Spikes are cool again! What’s next?

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IMPERIAL

neural-reckoning.org

My own spike history

A mathematician says "wtf?"

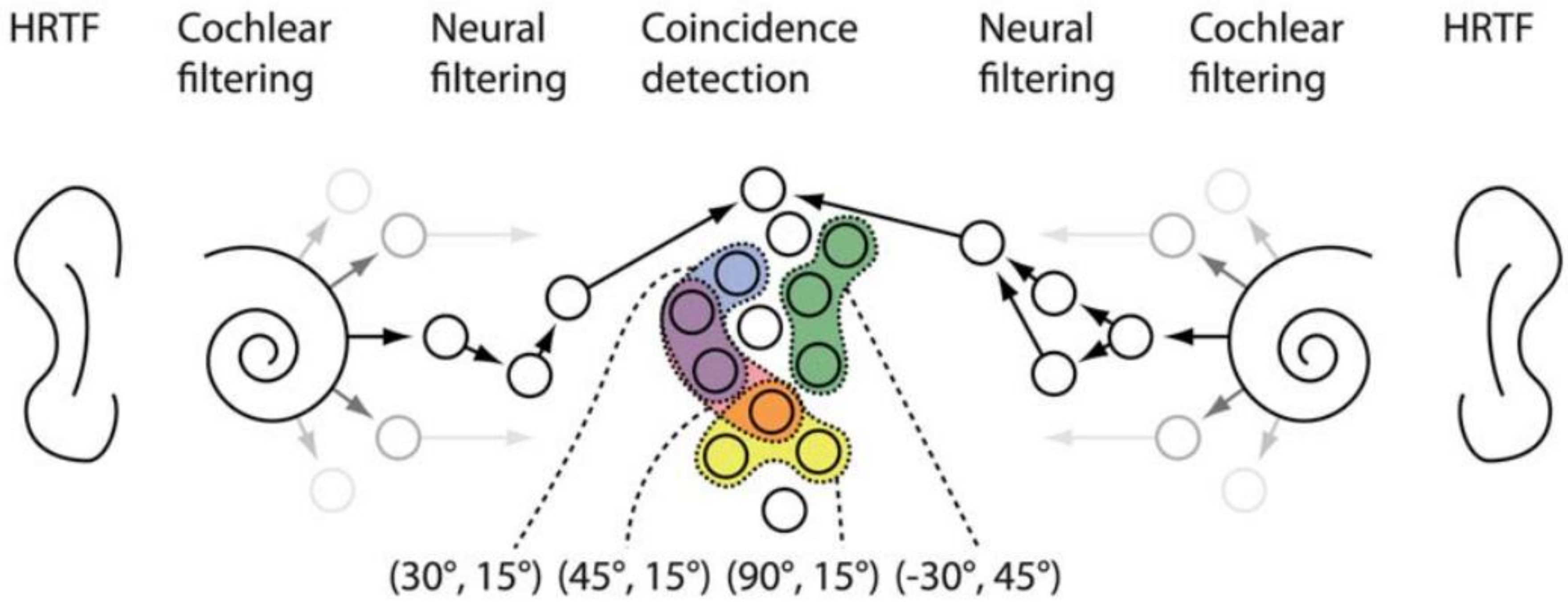
First project with Romain Brette: plan = synfire chains

Instead built "Brian" SNN simulator

Next project: sound localisation with SNNs

BRIAN

Goodman and Brette (2010)
PLOS CB



Goodman and Brette (2010)
NeurIPS

My own spike history 2

And that’s what SNN papers were like back then, until…

Machine learning happened.

I was a late convert.

My impression: SNNs went a bit dormant for a while?

2019: **SPyTorch** brought me back

Finally felt like I could do the two things I had wanted to do:

1. Study the brain when doing ‘real world’ tasks
2. Use spiking neural networks to do it.

SNN Cambrian explosion

SNUFA workshop: https://snufa.net

So: spikes are cool again!

Where do we go next with our cool new toys?

Zenke (2019)

Zenke, …, Goodman (2021) Neuron

Why spikes?

Easy: **power efficiency**.

✓Important in biology

✓Important for neuromorphic

End of talk, we can all go home?

How sure are we that this will keep the field relevant?

2016 AlphaGo drew 100-1000 kW ~ 5k-50k human brains

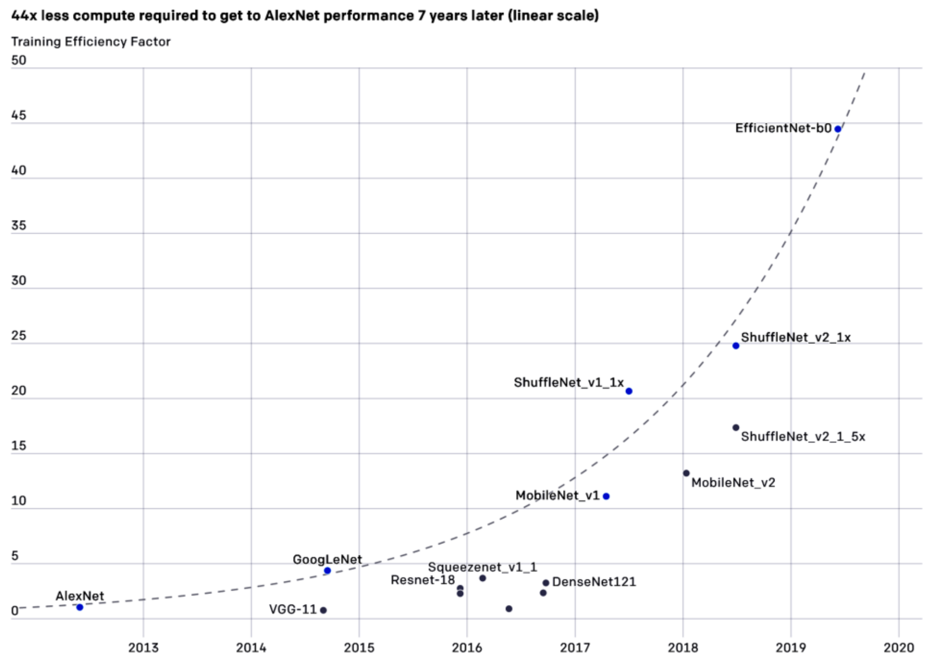
2017 AlphaGo Zero drew 1-2 kW ~ 50-100 human brains

AlexNet level performance reduced by 44x in 7 years

Huge interest in reducing power:

- Bit quantisation (e.g. DeepSeek)
- Approximate computing

Can neuromorphic compete? (I'm not taking a stand – genuinely don't know the answer!)



Why spikes? (2)

Implementation

Power? ✅ biology ✅ neuromorphic

Reliability? ✅ biology ❓ neuromorphic

Compactness?

- Important biological constraint, but unique to spiking?
- Important for neuromorphic?

Thorpe and Imbert (1989)

Behaviour

Speed? ✅ biology (Thorpe et al.) ❓ neuromorphic

- Can we extend and formalise this? Memory bandwidth bottlenecks?

Noise robustness? ✅ biology ❓ neuromorphic 🍸 🥳 e.g. cocktail party problem

Sample efficiency?

Performance? ✅ biology ❌ no examples of SNNs doing better

Generalisation? ✅ biology ❌ no examples of SNNs doing better

So what could be a fundamental advantage of spiking?

Nonlinearity and temporal dynamics

Coincidence detection

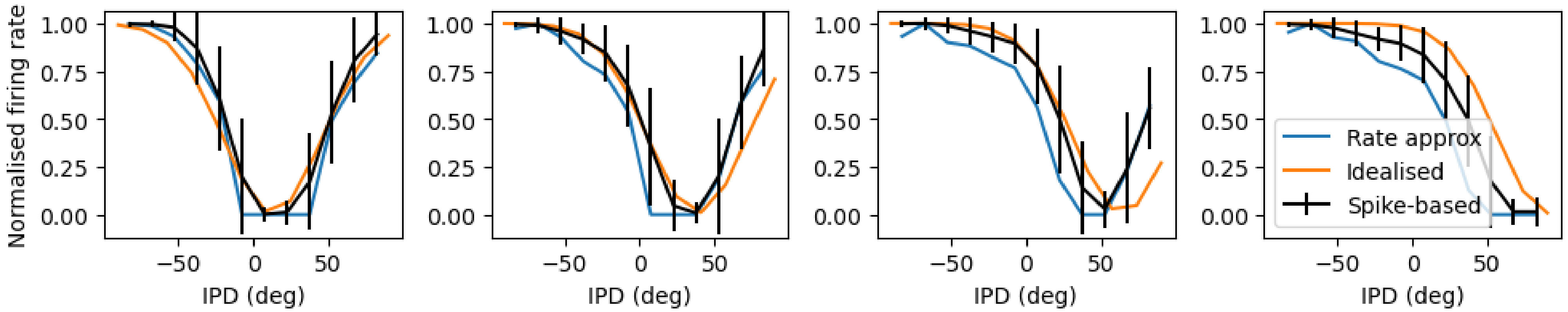
Sound localisation: Jeffress (1948)

Sound localisation: COMOB

- Open, online collaboration (31 researchers)
- New delay learning algorithm (Karim Habashy)
- (Smaller time constants = better performance) ⇒ coincidence detection?
- No, output well approximated by:

Output = inverted Gaussian tuning → Ricker wavelet weight matrix → sigmoidal activation

Ghosh et al. (2024 preprint)



Nonlinearity and temporal dynamics

Coincidence detection

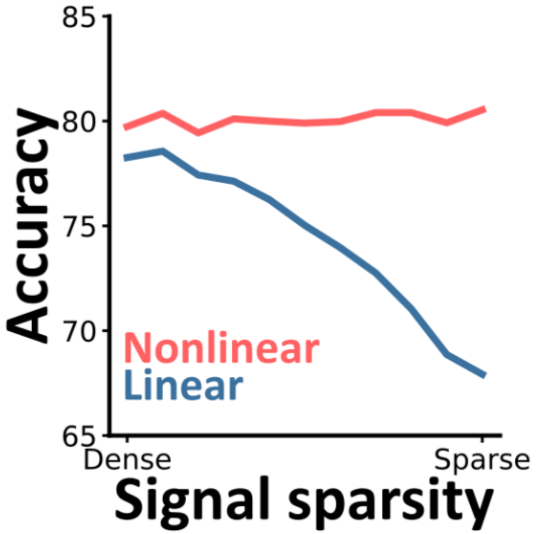
Sound localisation

Sensitivity to tiny population correlations

Computing in time

Processing multimodal signals

Advantage larger for sparser signals.



Rossant et al. (2011)

Ghosh et al. (2024)

Nonlinearity and temporal dynamics

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Delay networks and learning

Too much recent work to list it all

On temporal logic tasks:
delays more important than weights

Ongoing work in our group on delays:

- With Danyal Akarca and Pengfei Sun
- Systematic approach to delays versus weights, quantisation, task structure, etc.

Leader board SHD

Publication	Accuracy %	Network
Schöne et al. 2024	95.9 ± 0.9	Event-based linear state space model
Baronig et al.	95.8 ± 0.6	RSNN with adaptive LIF neurons and symplectic-Euler discretization
Hammouamri et al. 2023	95.1 ± 0.3	Fully connected SNN with learned delays
Bittar and Garner 2022	94.6	RSNN with adaptation
Nowotny et al. 2025	93.5 ± 0.7	RSNN with delay line input and augmentations
Mészáros et al.	93.2	RSNN with delay learning
Sun et al. 2023	92.45	Feed-forward SNN wit
Yu et al. 2022	92.4	Feed-forward SNN wit
Yao et al. 2021	91.1	RSNN with temporal at
D'Agostino et al. 2023	90.1% / 87.6 %	Feed-forward SNN wit (simulation/hardware,

Habashy et al. (2024)

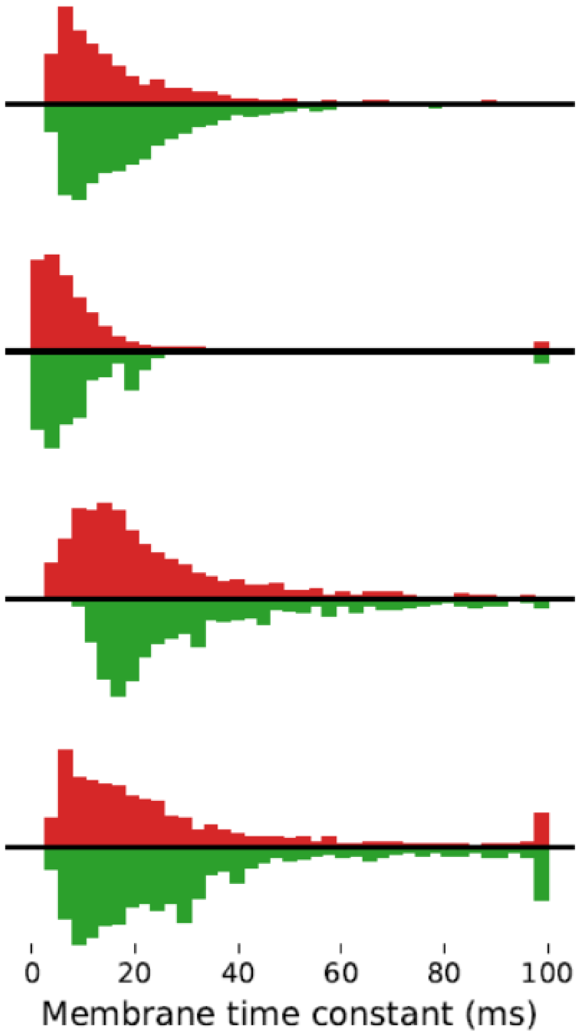
Heterogeneity

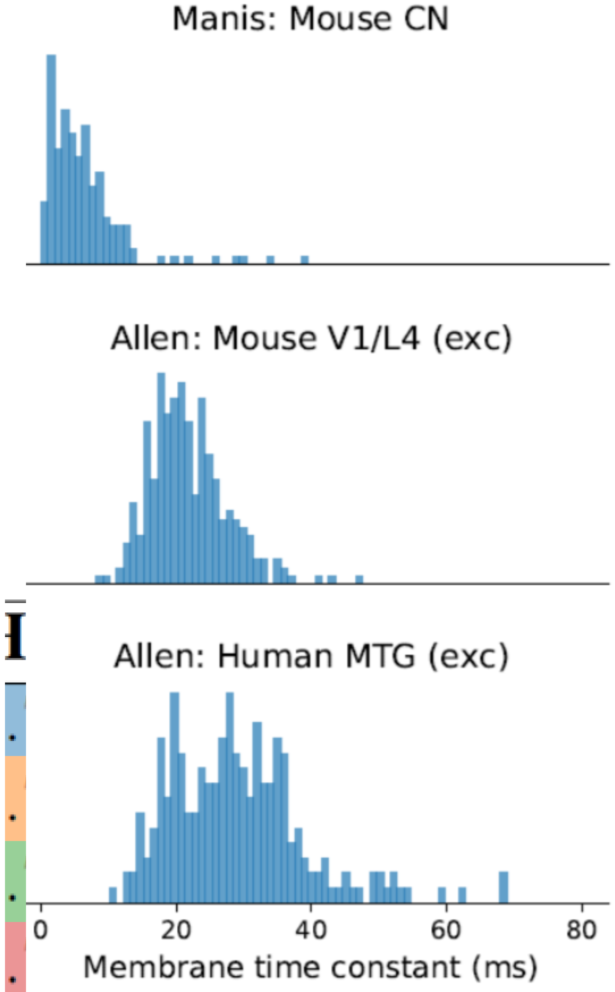
✅ Biology ❌ Artificial neural network

✅ Neuromorphic computing devices (some)

Perez et al. (2024)

Initialisation	Training	N-MNIST	F-M		H	
Homog.	Standard	97.4±0.0	80.1			
Heterog.	Standard	97.5±0.0	87.9			
Homog	Heterog.	96.6±0.2	79.7			
Heterog.	Heterog.	97.3±0.1	87.5			
	Chance level	10.0	10.0	10.0	5.0	2.9





Sparsity

Temporal sparsity (e.g. 100x faster training)

Spatial sparsity

- Neuromorphic: memory bottlenecks and locality
- Biology: wiring constraints, coordination between regions
- Modularity

Perez and Goodman (2021)

Béna and Goodman (2025)

Why is there modular structure in the brain?

Evidence:

Brain is “structurally modular”

Knocking out brain regions seems to lead to functional deficits

So…?

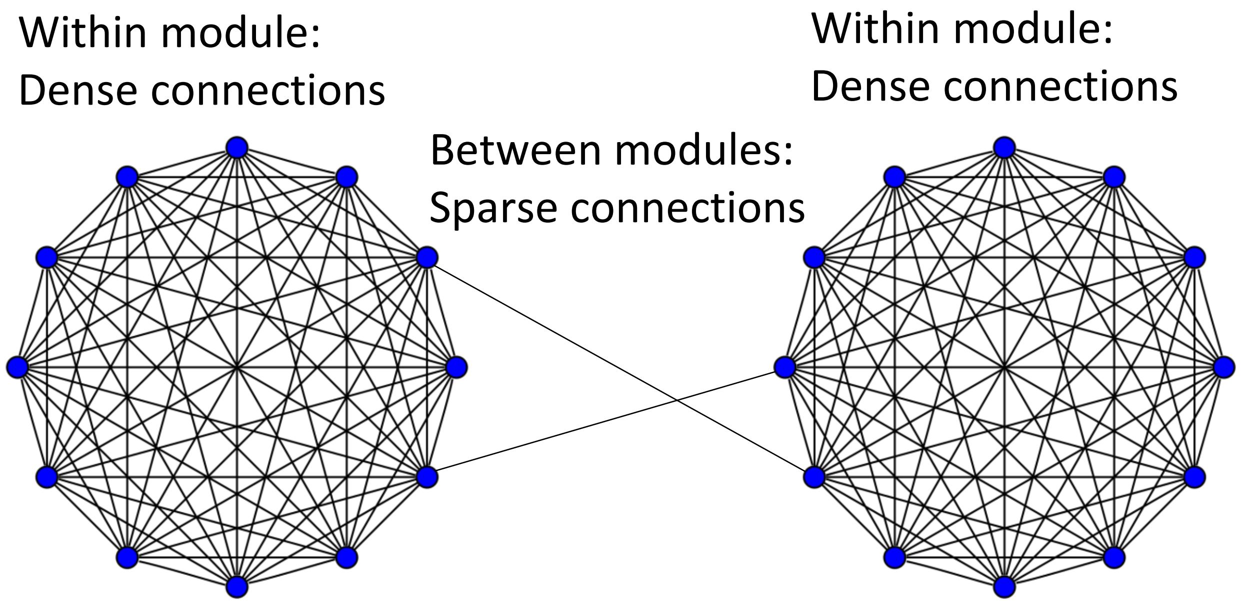
Functional specialisations a necessary consequence of structural modules?

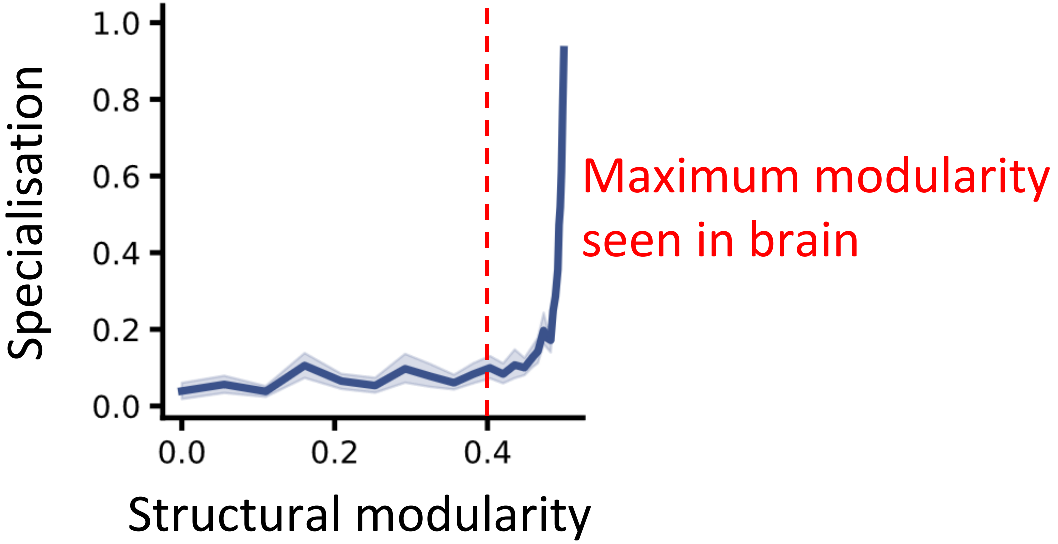
We tested this by training ANNs in a task designed to encourage specialisation

Negative answer: not necessarily.

⇒ We need additional features/constraints

e.g. tight resource constraints.





Challenges

No examples where SNNs are better

➢ Naturalistic tasks with rich and sparse temporal structure

Scaling up SNN training

➢ Algorithmic developments

➢ Conceptual understanding of biological learning

- Do we know if our algorithms are finding ‘spikey’ solutions?

Lacking a mathematical theory of hybrid systems

Generalisation of spiking

Thanks!

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Swathi Anil
Visiting PhD (2024)

Nicolas Perez
PhD student 2018-2023

All papers

And thanks to you for listening