Reverse-Engineering Biological Intelligence (RBI)

Building Energy-Efficient and Adaptive Learning Systems

The problem

We witnessed a tremendous development of Artificial Intelligence (AI) systems in the last decade, with AI outperforming humans in several domain specific tasks, such as handwriting recognition, speech and image recognition, reading comprehension, and predictive reasoning (1). While powerful, training these models requires excessive energy — often gigawatt-hours per model — and massive annotated datasets numbering trillions of datapoints (2). They also notoriously suffer from *catastrophic forgetting* — the loss of 60–100% of performance on previously learned tasks when trained sequentially on new data (3). These limitations are compounded by the slowing of Moore's law and the physical limits of silicon hardware.

Drawing inspiration from the brain

This situation calls for new approaches to learning and computation. The human brain, a product of ~500 million years of evolution, has been optimized for extreme energy efficiency (20 watts), unprecedented parallel processing (86 billion neurons with up to 10,000 synapses each), and highly efficient learning (4). Uncovering the mechanistic and algorithmic principles that make such biological intelligence efficient, adaptive, and robust would represent a step change in how we design and understand learning systems.

State-of-the-art approaches

Over the past decades, several attempts have been made to design computing systems inspired by the brain. One of the most developed approaches is to mimic biological intelligence through neuromorphic hardware and spiking neural networks (SNNs). Such systems show promise of a lifelong or continual learning, learning in the presence of sparse data, robustness in the presence of noise and variability and ultralow-power machine learning with real-time sensor data (5). In some cases neuromorphic computing demonstrated 1000x energy efficiency and 1000x faster processing time. However, it suffers from immature learning algorithms as most existing systems rely on simplified or hand-crafted plasticity rules, lack scalable training methods comparable to backpropagation, and cannot yet support robust continual learning or complex task learning at scale (6).

The need to extract learning algorithms and architectures from the brain is underscored as several major initiatives explicitly pursued this objective. One of the most prominents initiatives was Machine Intelligence from Cortical Networks (MICrONS). It was a major IARPA-funded project under the US BRAIN Initiative, MICrONS aimed to reverse-engineer a cubic millimeter of the mouse brain to understand how its circuits function and transfer that knowledge to machine learning.

However, studying networks in living brains provides limited insights into the architectures and mechanisms of learning due to the lack of control over the system. Therefore, I propose that we need to design efficient learning systems in biological substrate in order to uncover the fundamentals of intelligence.

Why now?

Recent technological advances have made it possible to design and control biological neural systems *in vitro*. Several nascent attempts have shown that biological neural networks can perform simple forms of learning and adaptation (7,8). Meanwhile, developmental biologists have demonstrated the capacity to engineer sophisticated, self-organized neuronal networks (9). These approaches show our emerging capability to design structured biological neural networks that could reveal the principles of learning and adaptation in living systems. Current efforts are sparse and fragmented, underscoring the need for a coordinated, interdisciplinary program with sustained resources.

The technological foundations, however, have converged. Microelectrode arrays and optical tools now provide stable, scalable interfaces to neurons. Culture protocols enable long-term survival of high-density networks. Soft lithography and microfluidics allow precise patterning of cells and connectivity. Machine learning frameworks offer tools for real-time training and adaptive control. The challenge is no longer feasibility but integration: bringing these advances together to create reproducible, programmable, and interpretable biological learning systems.

Challenge proposal

Here, I propose a SPRIN-D Challenge — Reverse-Engineering Biological Intelligence (RBI) — to build and train living neuronal networks that demonstrate superior learning, using them to reveal the principles that give rise to efficient, adaptive, and resilient intelligence. RBI will demonstrate these principles in living systems, enabling new forms of learning that are energy-efficient and capable of acquiring new knowledge without forgetting — capabilities that current AI and hardware architectures cannot yet achieve.

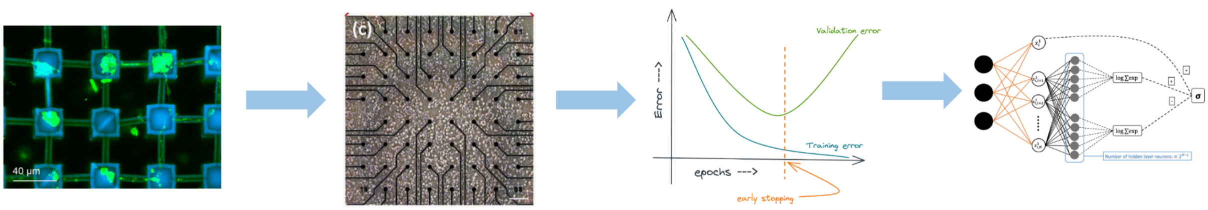
The Reverse-Engineering Biological Intelligence (RBI) Challenge

1. Designing and growing structured biological neural networks and self-assembling circuits in a dish

2. Connecting them with silicon computing systems via optical and electronic read & write interfaces

3. Training in ML tasks, optimising for efficiency and continual learning

4. Unpacking architectures and learning rules through the innovation ecosystem



Challenge timeline

Time: 33-month challenge; **Budget:** €25 M

• Stage 1 (6–8 teams, 9 months) Building stable biological networks:

Establish stable, reproducible neuronal systems (structured networks and organoids) and demonstrate controllable activity using write/read interfaces. Show first adaptive changes under closed-loop stimulation and define shared assays for learning and retention (Reproducibility: inter-batch CV ≤30%; bandwidth: >3000 read channels, >200 write channels;)

• Stage 2 (3–4 teams, 14 months) Training and learning optimisation for unified metrics:

Perform full scale closed loop learning for biological neural networks. Demonstrate at least two benchmark learning tasks (4 class discrimination: acc > 75%, Sequential A->B->C: backward transfer <30%) with measurable retention over ≥10 days, and characterize energy (joules per correct classification) and data needs (cross entropy reduction per sample). Optimisation for defined metrics.

• Stage 3 (1–2 teams, 10 months) Integrated biological intelligence systems & landmark demonstration:

Teams construct and operate a fully integrated, high-stability biological learning system that performs multi-step adaptive behavior under controlled conditions and meets externally relevant performance benchmarks.

Deliverables: Standardized protocols, Open benchmark datasets, Reference architectures, Simulation analogues of biological principles, Minimal executable examples (MEEs), Reproducibility toolkits

Work with transition enablers: ML researchers, neuromorphic hardware groups, theory/comp neuro teams, neural engineering labs, robotics groups.

Risks

Scientific Risks: slow or unstable systems; failure to discover learning rules, biological learning principles do not generalise to silicon;
Biological Risks: high variability and scaling problem, long-term instability, inconsistency
Technical Risks: insufficient read/write bandwidth; noisy or drifting signals; closed-loop instability or latency issues.
Programmatic Risks: divergent approaches; coordination and communication challenge; misalignment with biological timelines
Team & Execution Risks: personnel turnover, insufficient incentives
Ethical & Societal Risks: public perception concerns, emerging regulations
Translation & Impact Risks: failure to extract translational rules and algorithms, resistance of downstream uptake.

Impact

If successful, RBI will establish a new category of intelligent systems, combining the adaptability of biology with the programmability of technology. The program will deliver impact across three levels:

1. **Scientific:** uncovering the rules and architectures underlying biological learning, revealing how living systems achieve efficiency, adaptability, and stability.
2. **Technological:** enabling reproducible platforms for training, observing, and controlling living networks — integrating neural culture, high-bandwidth interfaces, and real-time learning frameworks.
3. **Applied:** creating new classes of adaptive processors, neuromorphic algorithms, and bio-hybrid interfaces that merge biological and artificial intelligence.

Together, these outcomes will define a new foundation for intelligent systems — one that learns efficiently, adapts continuously, and integrates the strengths of living and artificial computation. This foundational technology will open up numerous applications - from continuously learning AI assistants and robots that adapt in any environments to ultra-efficient edge devices and zero latency neural prosthetics.

References

1. The brief history of artificial intelligence: the world has changed fast — what might be next? https://ourworldindata.org/brief-history-of-ai
2. Will we run out of data? Limits of LLM scaling based on human-generated data. https://epoch.ai/blog/will-we-run-out-of-data-limits-of-llm-scaling-based-on-human-generated-data
3. Gido M. van de Ven. Continual Learning and Catastrophic Forgetting. https://arxiv.org/html/2403.05175v1
4. Sang Wan Lee , John P. O'Doherty, Shinsuke Shimojo. Neural Computations Mediating One-Shot Learning in the Human Brain, PLOS Biology, 2015 https://journals.plos.org/plosbiology/article?id=10.1371/journal.pbio.1002137
5. Kudithipudi et al., 2025. Neuromorphic computing at scale. Nature https://www.nature.com/articles/s41586-024-08253-8
6. Schuman et al., 2022. Opportunities for neuromorphic computing algorithms and applications, Nature Computational Science. https://www.nature.com/articles/s43588-021-00184-y#:~:text=It%20is%20worth%20noting%20that%20training%20a%20conventional%20DNN%20and,temporal%20aspect%20of%20SNN%20computation.
7. Kagan et al., 2022. Neuron. In vitro neurons learn and exhibit sentience when embodied in a simulated game-world. DOI:%2010.1016/j.neuron.2022.09.001
8. Cai et al., 2023. Nature Electronics. Brain organoid reservoir computing for artificial intelligence. https://doi.org/10.1038/s41928-023-01069-w
9. Alam El Din, DM., Moenkemoeller, L., Loeffler, A. *et al.* Human neural organoid microphysiological systems show the building blocks necessary for basic learning and memory. *Commun Biol* 8, 1237 (2025). https://doi.org/10.1038/s42003-025-08632-5