Intelligence as resource efficiency

⚠️ WIP – thinking out loud ⚠️

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What does it mean to understand the brain?

Aim: understand the brain

Requirement: study things only the brain can do

Nontrivial – many ‘neuroscience’ studies don’t do this

Let’s call the unique thing the brain does “intelligence”

Dangerous, loaded term! Many definitions

I don’t propose to find the ‘right’ definition

I’m certainly not going to try to measure it!

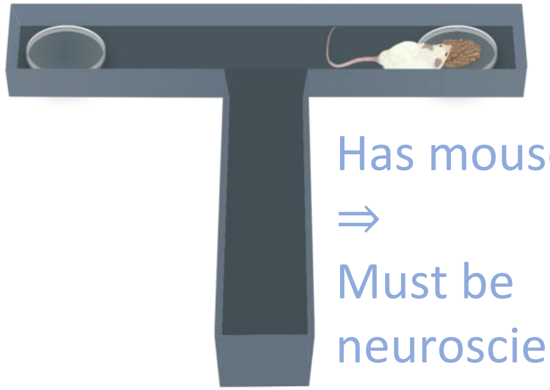
Working definition of “intelligence”

Emerged as a result of our work

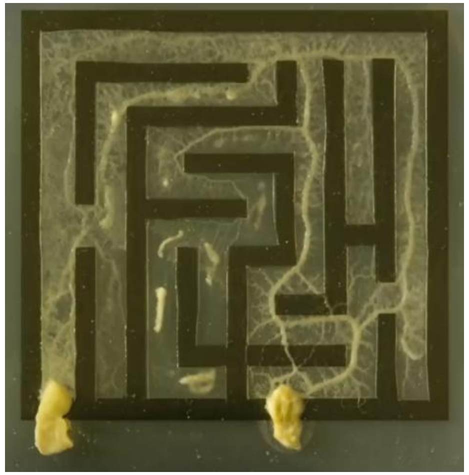
Turns out to have already been discussed in the literature

Useful for understanding my research

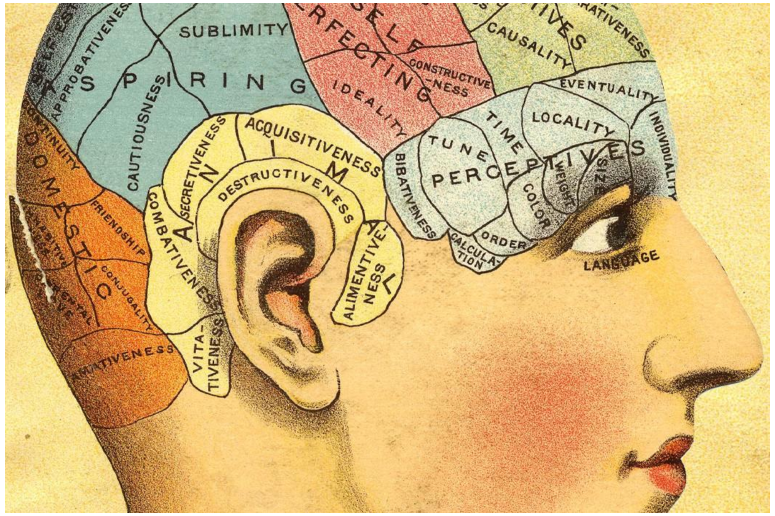
Suggests a research programme



Has mouse ⇒ Must be neuroscience



Slime mould ⇒ not neuroscience



Phrenology head (1905)

A “working definition” of intelligence

“*Intelligence is the ability for an information processing system to adapt to its environment **with insufficient knowledge and resources***” (Pei Wang 1995)

Modern update from training LLMs: knowledge *is* a resource

From the point of view of an organism

Unlimited resources: no need to interact with environment, no need for intelligence.

Unlimited knowledge and computational power: easy to guarantee optimal choices.

$$\text{selected choice} = \underset{\text{possible choices } c}{\operatorname{argmax}} \ \text{reward given } c$$

Things only get interesting when we impose limits.

Question becomes:

How can you approximate an ideal solution with a resource limited one?

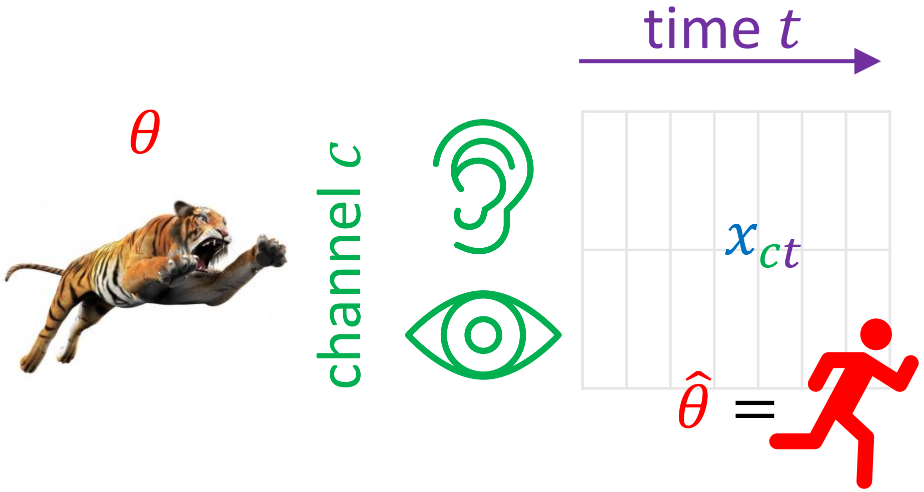
My aim for today is to convince you:

Not just idle philosophy, but a practical research programme for both neuroscience and AI

Case study 1: multimodal perception

Aim is to illustrate two points:

1. Conclusions change for more complex **environments**.
2. **Resource** limitations are a major determining factor.



Background: "Classical" theory of multimodal perception

Want to estimate some property of the world θ

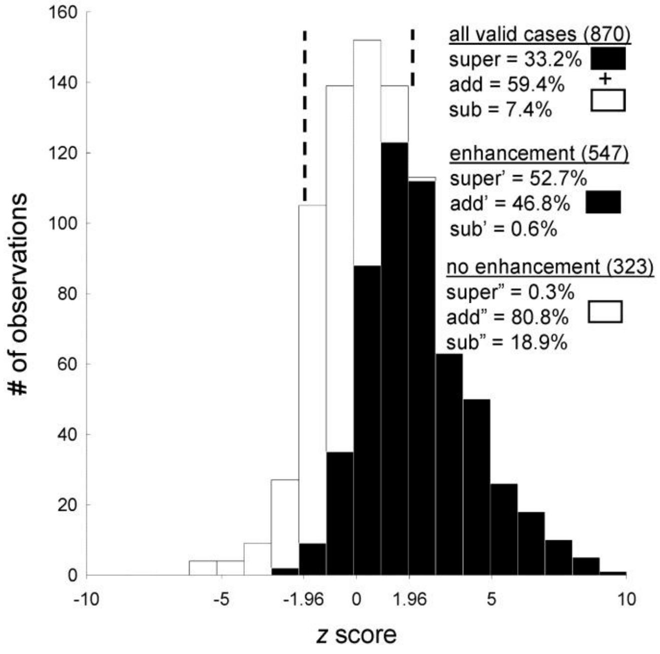
Given observations x_{ct} in channel c at time t

Assume x_{ct} are conditionally independent given θ

$$\hat{\theta} = \mathrm{argmax}_\theta \log P(\theta \mid \boldsymbol{x}) = \mathrm{argmax}_\theta \sum_c \sum_t \log P(x_{ct} \mid \theta)$$

Solution is linear and requires no cross-modal interactions

So why are there multimodal areas with mostly nonlinear neurons?



Stanford et al. 2005

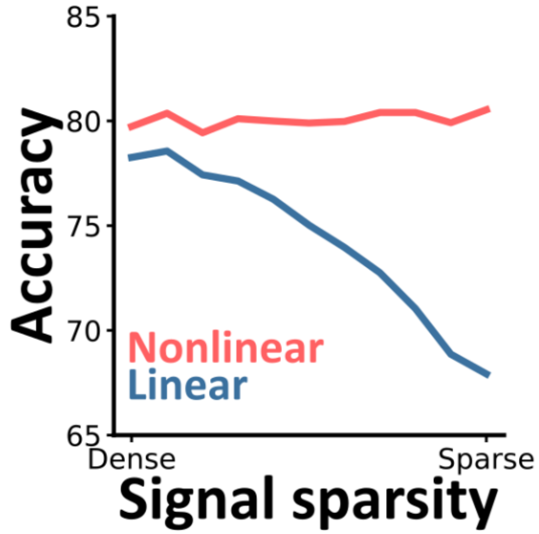
Step 1: introduce cross-modal dependency

Ghosh et al. (2024)

Classic multimodal task with one slight tweak:
Target emits signals at unknown times.
Creates a cross-channel conditional dependency

Reminder: multimodal problem setting
Want to estimate some property of the world θ
Given observations x_{ct} in channel c at time t
Solution is $\hat{\theta} = \text{argmax}_\theta \log P(\theta \mid \boldsymbol{x})$

Nonlinear multimodal area gives advantage.
Advantage larger for sparser signals.



Solution is now **not linear** because

$P(\boldsymbol{x} \mid \theta) \neq \prod_c P(\boldsymbol{x}_c \mid \theta)$

So $\log P(\boldsymbol{x} \mid \theta) \neq \sum_c \log P(\boldsymbol{x}_c \mid \theta)$

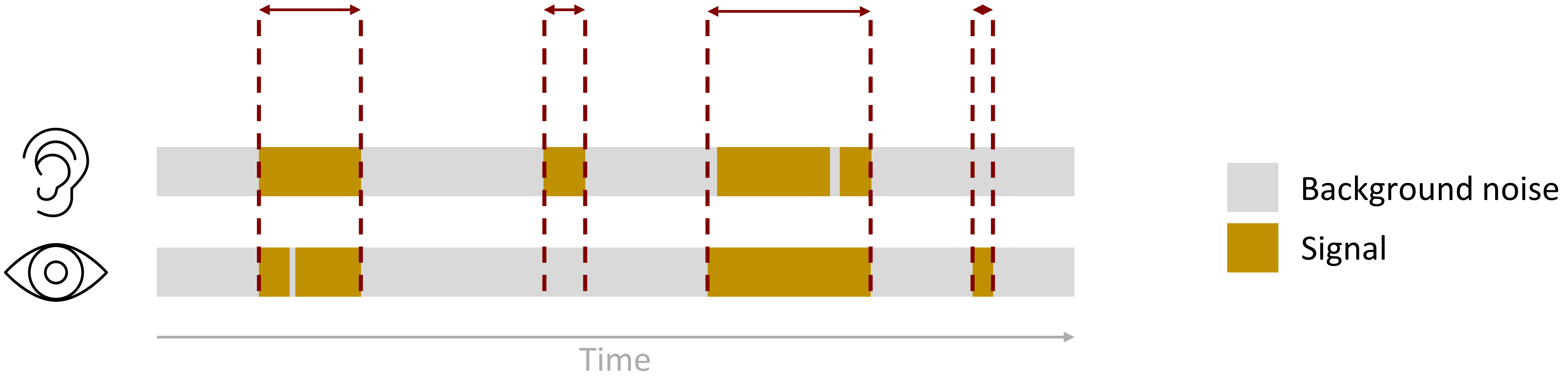
But $\log P(\boldsymbol{x} \mid \theta) = \sum_t \log P(\boldsymbol{x}_t \mid \theta)$

So still relatively easy to write down solution.

Step 2: introduce temporal dependency

Anil et al. (2024)

Information is **sparse** but arrives in bursts and is correlated across modalities



Reminder: multimodal problem setting
Want to estimate some property of the world θ
Given observations x_{ct} in channel c at time t
Solution is $\hat{\theta} = \mathrm{argmax}_{\theta} \log P(\theta \mid \boldsymbol{x})$

Now there is no nice analytic solution because
$\log P(\boldsymbol{x} \mid \theta) \neq \sum_t \log P(\boldsymbol{x}_t \mid \theta)$

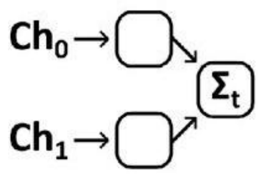
Solution looks like $\iiint \ldots \int \ldots$

So we approximate with neural networks…

Neural network architecture = resources

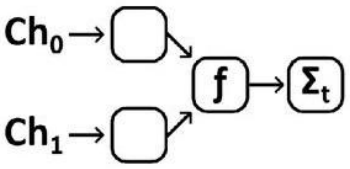
Anil et al. (2024)

Linear fusion



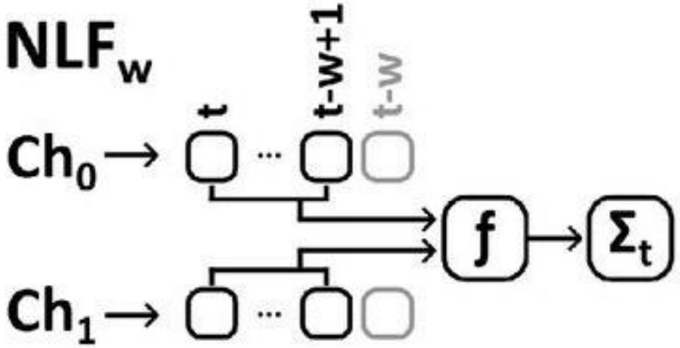
Classical multimodal setting
Solution is linear in c, t
$\sum_c \sum_t \log P(x_{ct} \mid \theta)$
6 parameters to learn

Nonlinear fusion

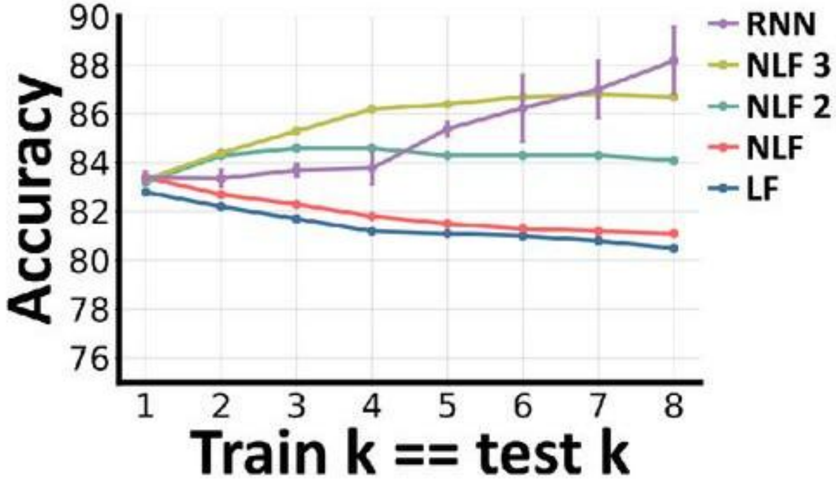


Ghosh et al. (2024)
Linear in t; nonlinear in c
$\sum_t \log P(\boldsymbol{x}_t \mid \theta)$
9 parameters to learn

NLF$_w$

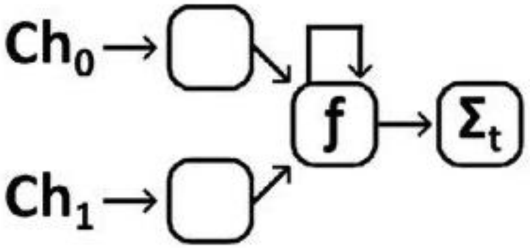


<u>Option 1:</u>
Generalise nonlinear fusion
Add memory window of length w
81 to 729 parameters (w=2,3)



k = length of signal bursts

RNN



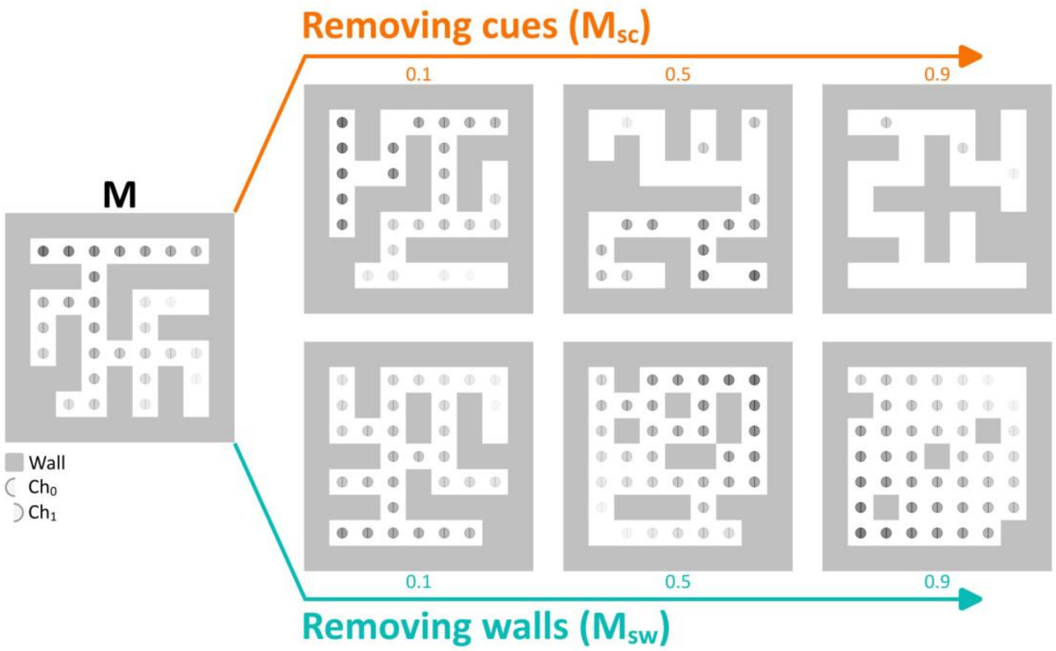
<u>Option 2:</u>
Recurrent neural network
In principle, arbitrary long memory
10,903 parameters

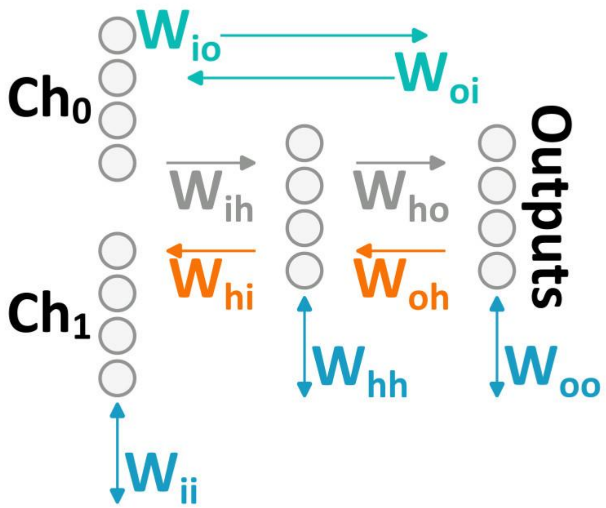
RNN wins if unlimited resources
- Params & Compute
- Knowledge (test in-distribution)

NLF$_w$ wins if resources limited

Step 3: introduce spatio-temporal dependency

Ghosh and Goodman (2026? 🙏)



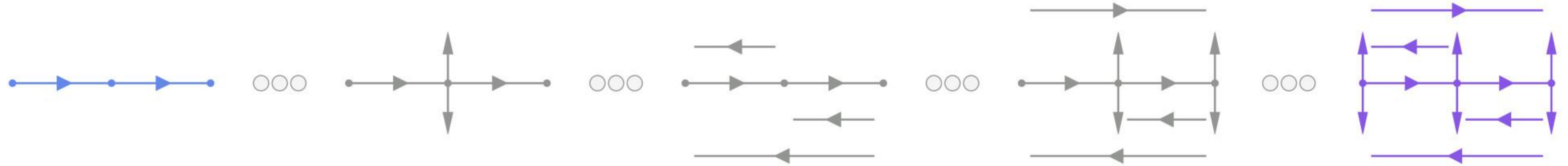


"Partially recurrent neural networks"

Feedforward

126
Partially recurrent architectures

Fully recurrent



Step 3: introduce spatio-temporal dependency

Ghosh and Goodman (2026?)

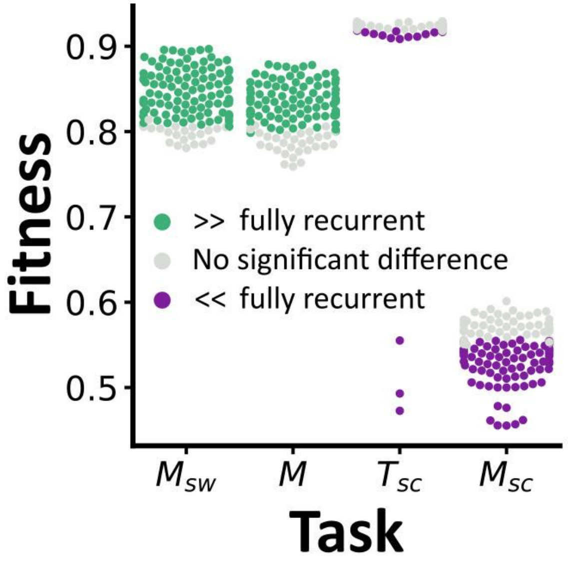
Firmly in the zone of “resource limited”

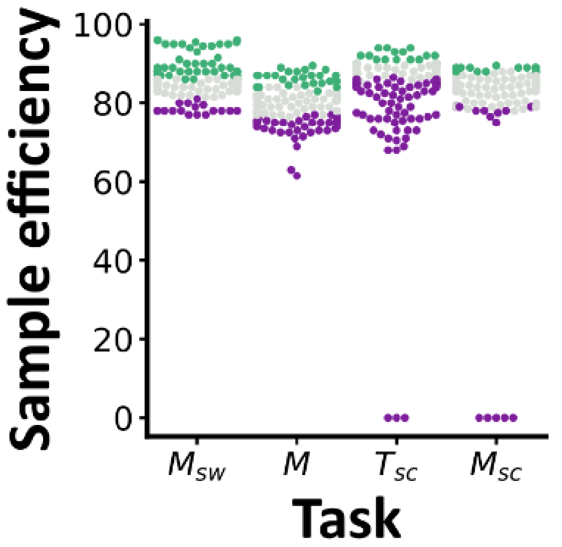
Bigger is not necessarily better

Many networks perform as well as bigger ones

Sometimes better

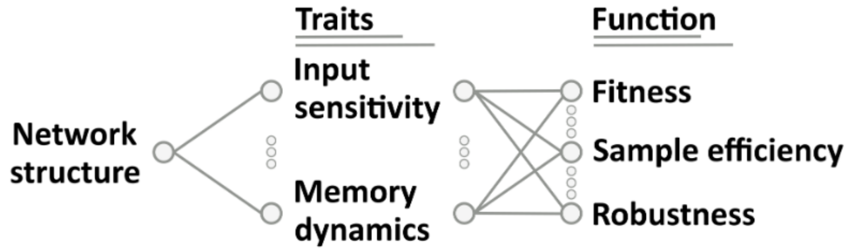
And they can train faster

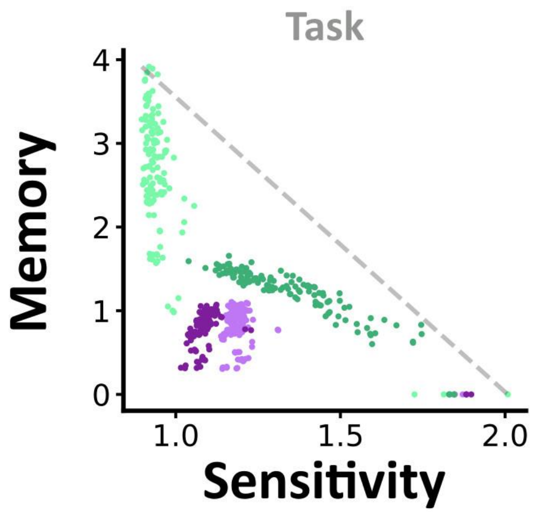




Brief mention of key finding of this paper:

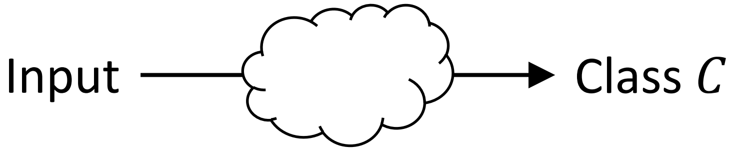
- Architecture itself does not seem to be the key property
- “Computational traits” enabled by architectures
- Sensitivity trades off again memory
- Easy to measure these in NNs





Case study 2: Modularity

"Dumb"

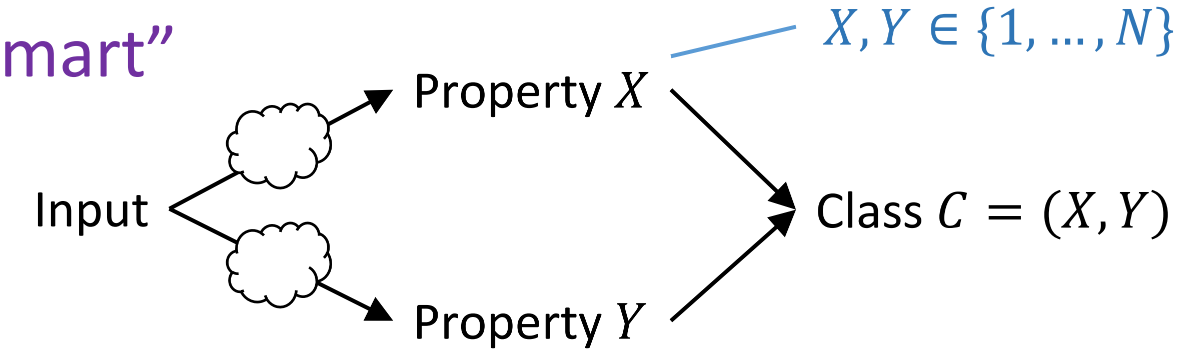


Resource cost cN^2 per trial

Needs to see every example (X, Y)

Error cost 0

"Smart"

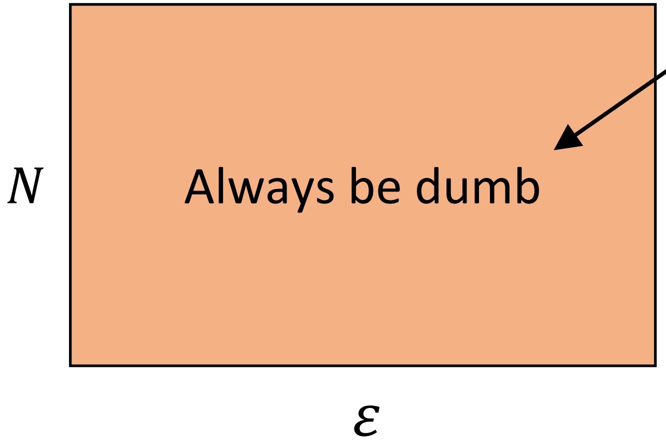


Resource cost cN per trial

Needs to see every X and every Y (generalisation)

Error cost ε per trial

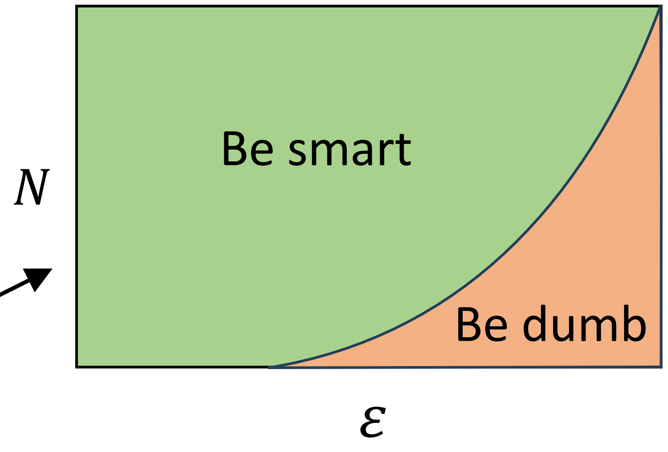
If resource cost $c = 0$



Industrial ML

Brains:
Sometimes smart,
sometimes dumb.

If resource cost $c > 0$



Trying to be "smart" with modules

Béna and Goodman (2025)

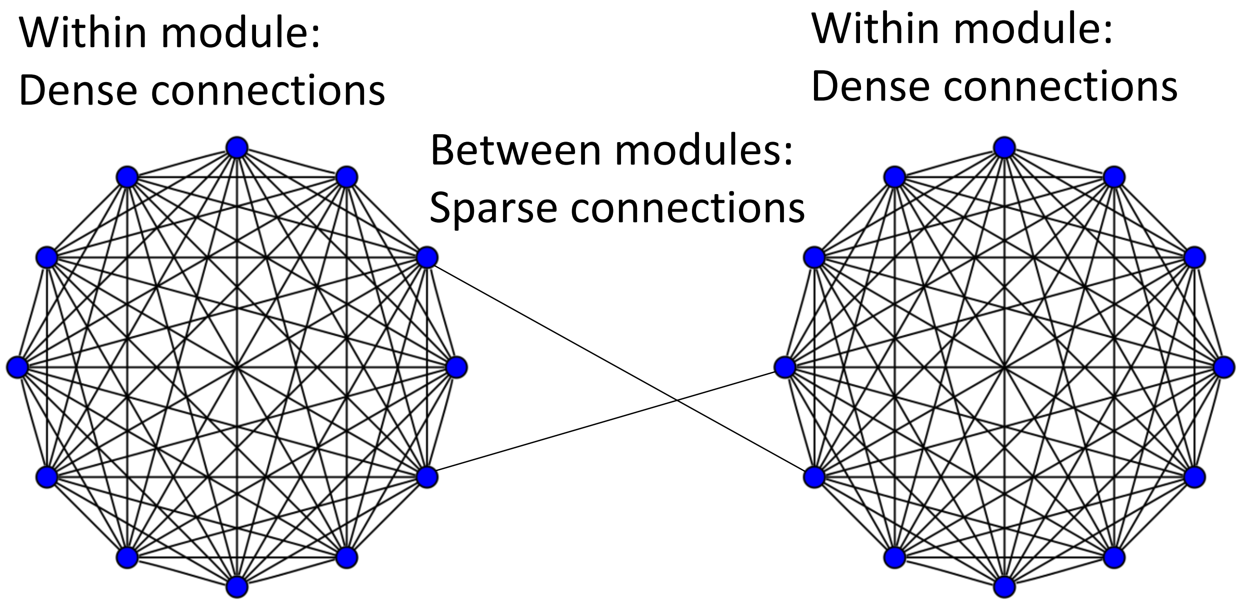
Evidence:

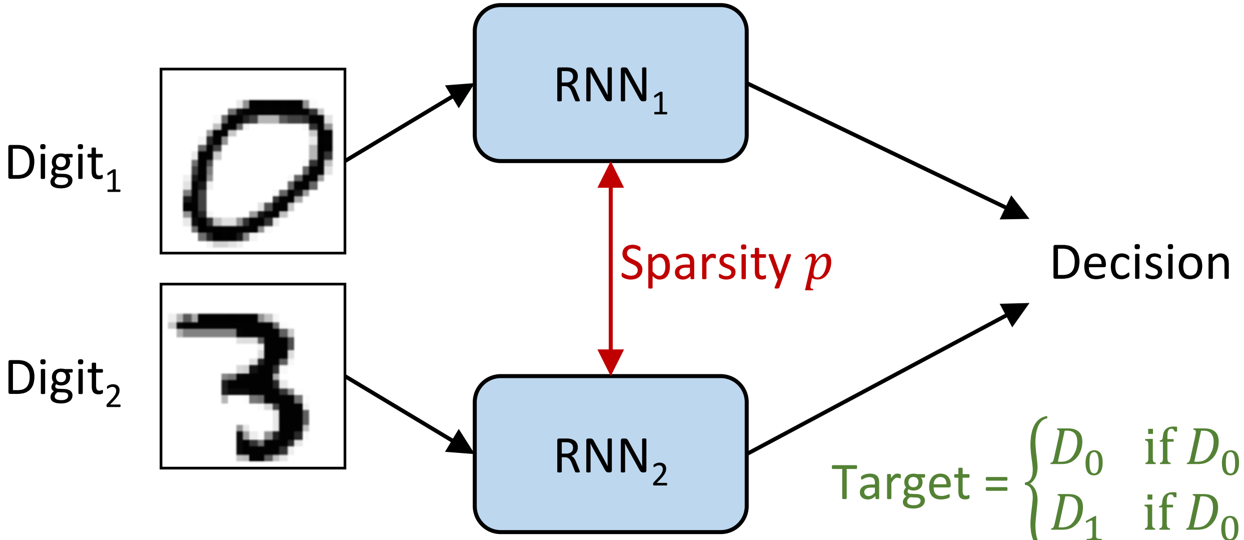
Brain is "structurally modular"

Knocking out brain regions seems to lead to functional deficits

So… functional specialisations a necessary consequence of structural modules?

We tested this by training ANNs in a task designed to encourage specialisation





$$\text{Target} = \begin{cases} D_0 & \text{if } D_0 \% D_1 = 0 \\ D_1 & \text{if } D_0 \% D_1 = 1 \end{cases}$$

But modules want to be "dumb"

Béna and Goodman (2025)

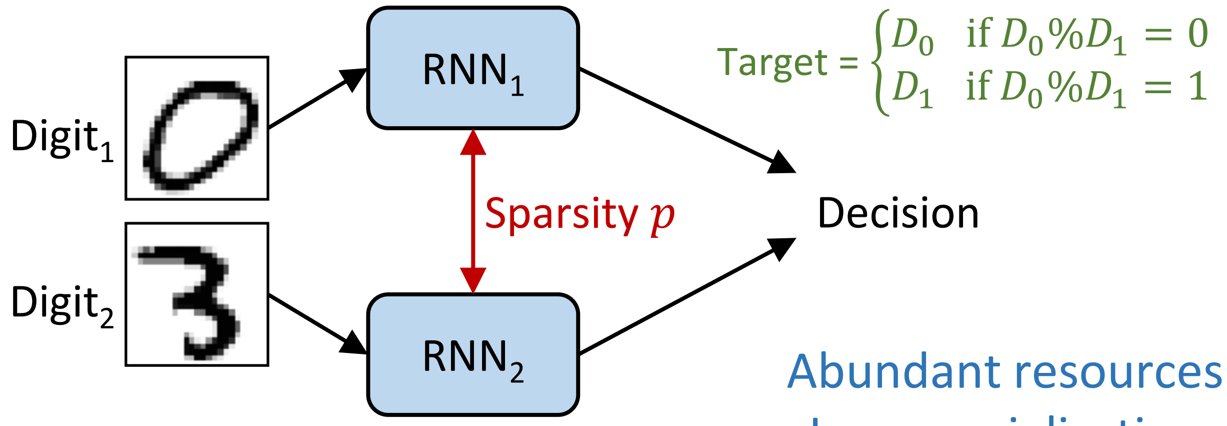
Trained modular ANNs in a task designed to encourage specialisation. Does it work?

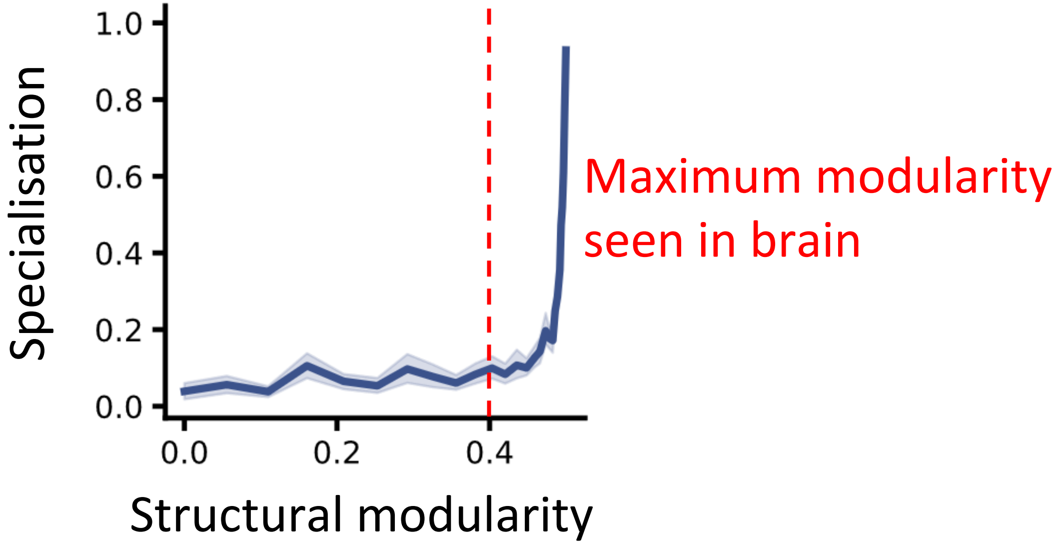
Negative answer: not necessarily.

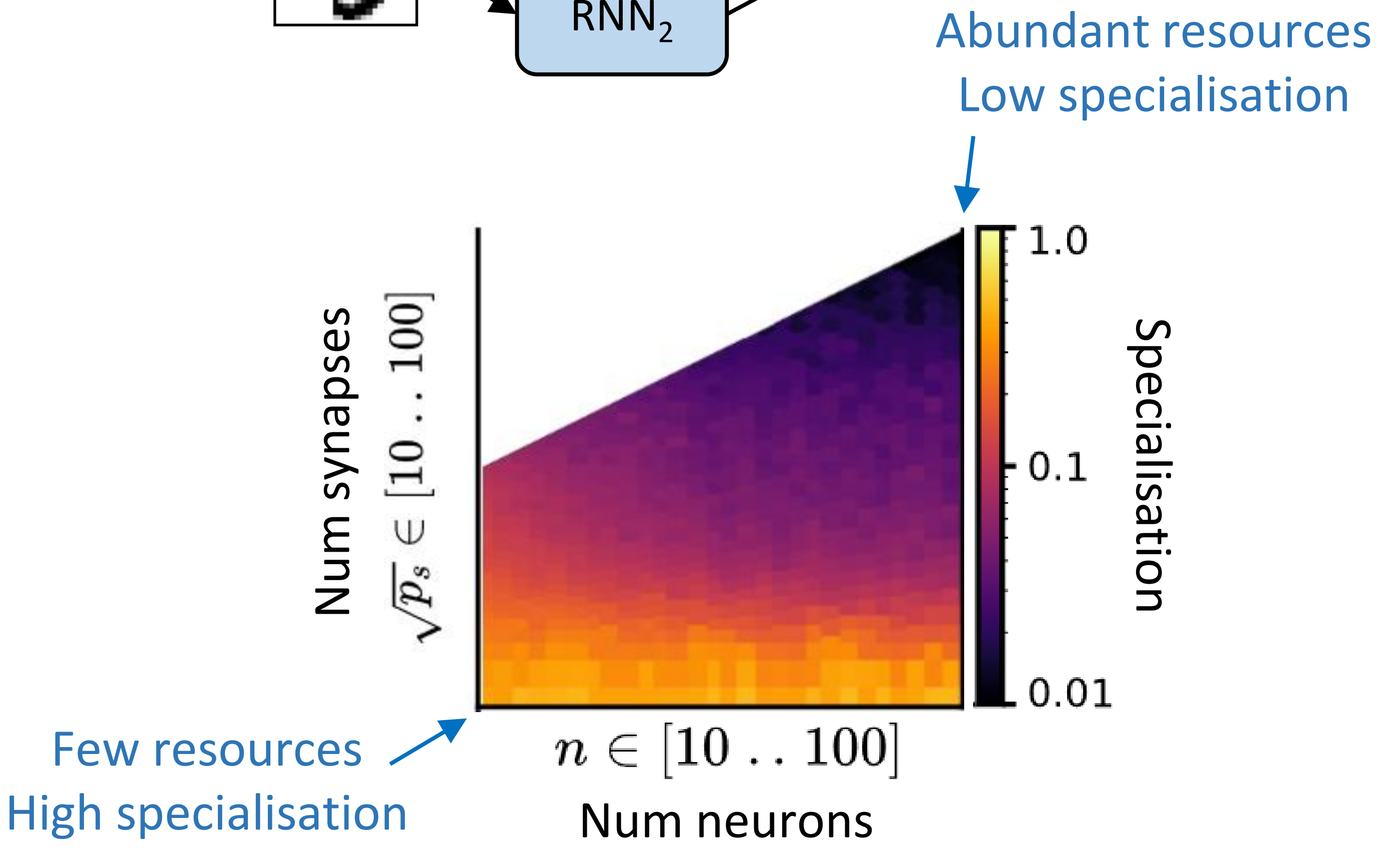
It emerges with tight resource constraints.

WIP-1: generalisation (yes!)

WIP-2: mathematical explanation







Programme for the future

Low hanging fruit: **build resource constraints into models**

"Blood and modularity"

- Fix total blood / energy supply
- Do we get more modularity? (Seems like yes!)
- Do we get better generalisation? (WIP)

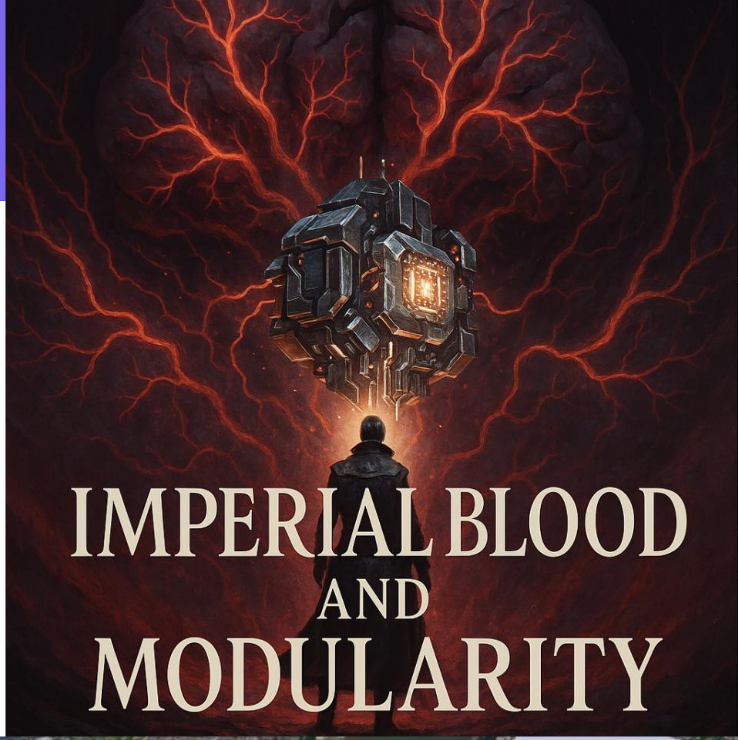
Is this useful for neuromorphic computing?

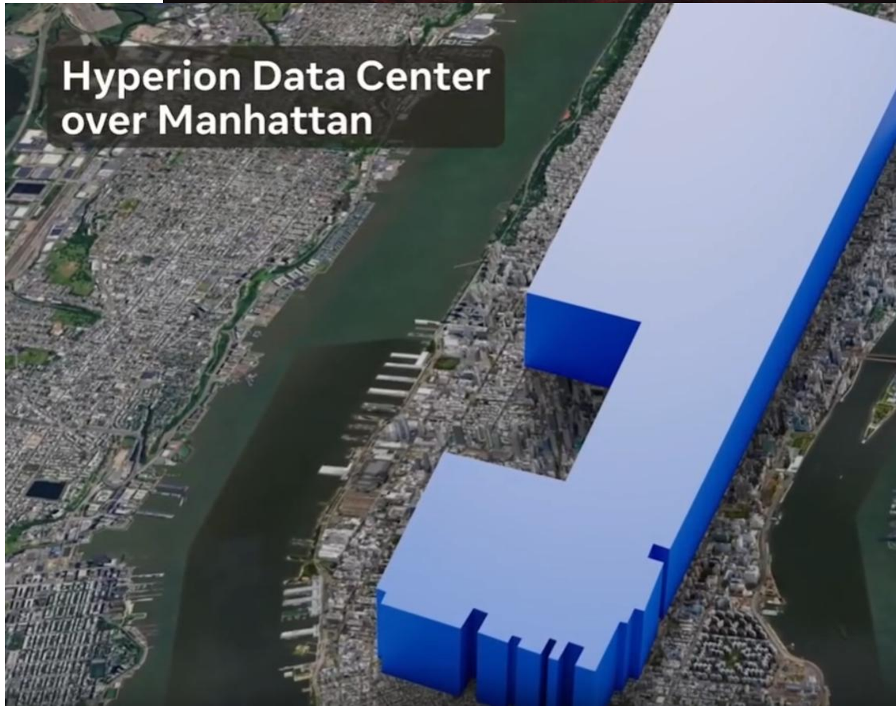
Biological features can improve accuracy **and** efficiency

- Neural heterogeneity (Perez-Nieves et al. 2021)
- Delays and quantisation (Sun et al. 2025ab)
- Neuromodulation (AlKilany and Goodman 2025)

For AI/ML people:

The resource constraints will come eventually





Thanks!

Recap

"Intelligence is the ability for an information processing system to adapt to its environment with insufficient knowledge and resources" (Pei Wang 1995)

Multimodal processing and neural architectures
- Conclusions change for more complex environments.
- Resource limitations are a major determining factor.

Modularity
- "Smart" solution more resource efficient and generalises
- But at the cost of higher error
- Can we train for this directly by limiting resources?

Neuromorphic computing
- Biological features can improve accuracy and efficiency

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Postdoc fellow 2021-

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Visiting PhD (2024)

And **thank you** for listening!