Welcome note

BAMB! Summer School

19-27 July 2023

Kenji Doya

OIST Okinawa

Maria Eckstein

Deepmind

Alex Hyafil

CRM Barcelona

Jakob Macke

Tübingen University

Yael Niv

Princeton University

Heike Stein

ENS Paris

Chris Summerfield

Oxford University / Deepmind

Anne Urai

Leiden University

Klaus Wimmer

CRM Barcelona

Nuria Hernández

Centre de Recerca Matemàtica

General structure

- **Lectures**
- **Tutorials** (lead by TAs)
- **Scientific keynote talks** (by Kenji Doya & Yael Niv)
- **Group project**
- **One-on-ones**: schedules emailed

General tips

- Speak up! Let us know if you need help with anything
- Keep Slack open for information
- Please show up / be on time
- Feedback will help us grow: survey will be sent at the end
- It’s a packed schedule, but don’t overdo it
- Don’t lose your badge
- No drinks in the sala please

General Safety

- Covid-19. It’s still a thing!! Please be responsible, if you don’t feel well and have Covid-19 compatible symptoms, let us know and get tested.
- Please be respectful of others. There is a code of conduct in the booklet. Please let us know if you feel uncomfortable about anything.
- Barcelona is generally safe but be on your guard, especially at night.

Bon Viatge!!

What is a model?

Christopher Summerfield
University of Oxford

BAMB! Summer School 2023

funding

European Research Council
Executive Agency

erc

National Institutes of Health

Human Brain Project

Google

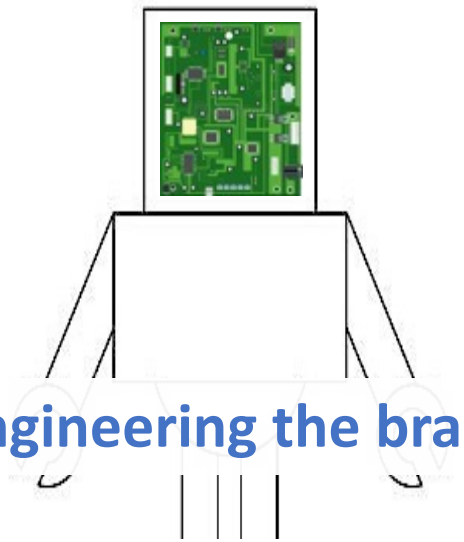
wellcome

Models

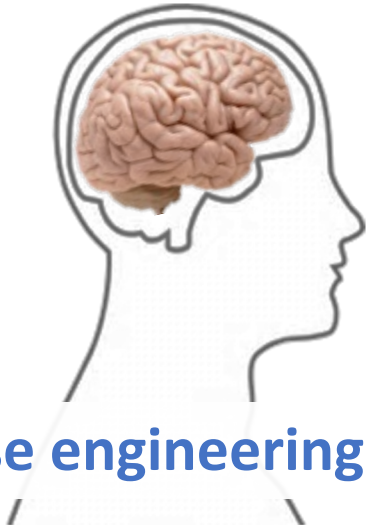
A computational model is a quantitative simulation of a natural phenomenon, typically implemented in computer code

Global finance
Weather Forecasting
Structural Biology (e.g. Protein Folding)
Chess Engine
Language (LLMs)
Ideal Gas Law
etc

Outline



Engineering the brain



Reverse engineering the brain

Artificial Intelligence: to build intelligent information processing systems *in silico*

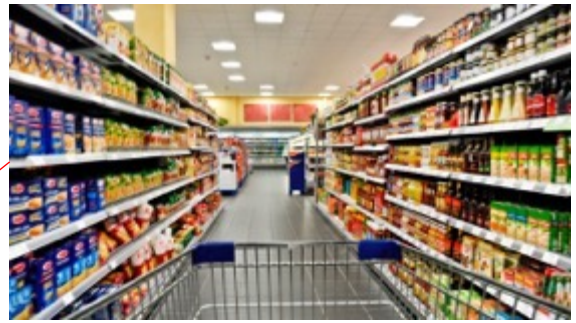
Machine Learning: to use statistical principles to optimize information processing systems

Psychology: to understand the organisation of behavior and its foundations in cognition

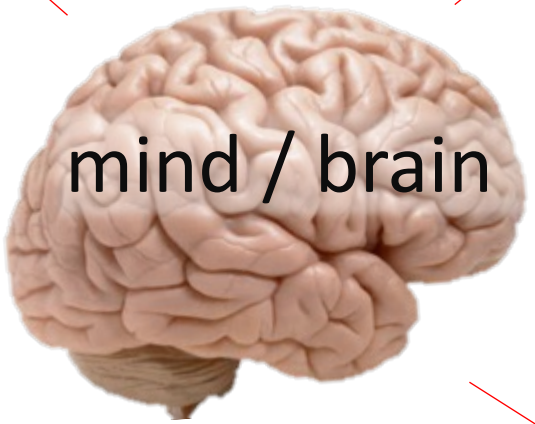
Neuroscience: to understand neural coding and computation, and localise brain function

Why are we here?

predator-prey interactions



consumer behavior



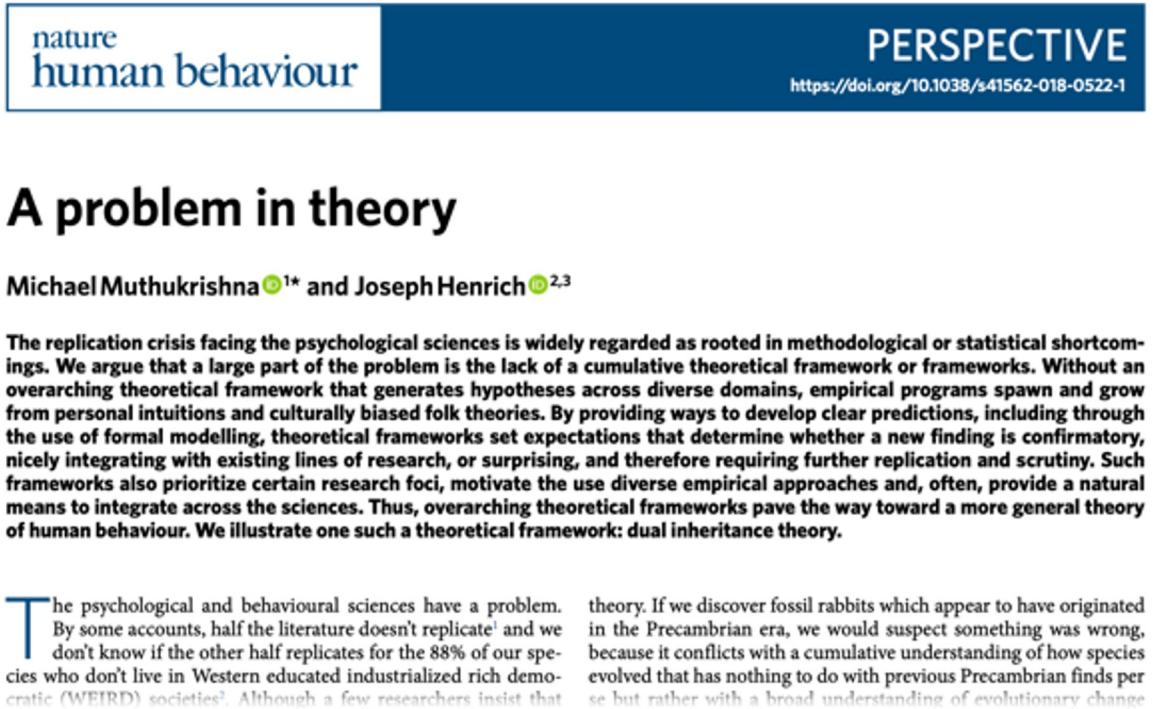
social group dynamics

global finance

education

mental health

A problem in theory



nature human behaviour

PERSPECTIVE

https://doi.org/10.1038/s41562-018-0522-1

A problem in theory

Michael Muthukrishna[1*] and Joseph Henrich[2,3]

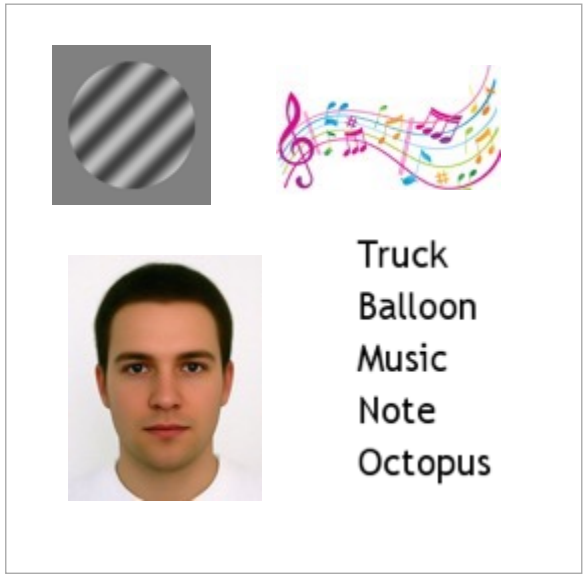
The replication crisis facing the psychological sciences is widely regarded as rooted in methodological or statistical shortcomings. We argue that a large part of the problem is the lack of a cumulative theoretical framework or frameworks. Without an overarching theoretical framework that generates hypotheses across diverse domains, empirical programs spawn and grow from personal intuitions and culturally biased folk theories. By providing ways to develop clear predictions, including through the use of formal modelling, theoretical frameworks set expectations that determine whether a new finding is confirmatory, nicely integrating with existing lines of research, or surprising, and therefore requiring further replication and scrutiny. Such frameworks also prioritize certain research foci, motivate the use diverse empirical approaches and, often, provide a natural means to integrate across the sciences. Thus, overarching theoretical frameworks pave the way toward a more general theory of human behaviour. We illustrate one such a theoretical framework: dual inheritance theory.

The psychological and behavioural sciences have a problem. By some accounts, half the literature doesn't replicate[1] and we don't know if the other half replicates for the 88% of our species who don't live in Western educated industrialized rich democratic (WEIRD) societies[2]. Although a few researchers insist that theory. If we discover fossil rabbits which appear to have originated in the Precambrian era, we would suspect something was wrong, because it conflicts with a cumulative understanding of how species evolved that has nothing to do with previous Precambrian finds per se but rather with a broad understanding of evolutionary change

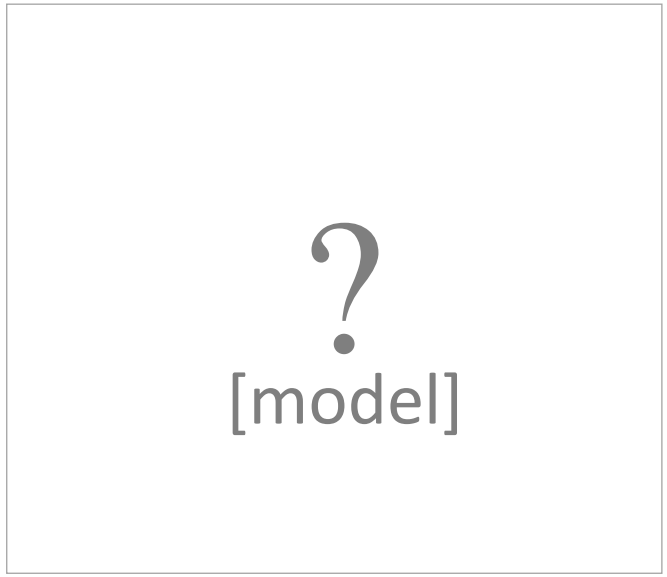
"Many subfields within psychology…lack any overarching, integrative general theoretical framework that would allow researchers to derive specific predictions from more general premises"

"Rather than building up principles that flow from overarching theoretical frameworks, psychology textbooks are largely a potpourri of disconnected empirical findings on topics that have been popular at some point in the discipline's history, and clustered based on largely American and European folk categories"

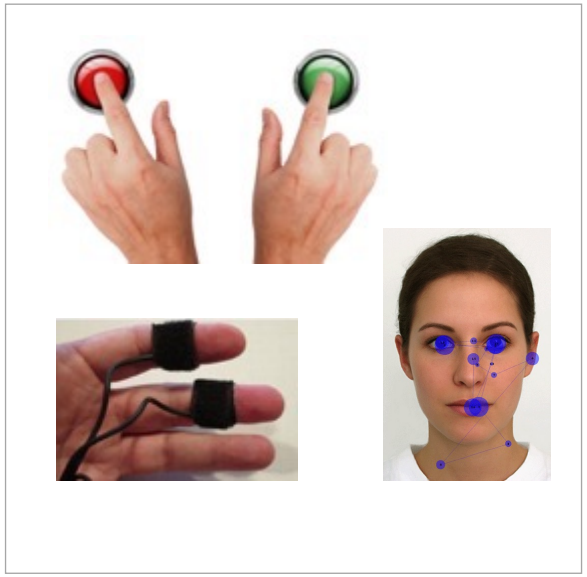
The information processing approach



input
(known)



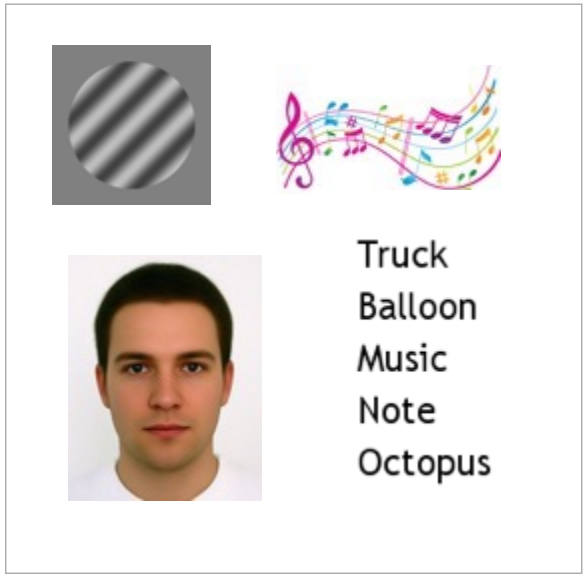
computation
(unobservable)

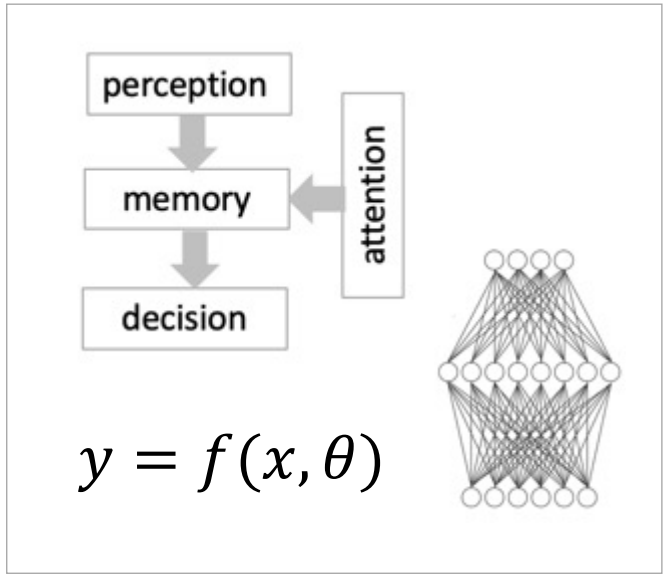


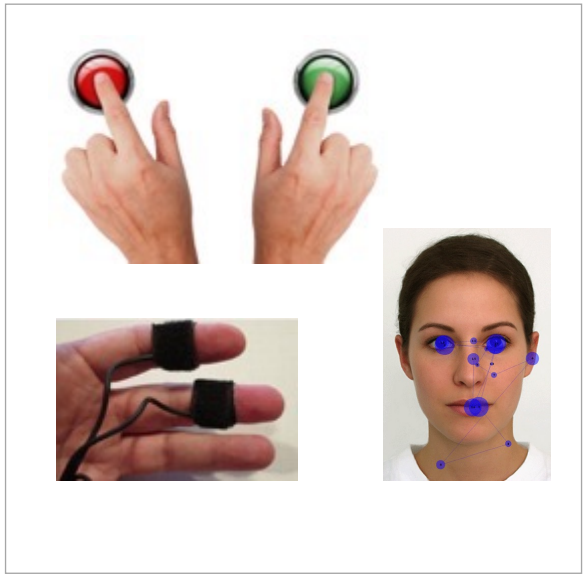
output
(measured)

Interventions

The information processing approach







input
(known)

model
(inferred)

output
(measured)

What is a model?

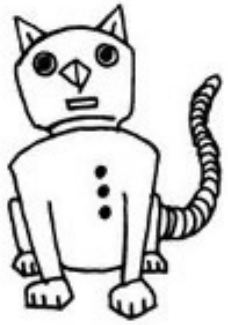
ground truth

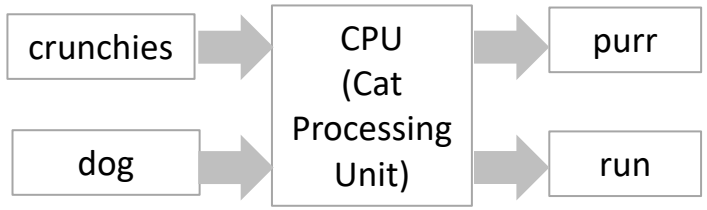
simulated (comp. neuro/cog. sci)

$$p(purr) = f(crunchies, hunger)$$

simulated
(same cat)

simulated
(robotics)





simulated (psychology)

"The best model of a cat is another cat, or preferably the same cat"

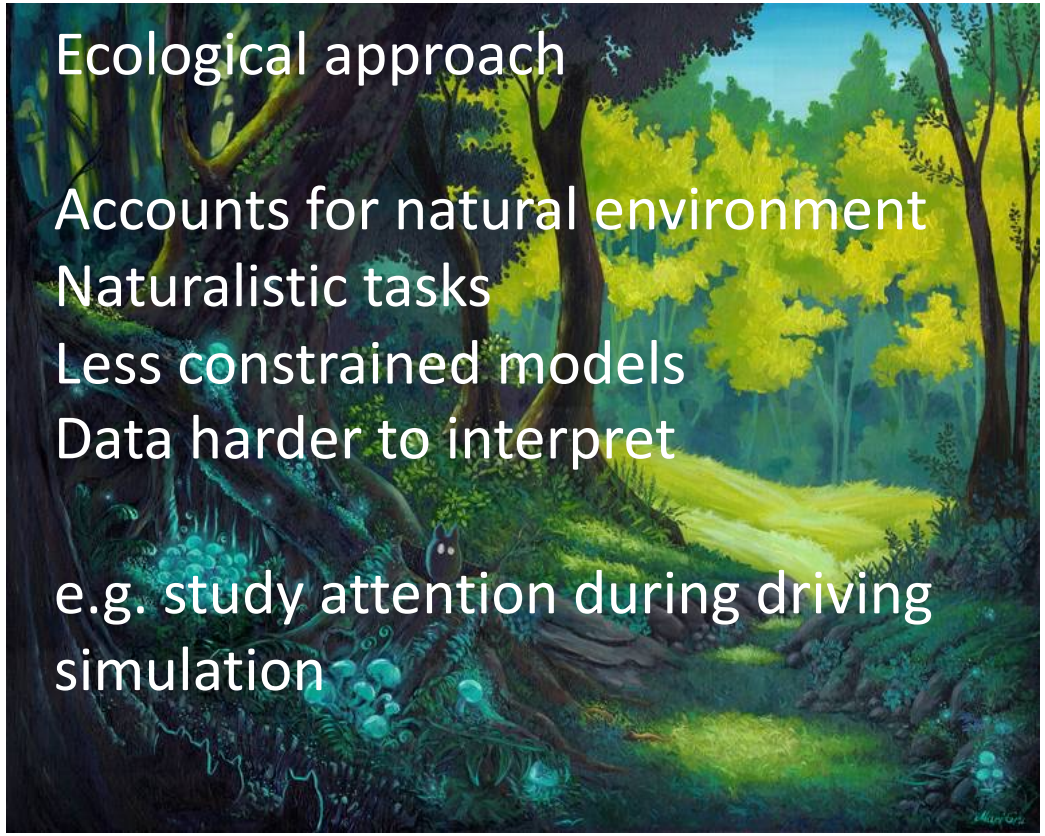
Norbert Weiner, Founder of Cybernetics

Levels of description

Computational theory	Representation and algorithm	Hardware implementation
What is the goal of the computation, why is it appropriate, and what is the logic of the strategy by which it can be carried out?	How can this computational theory be implemented? In particular, what is the representation for the input and output, and what is the algorithm for the transformation?	How can the representation and algorithm be realized physically?

Marr

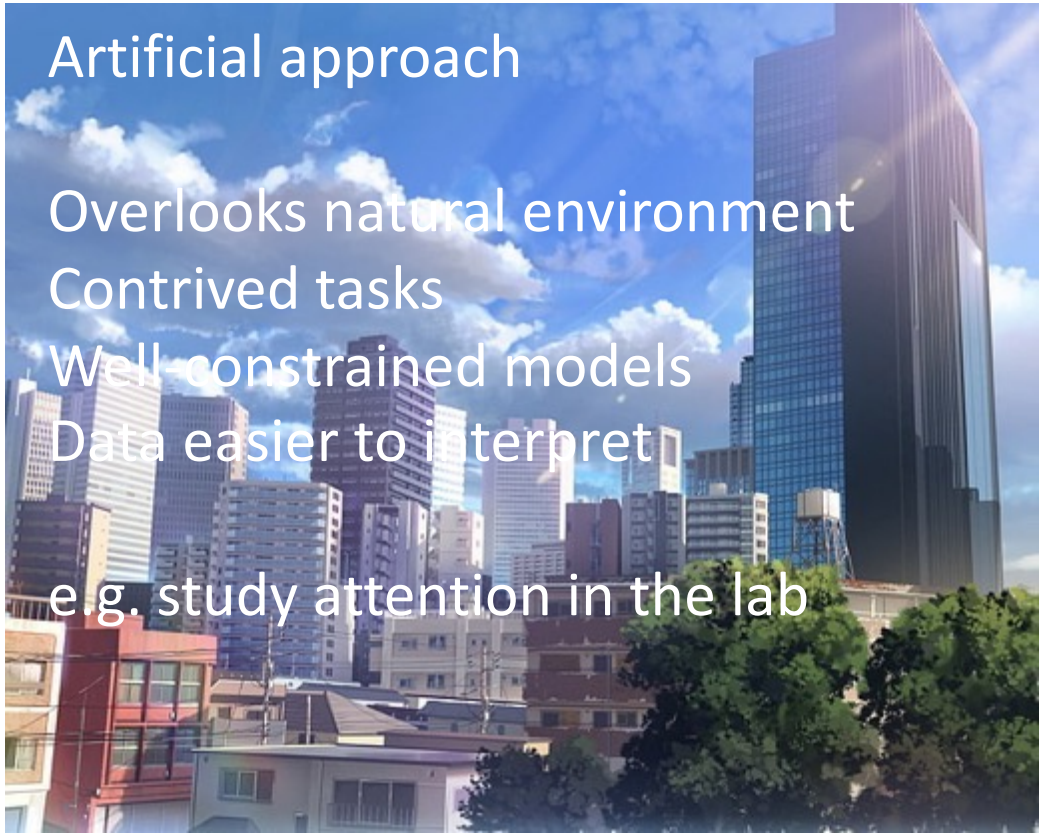
Approaches



Ecological approach

Accounts for natural environment
Naturalistic tasks
Less constrained models
Data harder to interpret

e.g. study attention during driving simulation



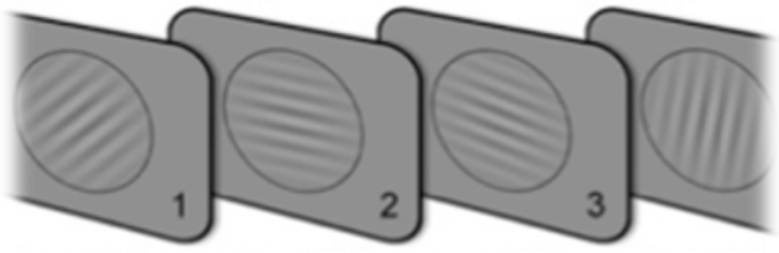
Artificial approach

Overlooks natural environment
Contrived tasks
Well-constrained models
Data easier to interpret

e.g. study attention in the lab

Model fitting: the basics (to be covered later!)

participants



stimuli

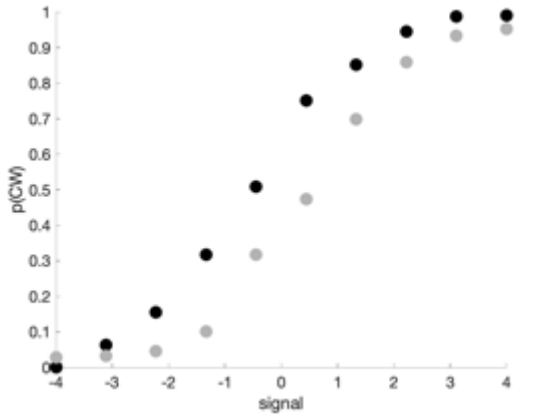
signals

$[0.2, -0.2, 0.4, 0.8, 0.8, -0.4]$

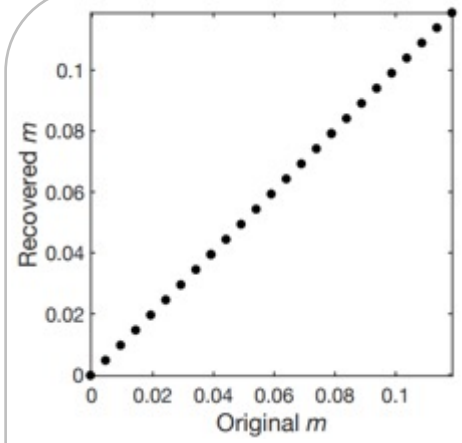
choices

$[0,1,1,0,0,0,1,1,0,0,0,1]$

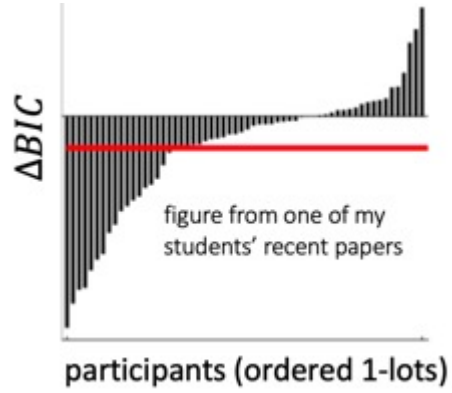
raw data



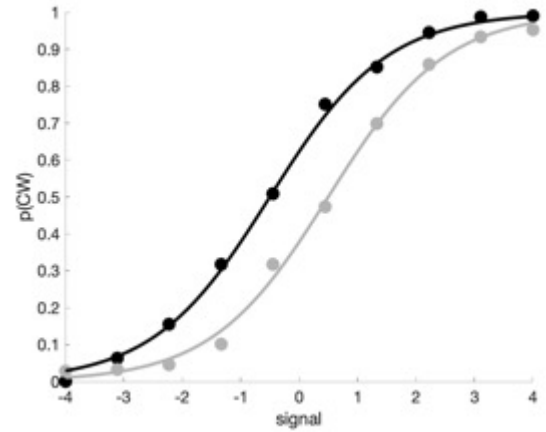
summaries



recovery



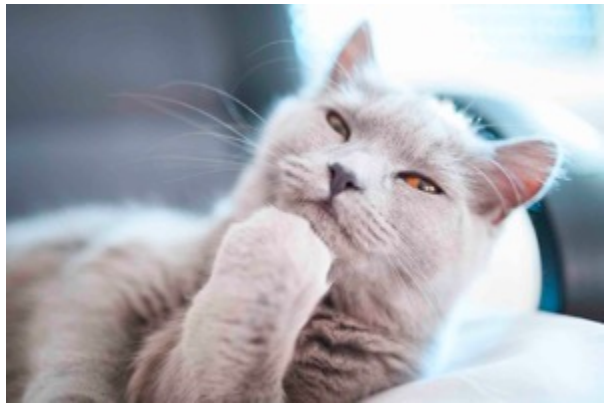
model fits



simulations

What nobody teaches you

You can read thousands of papers about how to compute model evidence and compare models (and this course will help!).



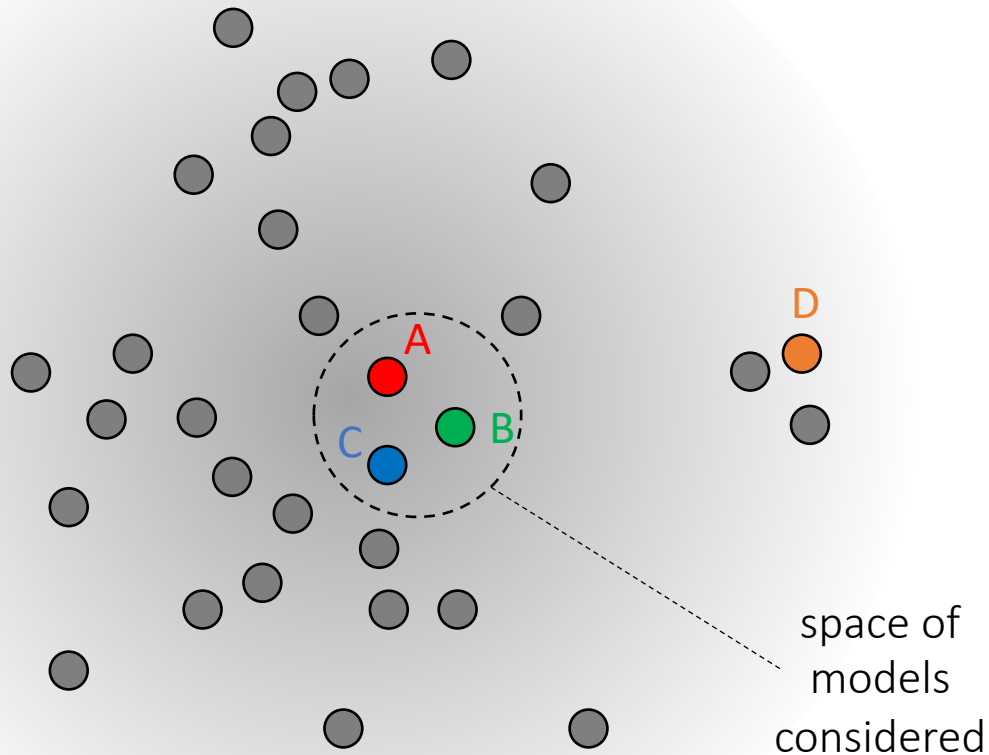
vague thoughts about cognition/computation

what actually happens here?

sit down to write model

But nobody ever tells you how to identify the space of models that you should consider in the first place.

Limitless models



universe of models

The universe of models is theoretically limitless.

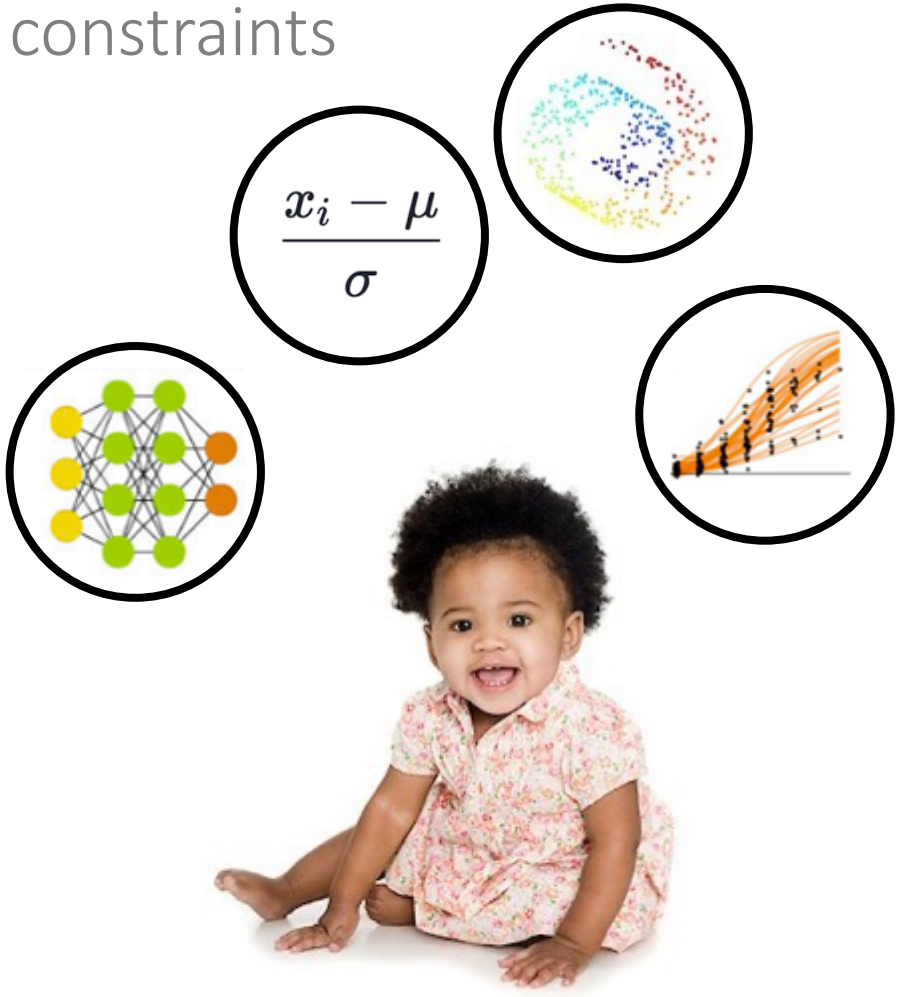
How do I know if my model space is sensible or not?

So, how do I know where to start?

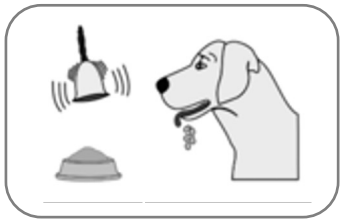
Inductive biases

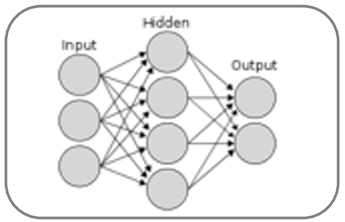
prior beliefs

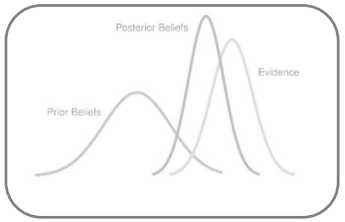
computational constraints



The search for a unified theory







1900 1920 1940 1960 1980 2000 2020

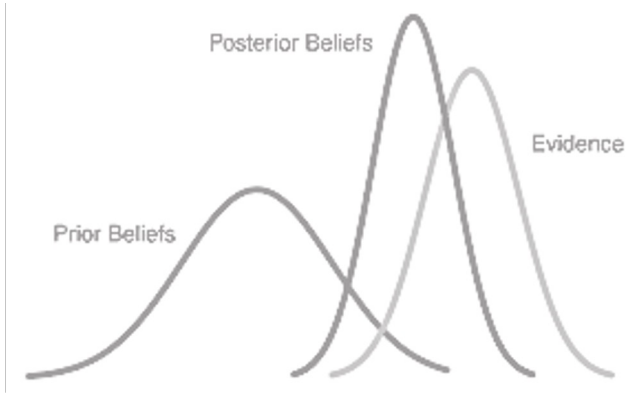
Pavlov Watson Skinner behaviourism

connectionism Hinton, McClelland DiCarlo

Bayesianism Tenebaum, Friston

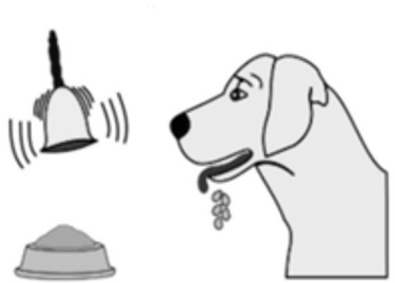
cognitivism Marr, Chomsky Posner, Shallice

Model classes

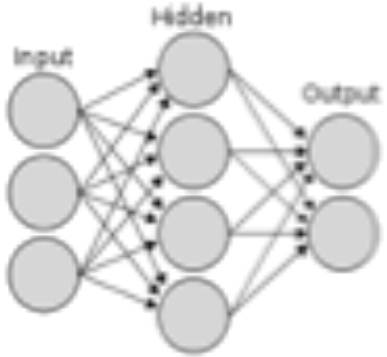


Bayesianism

cognitivism

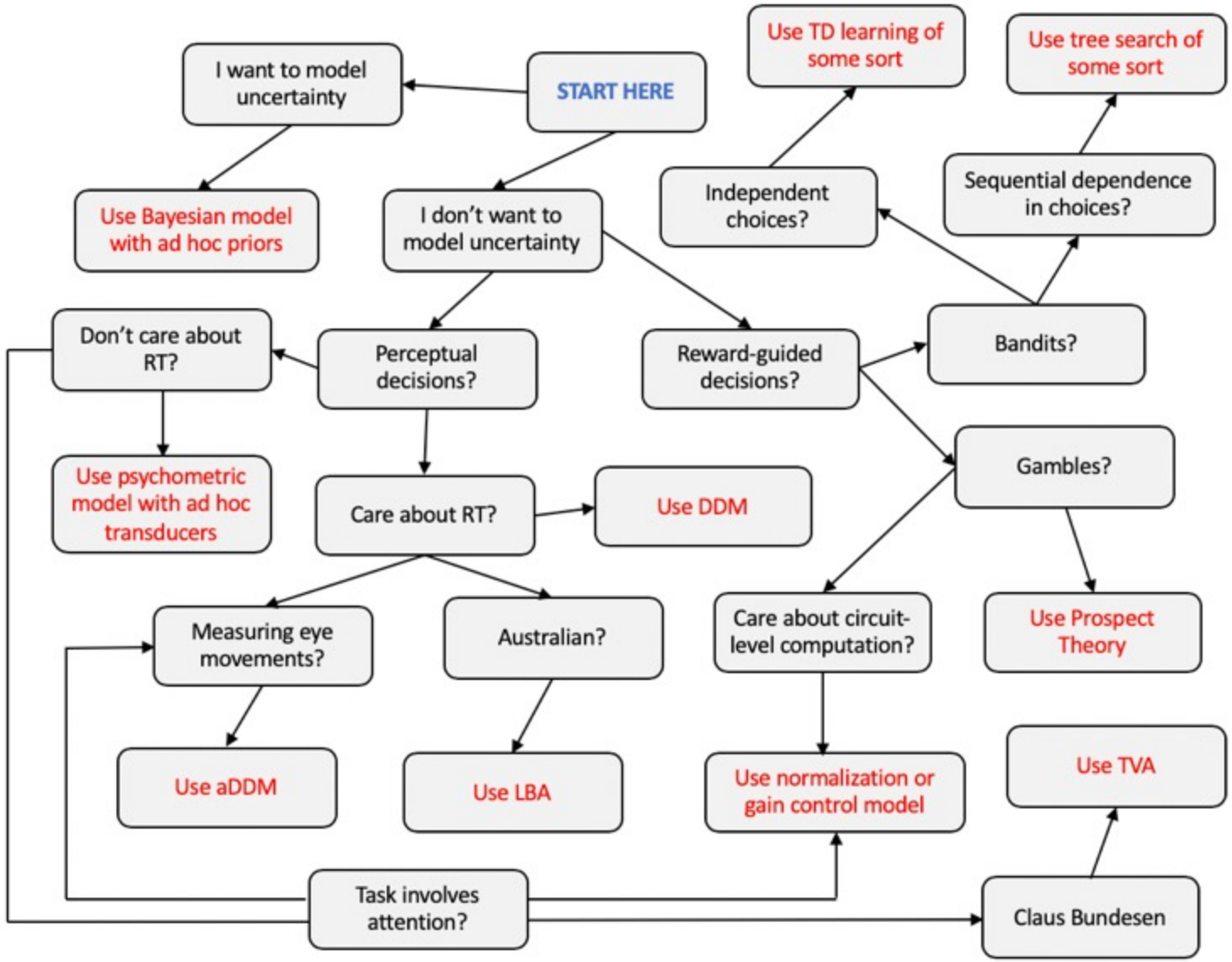


behaviourism



connectionism

Solution 1: use past models as theories

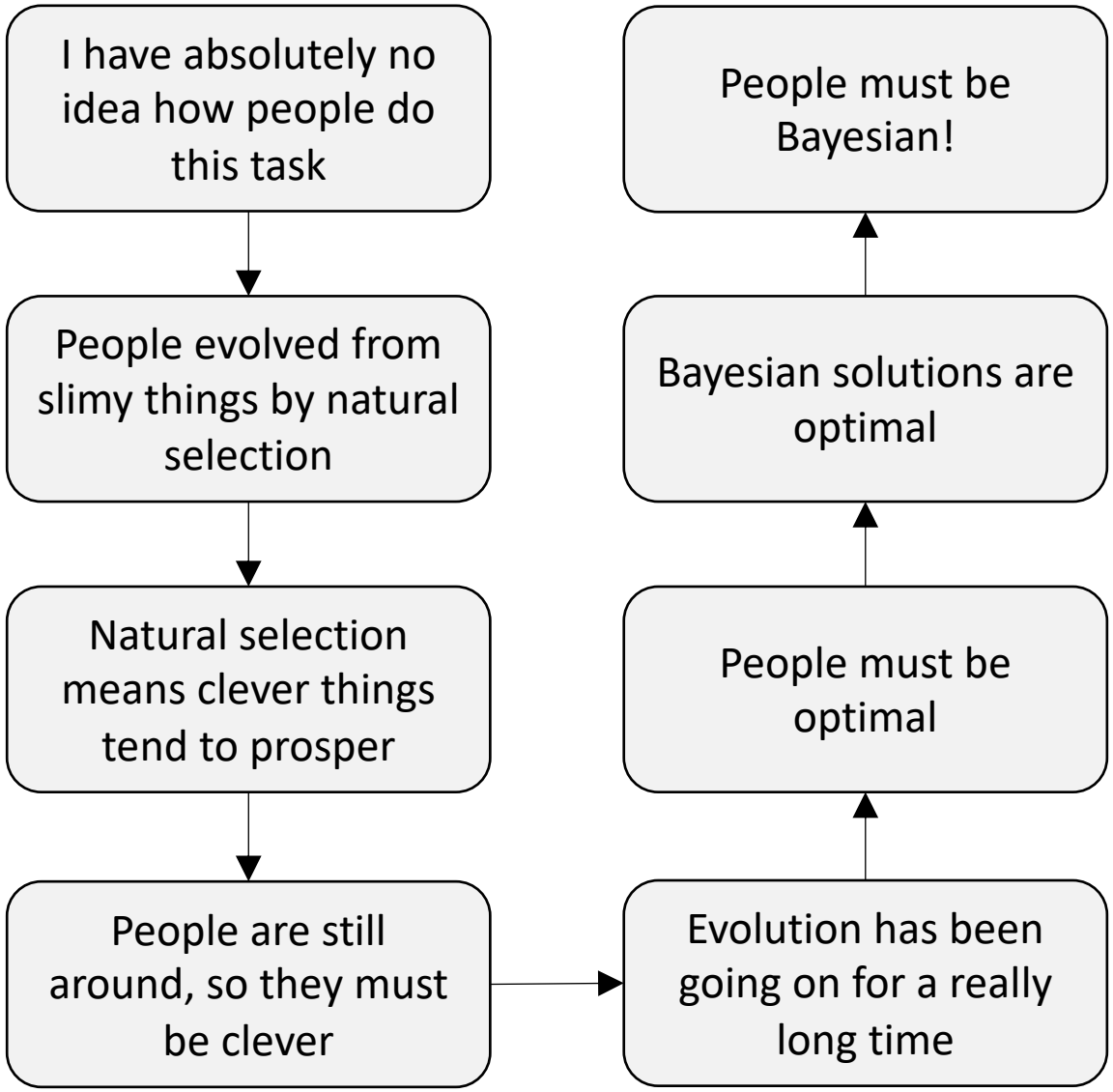


Science is an incremental endeavour.

So, many people use a sort of mental modelling cheat sheet that involves copying what others have done.

BUT sometimes this is done without thinking very hard about why (more on this later).

Solution 2: take a normative stance



I built the task, so I know the generative model. I just need to assume that people optimally invert this model for inference.

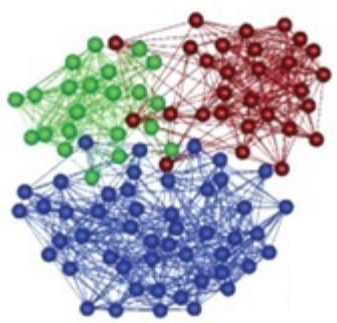
I don't even need any free parameters!

Problem solved!

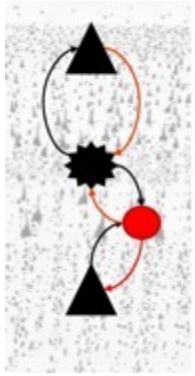
c.f. Anderson, rational analysis

Solution 3: draw inspiration from neurobiology

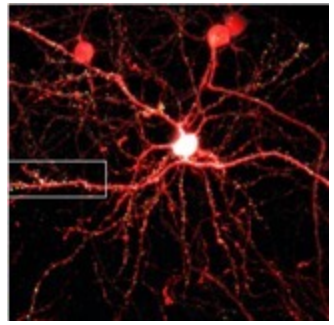
systems



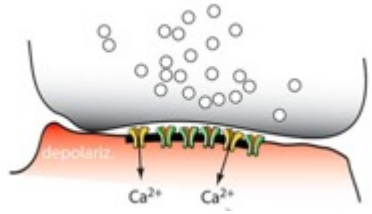
networks



circuits



cells

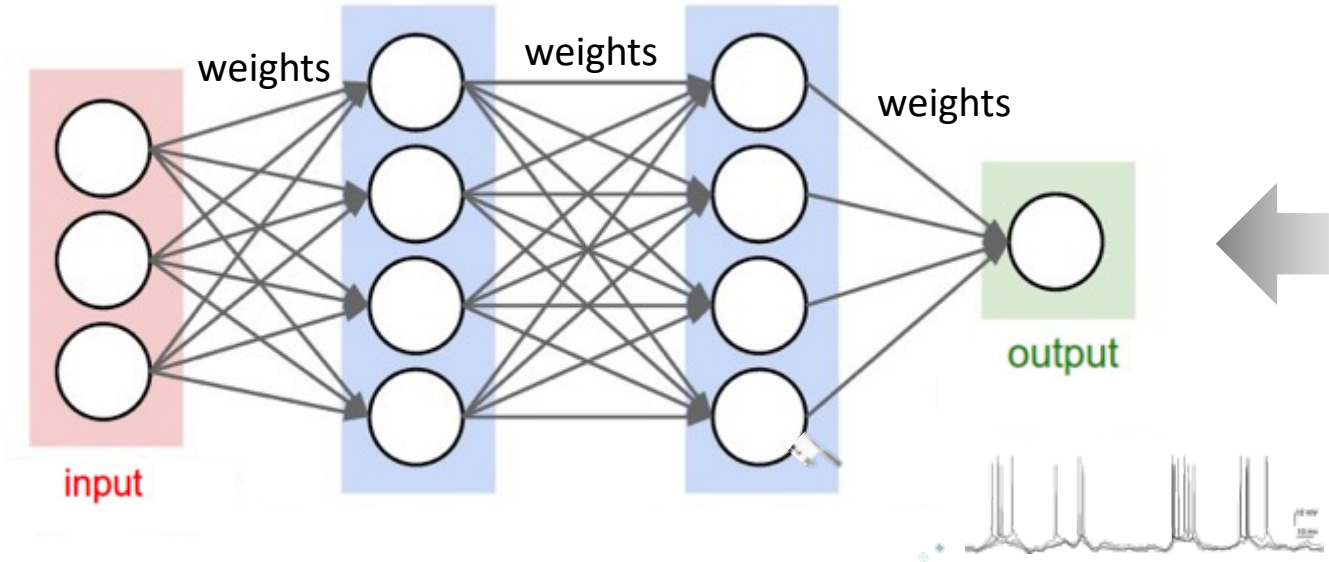


synapses

There are at least 50,000 neuroscientists out there. And they know some stuff (a little, at least).

We can draw inspiration from what we know about the brain to build our models. For example, tuning curves are Gaussian, neurons are mutually inhibitory, and exhibit recurrent excitation, coding is adaptive in time and space, etc, etc.

Solution 4: design a cost function instead



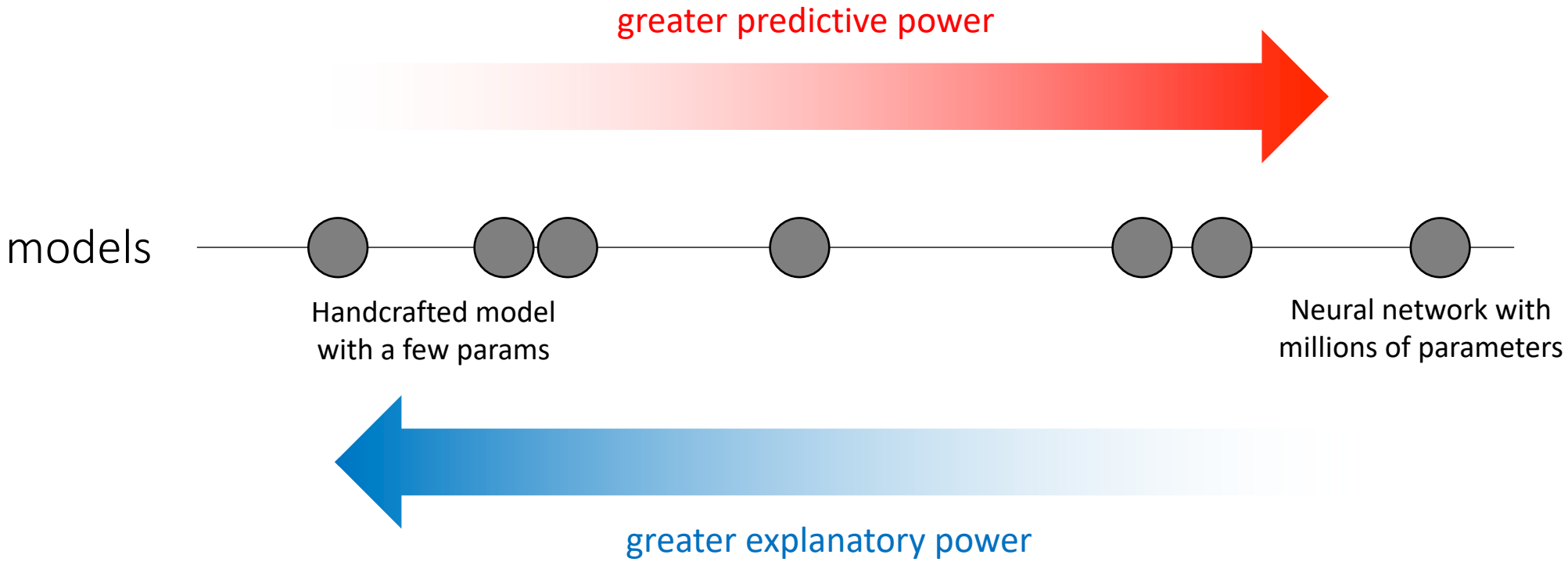
cost function:
minimise classification error
minimise reconstruction error
maximise external reward
+ intrinsic costs
etc

Why not forget hand-designing your model? Focus on the optimisation principle instead. If the network is powerful enough, it will learn the requisite set of computations through raw function approximation.

But….interpretability!

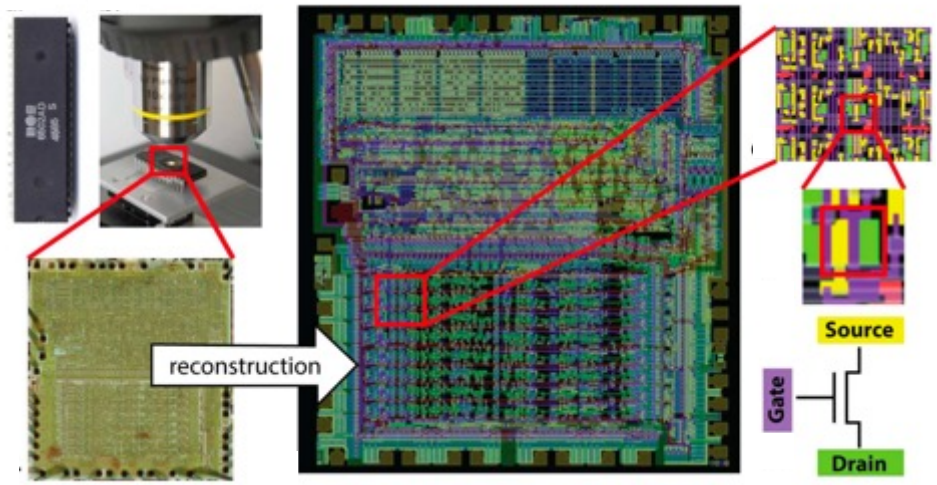
Marblestone et al

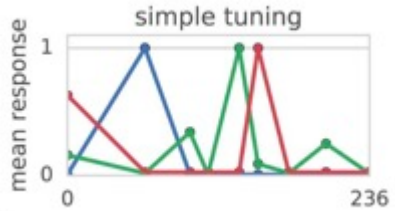
Predicting and explaining

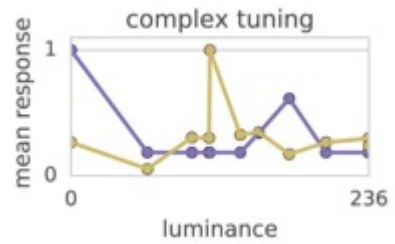


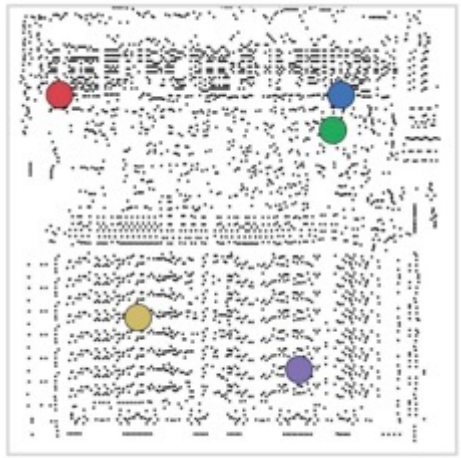
Models are useful for predicting and explaining, and these two virtues typically trade off with complexity

Be humble about your model









Take a system that is fully understood because we built it (e.g. a microprocessor)

do cognitive neuroscience e.g. single cell recordings, brain imaging, lesion studies

Results reveals tuning curves, connectivity profiles, lesion-symptom maps and oscillatory activity just as in the real brain.

But we know that the interpretative logic applied to these phenomena is completely wrong!

Jonas & Kording 2017

Thanks