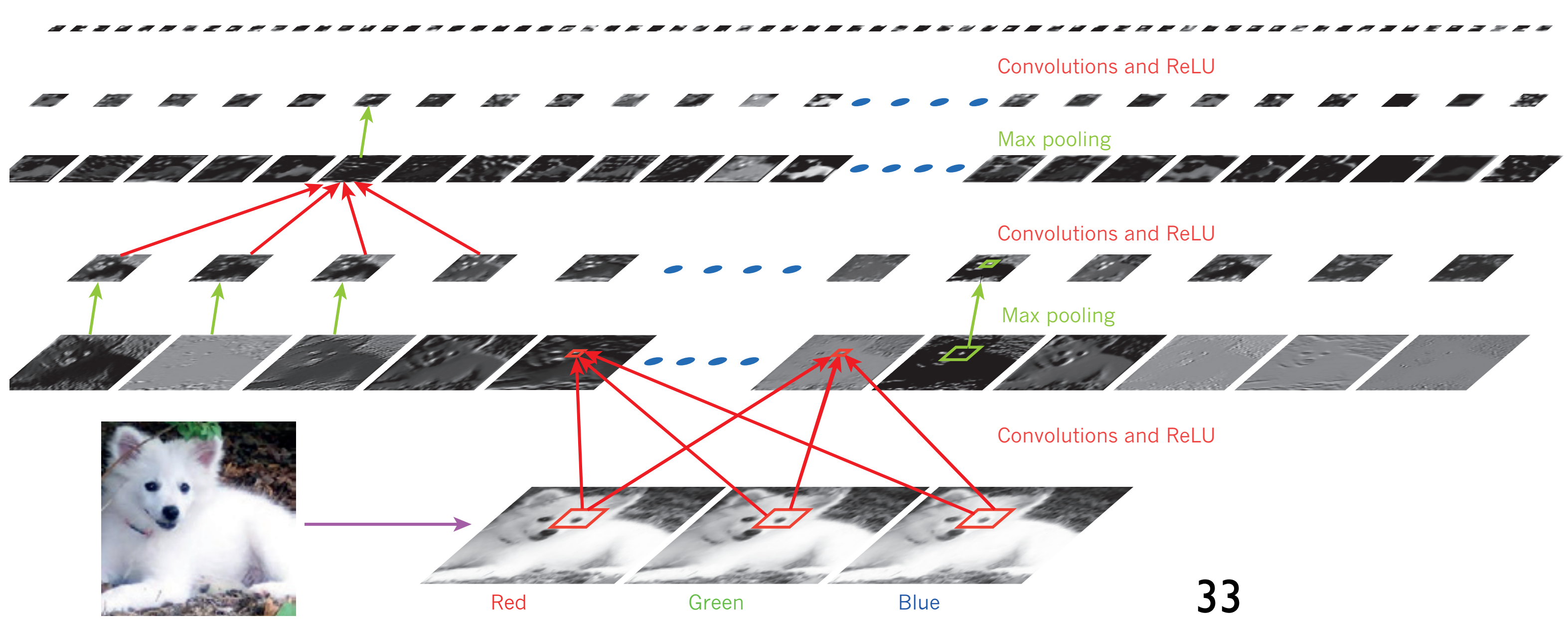
Recurrent neural networks

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

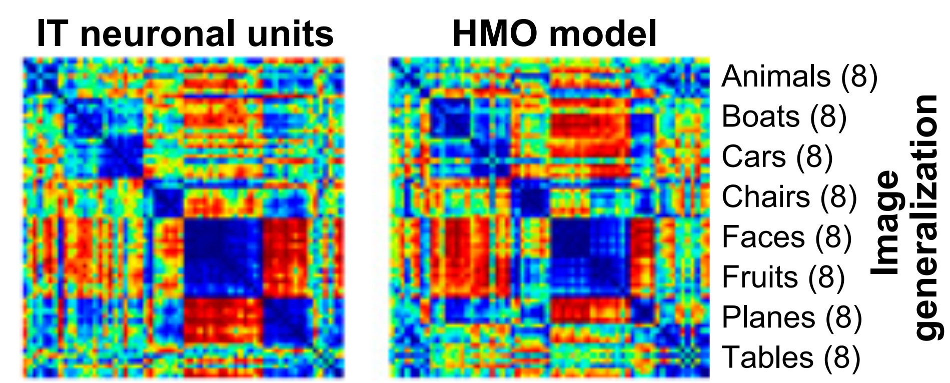




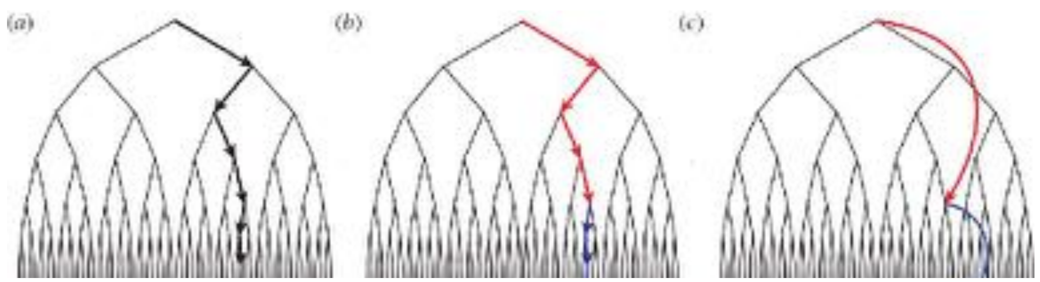
convolutional neural networks

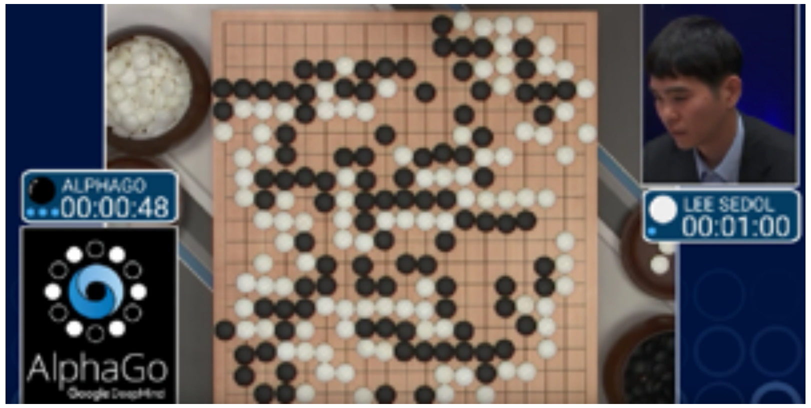


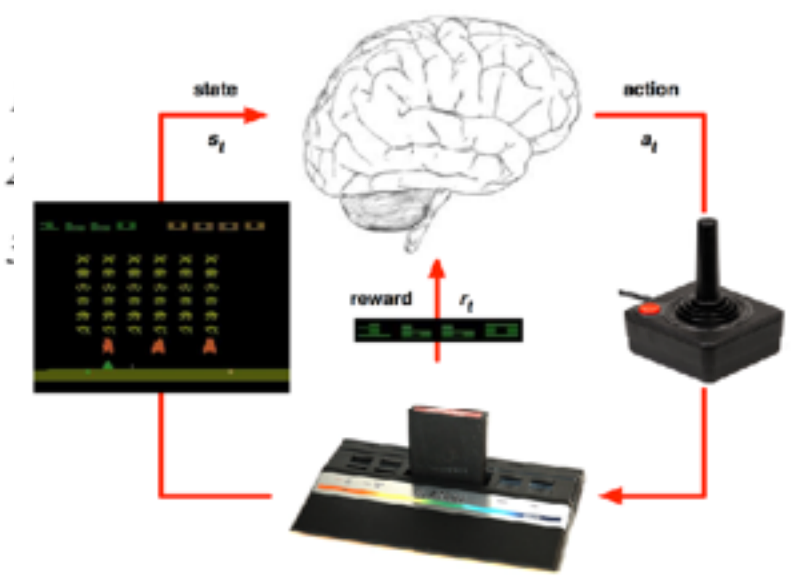
applications in neuroscience and cognitive science

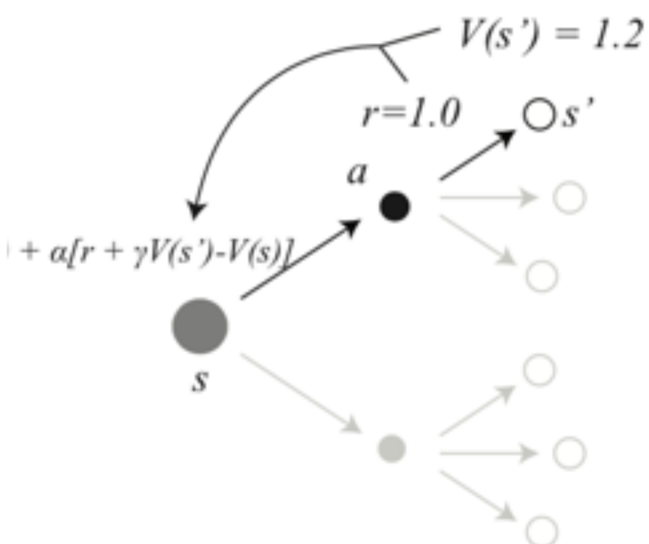


Reinforcement learning

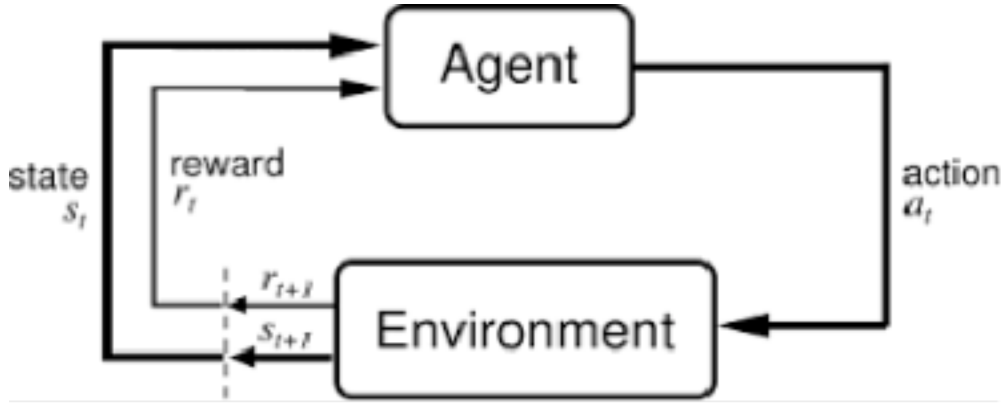








"Recalculating ... recalculating ..."



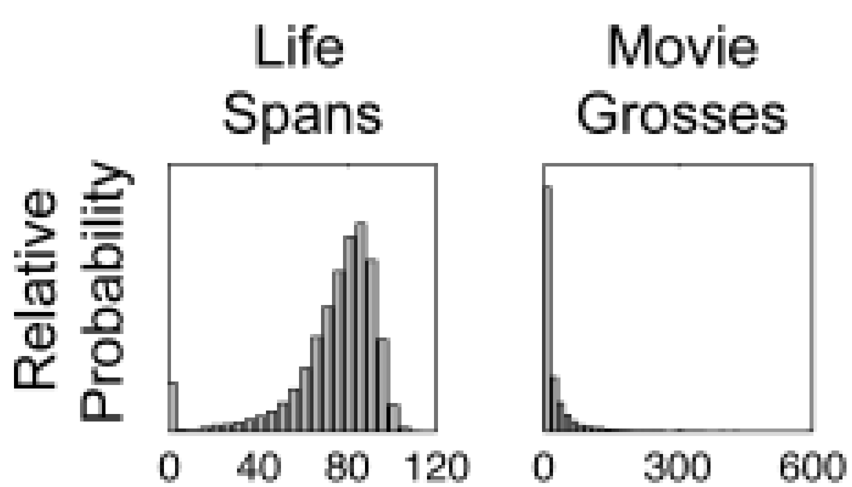
Bayesian modeling

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

h : hypothesis $\quad D$: 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?



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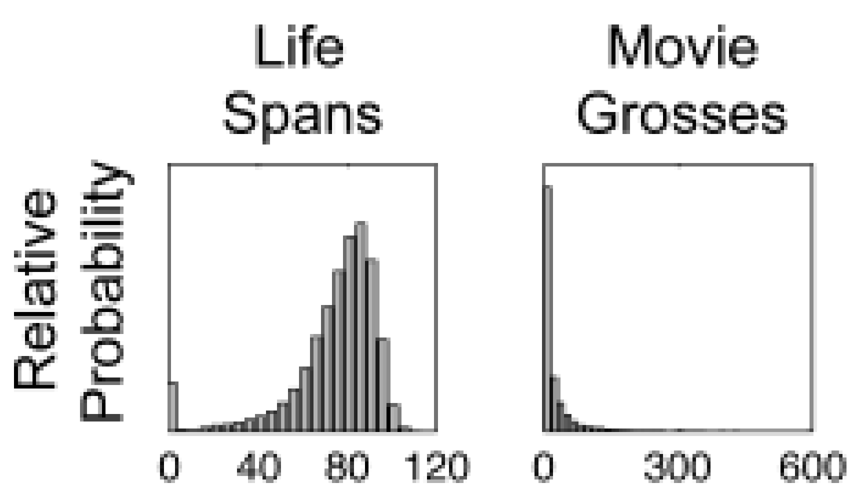
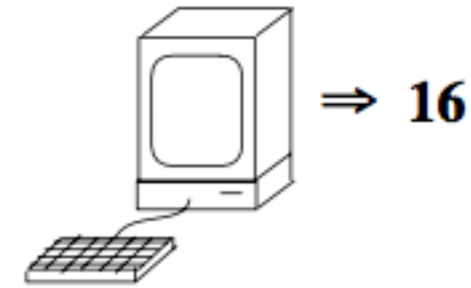


1 random "yes" example:



Which numbers will be accepted by the same computer program?

15? 128?

Bayesian modeling

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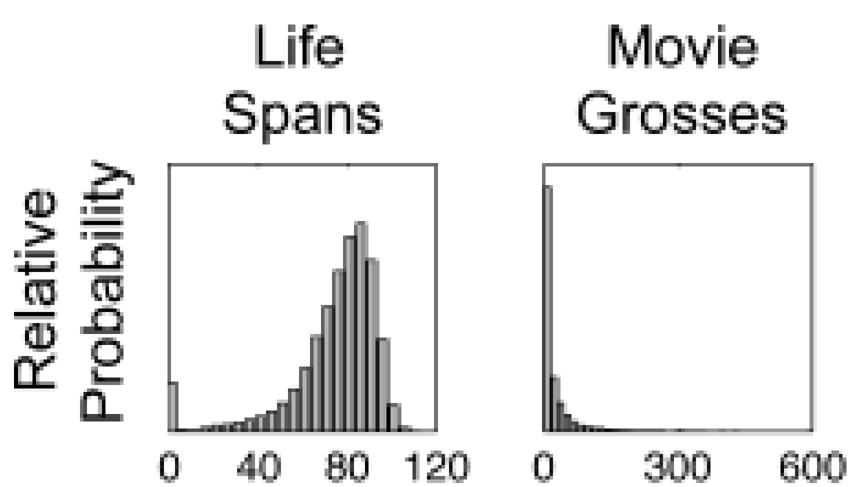
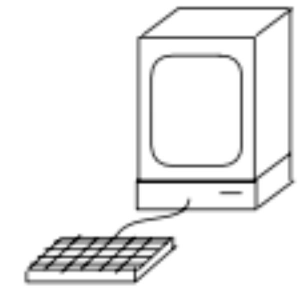


1 random "yes" example:



⇒ 16

Which numbers will be accepted by the same computer program?

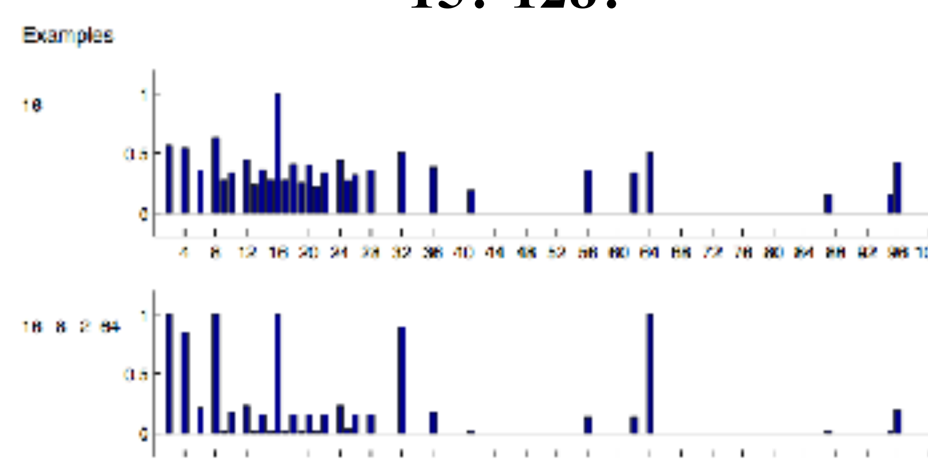
15? 128?

4 random "yes" examples:

⇒ 16 8 2 64

Which numbers will be accepted by the same computer program?

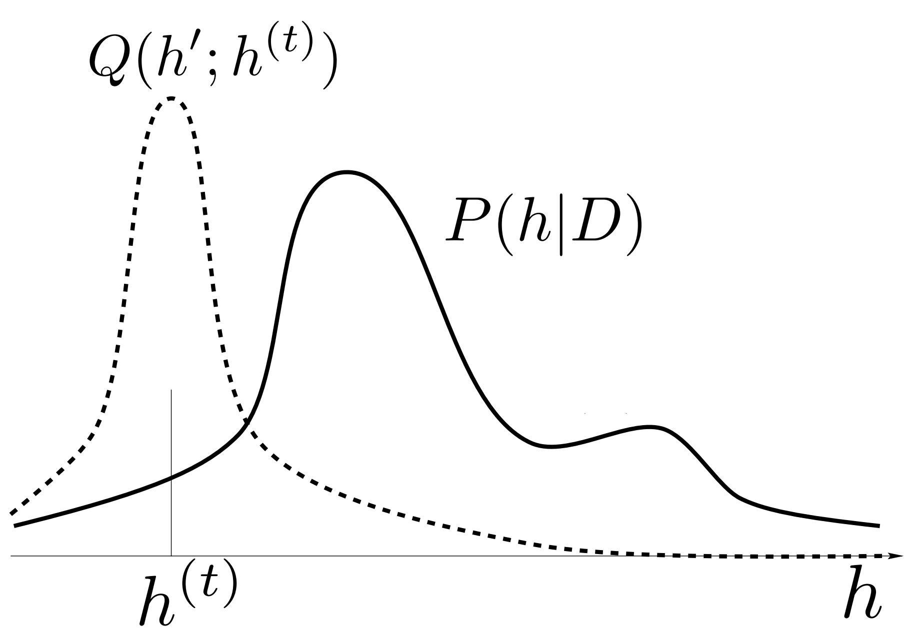
15? 128?

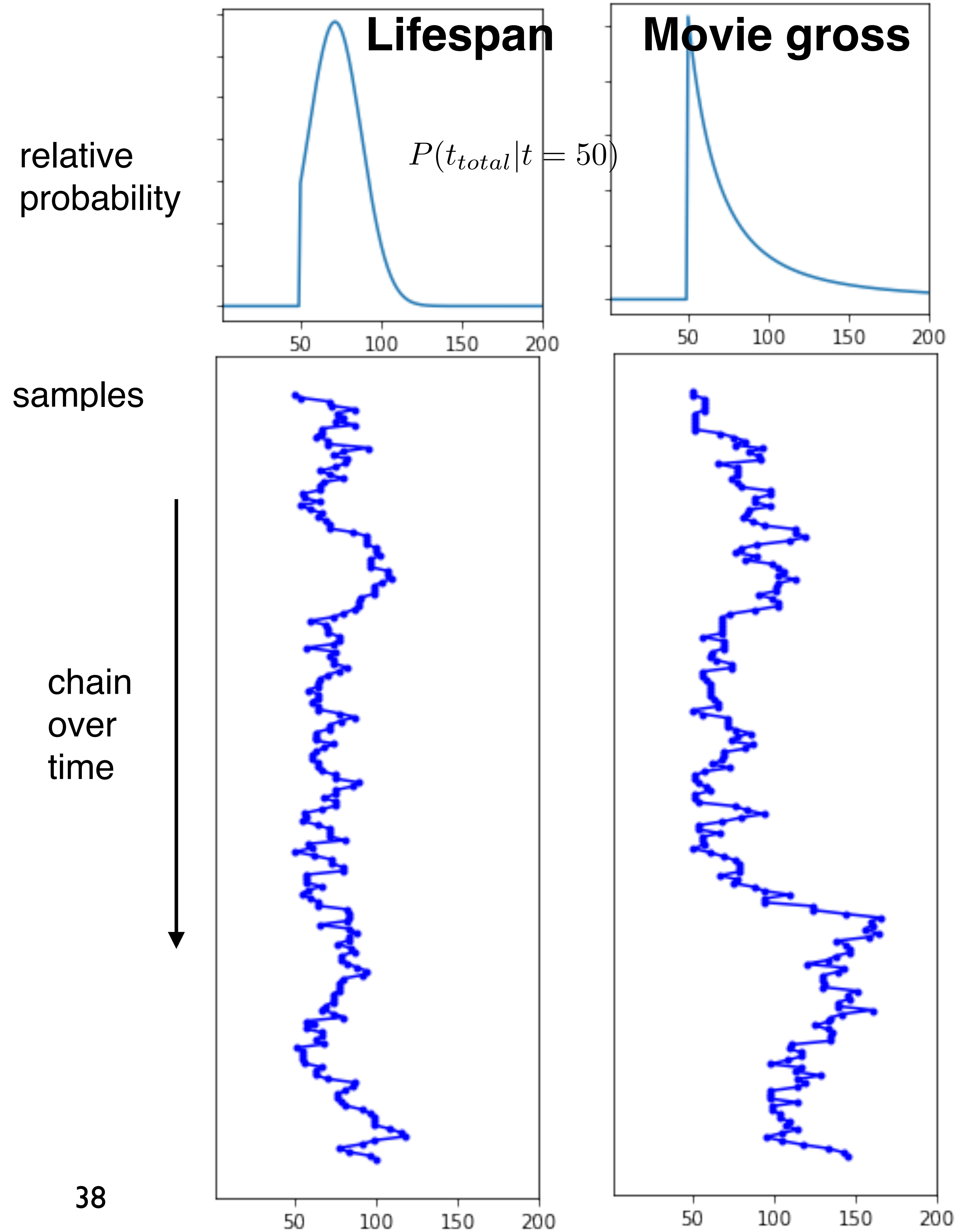


Inference in Bayesian models

- Exact inference
- Monte Carlo methods
  - Importance sampling
  - Markov Chain Monte Carlo

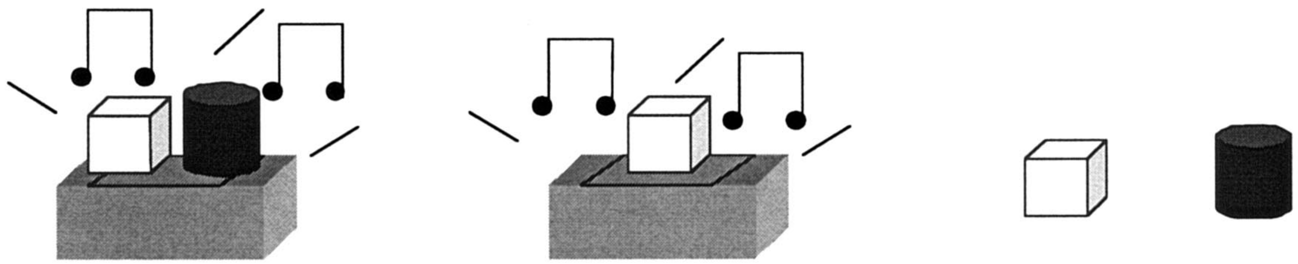
$$E[\phi(h)|D] \approx \frac{1}{T}\sum_{t}\phi(h^{(t)})$$





Probabilistic graphical models

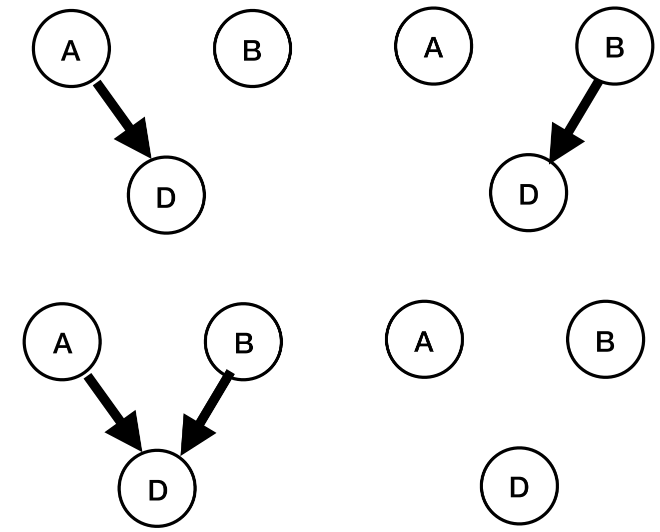
Causal learning as structure learning



Both objects activate the detector

Object A activates the detector by itself

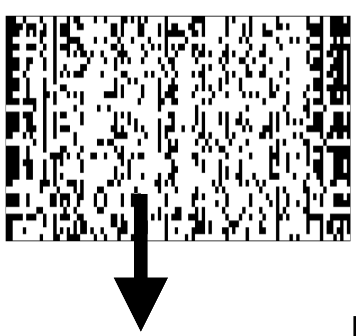
Children are asked if each is a blicket, then they are asked to make the machine go

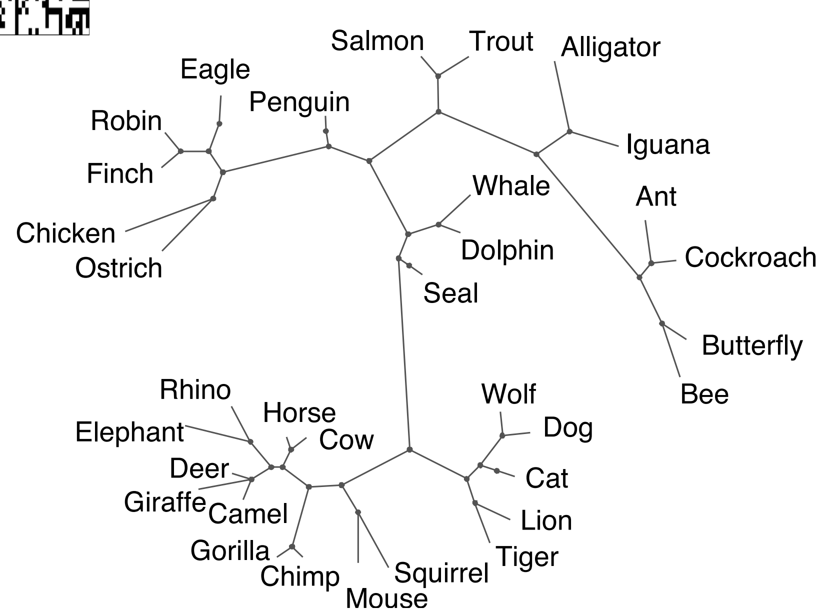


Structure discovery and evaluating inductive arguments

features

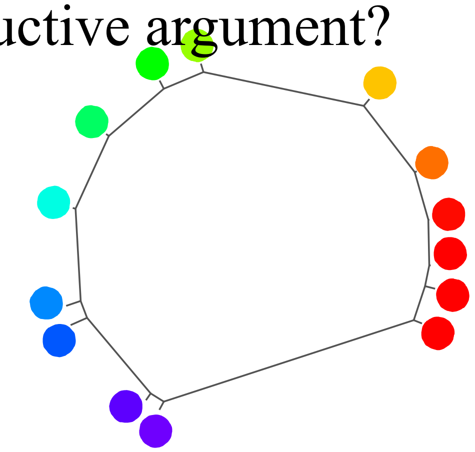
animals





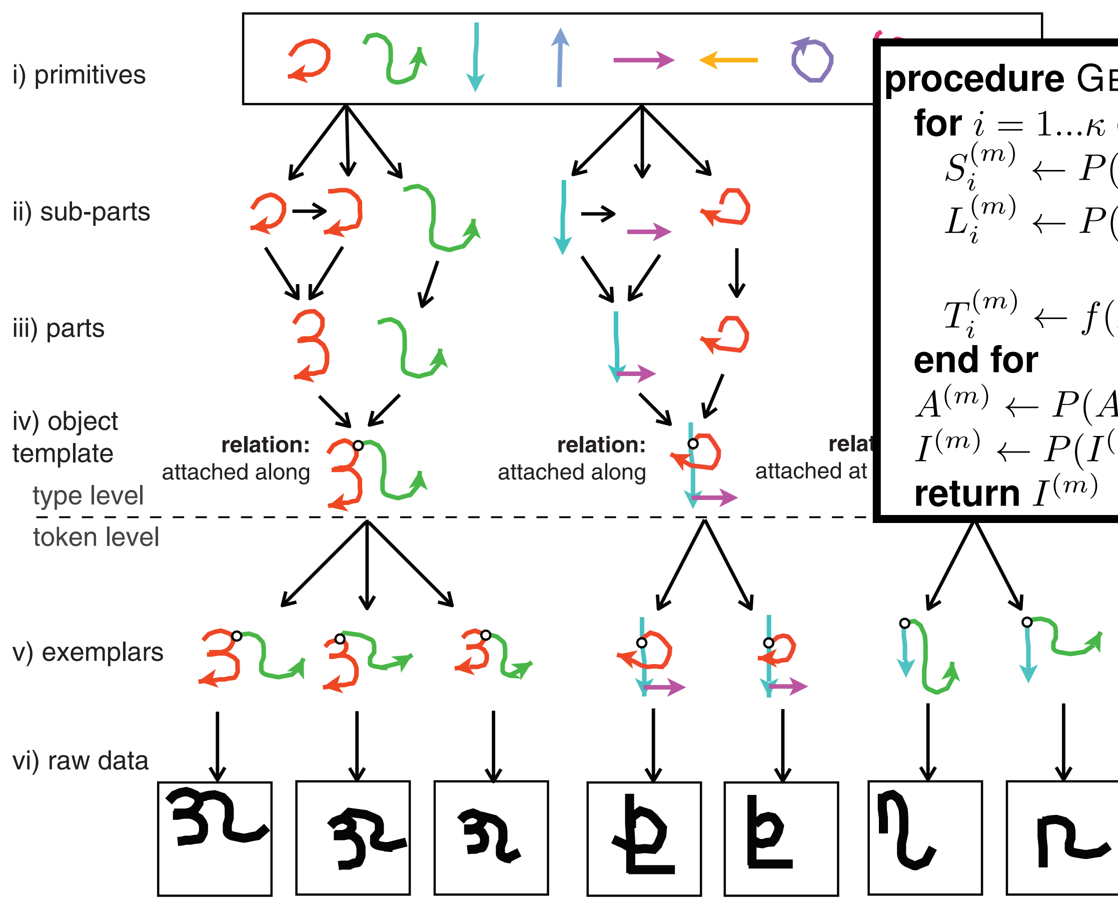
Cows use biotin for hemoglobin synthesis
Seals use biotin for hemoglobin synthesis
—Therefore—
All mammals use biotin for hemoglobin synthesis

How strong is this inductive argument?



Program induction and language of thought models

one-shot concept learning



procedure GENERATETOKEN(ψ)

for $i = 1...\kappa$ **do**

$S_i^{(m)} \leftarrow P(S_i^{(m)}|S_i)$ ▷ Add motor variance

$L_i^{(m)} \leftarrow P(L_i^{(m)}|R_i, T_1^{(m)}, ..., T_{i-1}^{(m)})$ ▷ Sample part's start location

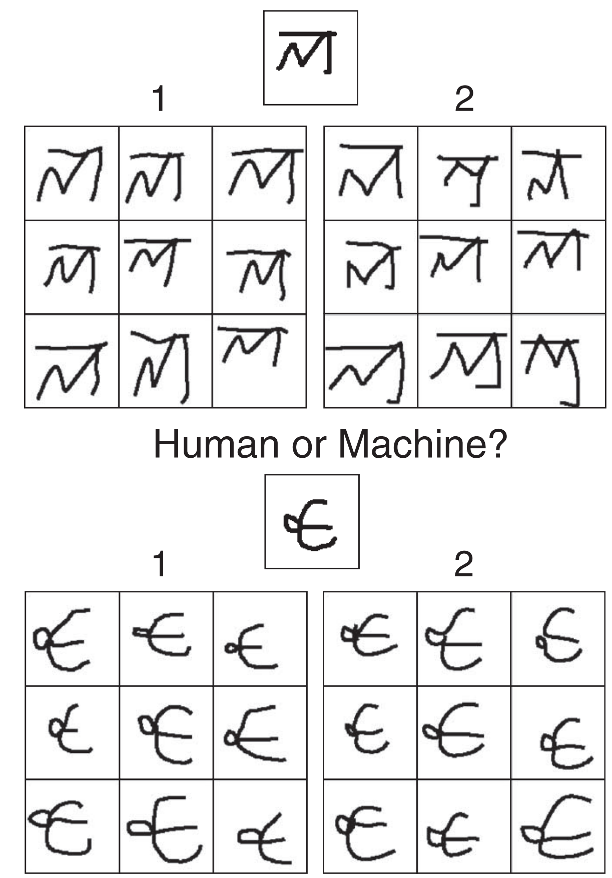
$T_i^{(m)} \leftarrow f(L_i^{(m)}, S_i^{(m)})$ ▷ Compose a part's trajectory

end for

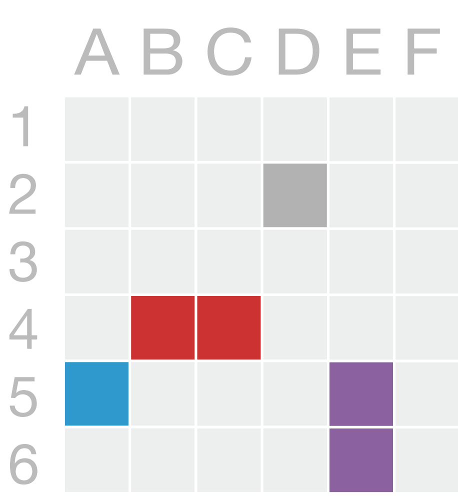
$A^{(m)} \leftarrow P(A^{(m)})$ ▷ Sample affine transform

$I^{(m)} \leftarrow P(I^{(m)}|T^{(m)}, A^{(m)})$ ▷ Sample image

return $I^{(m)}$



question asking
(your TA Anselm's work!)



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)))
```

Is this course a substitute for machine learning?

- **No. It's not a substitute, it's complementary.**
- This course does survey different computational paradigms (deep learning, reinforcement learning, Bayesian modeling, classification, graphical models, etc.), and there is some overlap with ML classes in terms of technical content.
- But unlike ML classes, this is also a cognitive science class. **Our examples and applications aim to understand human learning, reasoning, and development, and to understand intelligent behavior more generally.**
- We get into some mathematical background, but most ML courses will take a more formal approach than we do here.
- You will get hands on experience with running and analyzing complex models, implementing some (but not all) models, and analyzing behavioral data with computational models. Extensive final project.


LOGISTICS

Course website

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

View on GitHub

Computational cognitive modeling

NYU PSYCH-GA 3405.002 / DS-GS 3001.005

Instructors: Brenden Lake and Todd Gureckis

Teaching Assistants: Reuben Feinman and Anselm Rothe

Meeting time and location:
Lecture
Mondays 1:45-3:25 PM
60 Fifth Ave. Room 110

Lab
Tuesdays 2:40-3:30 PM
60 Fifth Ave. Room 110

Course numbers:
DS-GA 3001.005 (Data Science)
PSYCH-GA 3405.002 (Psychology)

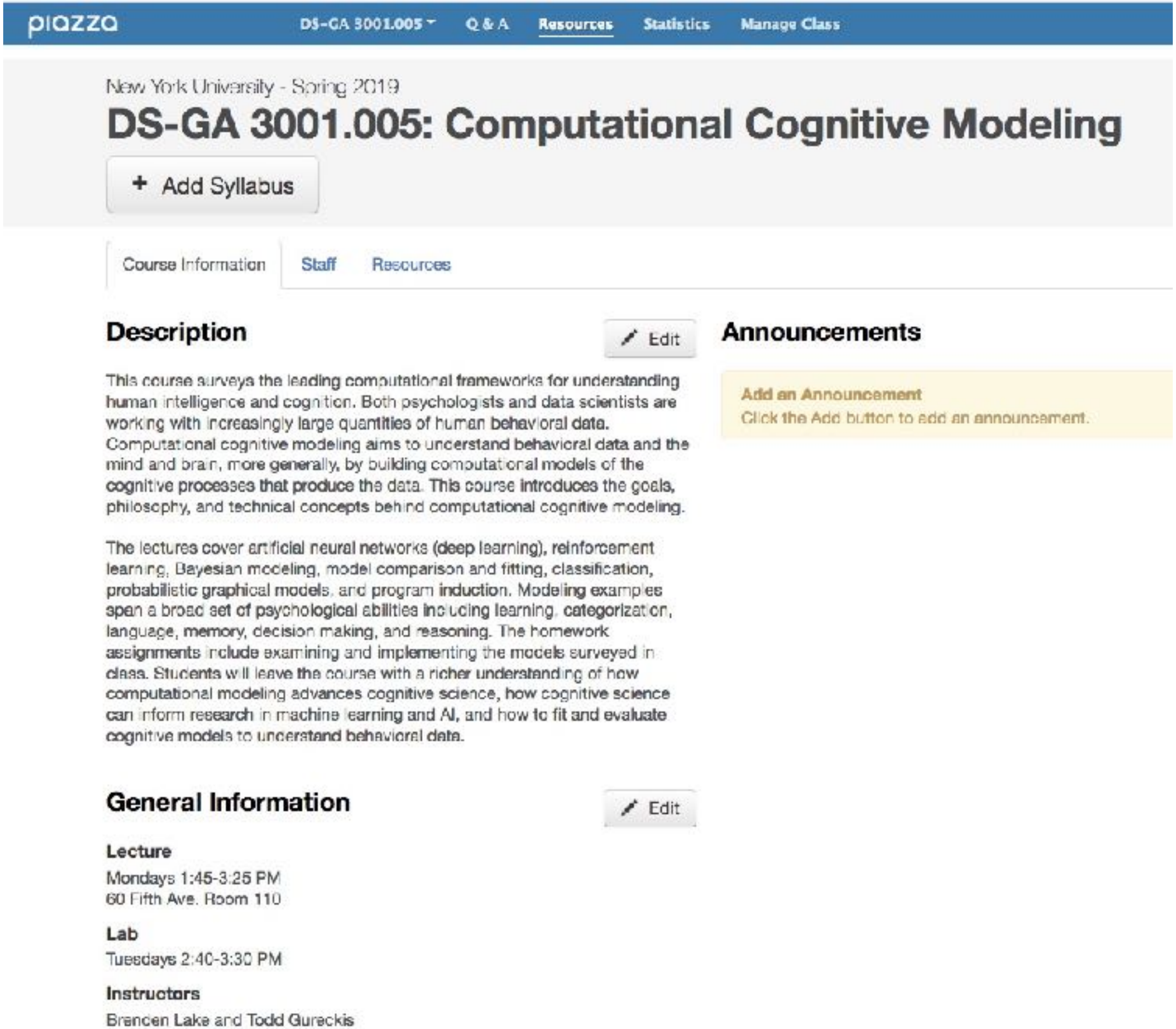
Contact Information and Piazza:
We use Piazza for questions and class discussion. Piazza gets you help efficiently from classmates, the TA, and the instructors. Rather than emailing questions to the teaching staff, please post your questions on Piazza.

The signup link for our Piazza page is available here (https://piazza.com/nyu/spring2019/dsga3001005).

Once signed up, our class Piazza page is available here (https://piazza.com/nyu/spring2019/dsga3001005/home).

If there is a need to email the teaching staff directly, please use the following email address: instructors-ccm-spring2019@nyuccl.org

Course discussion: piazza



Getting in touch

Piazza should be your main point of contact. If you have a question, and you think there is a possibility that someone may have the same question, please post it to piazza for everyone benefit. (You can also post anonymously)

If you need to send an individual message,

Email address for instructors and TAs:
instructors-ccm-spring2019@nyuccl.org

Class times

Lecture:
Mondays 1:45-3:25 PM
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Lecture schedule

1/28 Introduction
2/4 Neural networks / Deep learning (part 1)
    Homework 1 assigned (Due 2/25) (instructions for accessing here)
2/11 Neural networks / Deep learning (part 2)
2/18 PRESIDENT'S DAY - NO CLASS
2/25 Reinforcement learning (part 1)
    Homework 2 assigned (Due 3/25) (instructions for accessing here)
3/4 Reinforcement learning (part 2)
3/11 Reinforcement learning (part 3)
3/18 SPRING RECESS - NO CLASS
3/25 Bayesian modeling (part 1)
    Homework 3 assigned (Due 4/8) (instructions for accessing here)
4/1 Bayesian modeling (part 2)
    Final project proposal due
4/8 Rational vs. mechanistic modeling
    Homework 4 assigned (Due 4/22) (instructions for accessing here)
4/15 Model comparison and fitting, tricks of the trade
4/22 Categorization
4/29 Probabilistic Graphical models
5/6 Program induction and language of thought models
5/13 TBD
Final project due (Tuesday 5/14)

Lab schedule

1/29 NO LAB
2/5 Python and Jupyter notebooks review
2/12 Introduction to PyTorch
2/19 HW 1 questions
2/26 TBD
3/5 TBD
3/12 HW 2 questions
3/19 SPRING RECESS
3/26 Probability review
4/2 HW 3 question
4/9 TBD
4/16 HW 4 question
4/23 TBD
4/30 TBD
5/7 TBD
5/14 NO LAB

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 a good position for approaching the material. Familiarity with probability is also assumed. We will, when needed, review some of the basic technical concepts in lab.

- *Programming:* For the homework/assignments, we will assume basic familiarity with programming in Python using the Jupyter Notebook system (http://jupyter.org). We will review some of the programming basics in lab. This is a link to helpful tutorial for learning the basics of Python (http://openbookproject.net/thinkcs/python/english3e/). We recommend Python 3 for use in this course.

Grading:

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

Final project:

- The final project will be done in groups of 1-4 students. A short paper will be turned in describing the project (approximately 6 pages). 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 extending an existing cognitive modeling paper, or a cognitive modeling project related to your research.

Homeworks — programming requirements

Programming: We assume you are familiar with programming in Python (some basics will be reviewed in lab)

Homeworks use this setup:

- Python 3
- Jupyter notebooks
- Standard Python packages for scientific computing
    - numpy
    - scipy
    - pandas
    - matplotlib
- PyTorch 1.0 library for neural networks

Using your laptop setup is encouraged!

Jupyter notebooks

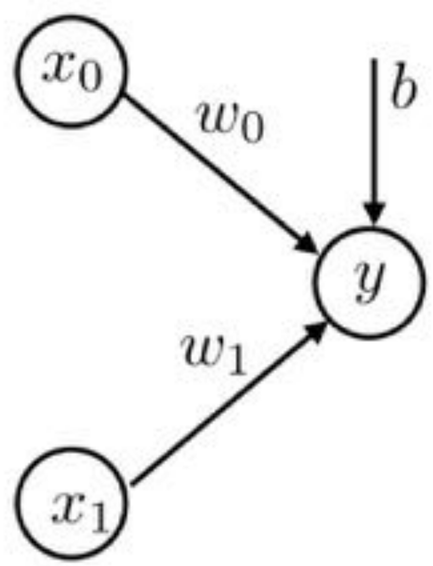
Homework - Neural networks - Part B (20 points)

Gradient descent for an artifical neuron

by *Brenden Lake* and *Todd Gureckis*
Computational Cognitive Modeling
NYU class webpage: https://brendenlake.github.io/CCM-site/
email to course instructors: instructors-ccm-spring2019@nyuccl.org

This homework is due before midnight on Monday, Feb. 25, 2019.

This assignment implements the gradient descent algorithm for a simple artificial neuron. As covered in lecture, the neuron will learn to compute logical OR. The neuron model and logical OR are shown below, for inputs x_0 and x_1 and target output y.



logical OR

x_0	x_1	y
0	0	0
0	1	1
1	0	1
1	1	1

This assignment requires some basic PyTorch skills, which were covered in lab. You can also review two basic PyTorch tutorials, "What is PyTorch?" and "Autograd", which have the basics you need.

In [ ]:
```
# Import libraries
from __future__ import print_function
%matplotlib inline
import matplotlib
import matplotlib.pyplot as plt
import numpy as np
import torch
import torch.nn as nn
```

Let's create `torch.tensor` objects for representing the data matrix `D` with targets `Y`. Each row of `D` is a different data point.

In [ ]:
```
# Data
D = np.zeros((4,2),dtype=float)
D[0,:] = [0.,0.]
D[1,:] = [0.,1.]
D[2,:] = [1.,0.]
D[3,:] = [1.,1.]
```

Pre-configured cloud environment

Students registered for the course have the option of completing homework assignments on their personal computers, or in a cloud Jupyter environment with all required packages pre-installed. Students can log onto the environment using their github login information.

(we will send around survey request for GitHub login)

Generously sponsored by Google!

Course policies

Collaboration policy:

- We encourage you to discuss the homework assignments with your classmates. You must 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 or code, or write-ups or code from previous years.

Late work:

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

Laptops in class:

- Laptops in class are discouraged. We know many try to take notes on their laptops, but it's easy to get distracted (social media, etc.). **This can also distract everyone behind you!**

We encourage you to engage with the class and material, and engage with us as the instructors. Ask questions!

All slides are posted so there is no need to copy things down, and paper notes are great too.

Background survey

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

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

- Who knows about:
  - Classical conditioning?
  - Prototype vs. exemplar models?
  - Categorical perception?
  - Semantic networks?
  - Logistic regression?
  - Backpropagation algorithm?
  - Simple recurrent network?
  - Model-based vs. model-free reinforcement learning?
  - Bayes' rule?
  - Conditional independence?
  - Conjugate prior?
  - Metropolis-Hastings?
  - Explaining away?
  - Probabilistic programming?

What you will come away with…

1. Experience with the major paradigms for computational cognitive modeling

2. 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

3. How to build computational models to test and evaluate psychological theories, and to understand behavioral data by modeling the underlying cognitive processes.

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 for the next two lectures (available on NYU Classes; “Resources” folder)

- McClelland, J. L., Rumelhart, D. E., & Hinton, G. E. The Appeal of Parallel Distributed Processing. Vol I, Ch 1.
- LeCun, Y., Bengio, Y. & Hinton, G. (2015). Deep learning. Nature 521:436–44.
- McClelland, J. L., & Rogers, T. T. (2003). The parallel distributed processing approach to semantic cognition. Nature Reviews Neuroscience, 4(4), 310-322.
- Elman, J. L. (1990). Finding structure in time. Cognitive Science, 14(2), 179-211.
- Peterson, J., Abbott, J., & Griffiths, T. (2016). Adapting Deep Network Features to Capture Psychological Representations. Presented at the 38th Annual Conference of the Cognitive Science Society.

Homework 1 on neural networks will be released next class (and due 2/25)

Questions?