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The NIH BRAIN Initiative®: AI in Neuroscience

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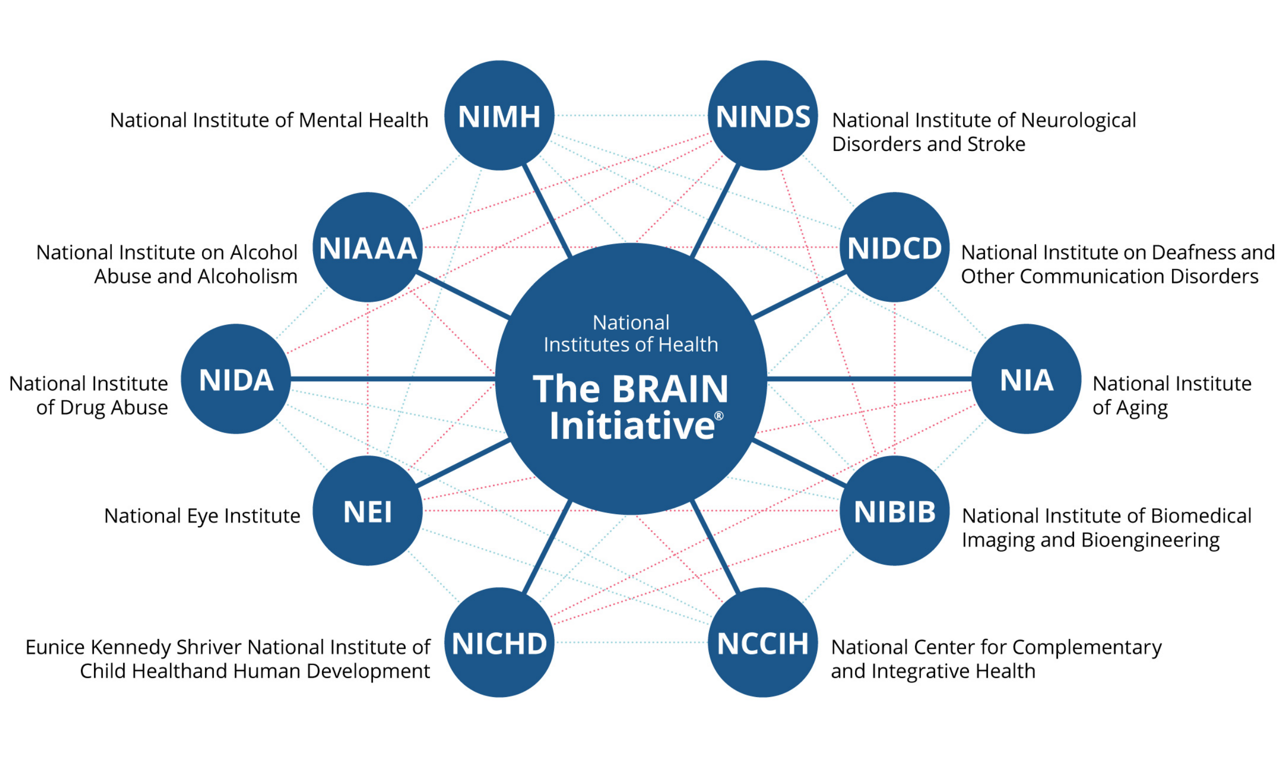
Scientific Program Manager [C]
Office of the BRAIN Director
NIH/NINDS

AIM-AHEAD AI-CARES — August 28th, 2024

The NIH BRAIN Initiative

Goal: to develop and apply new tools for understanding how neural circuits underlie complex behaviors in health and disease



- Leverage ***emerging technologies*** to enable new discoveries about neural circuit function
- Use these discoveries as a foundation for ***new therapeutic strategies*** for human brain disorders
- ***Disseminate*** and ***democratize*** technologies for basic discovery and clinical applications

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BRAIN Research Areas Overview

- Brain Cell & Circuit Technologies
- Neural Recording & Modulation
- Neuroimaging Technologies Across Scales
- Systems Neuroscience
- Human Neuroscience

- Data Science & Informatics
- Training, Inclusion, and Equity
- Neuroethics
- Dissemination & Commercialization

Finding BRAIN Funding Opportunities

https://braininitiative.nih.gov/funding/funding-opportunities

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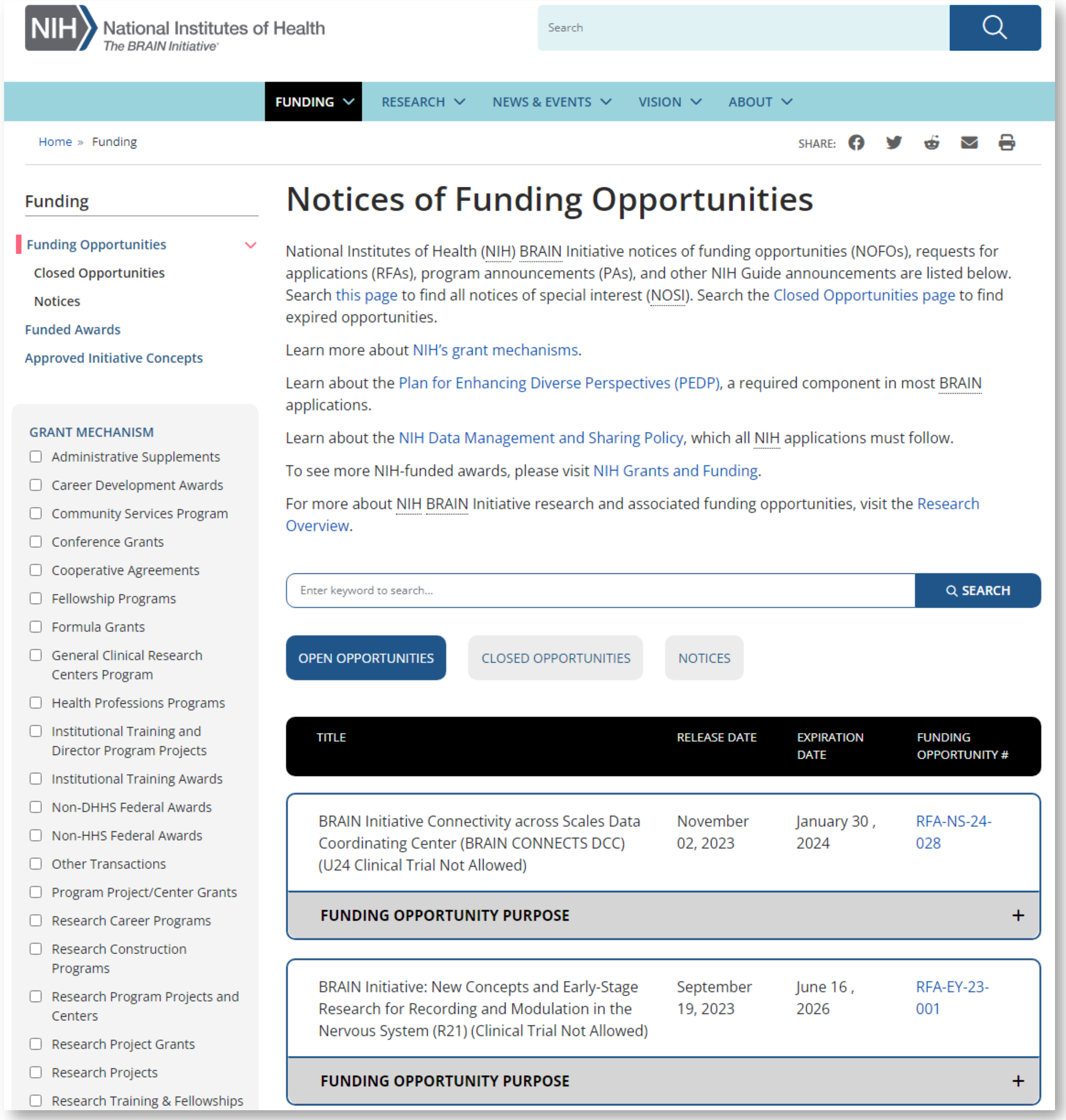
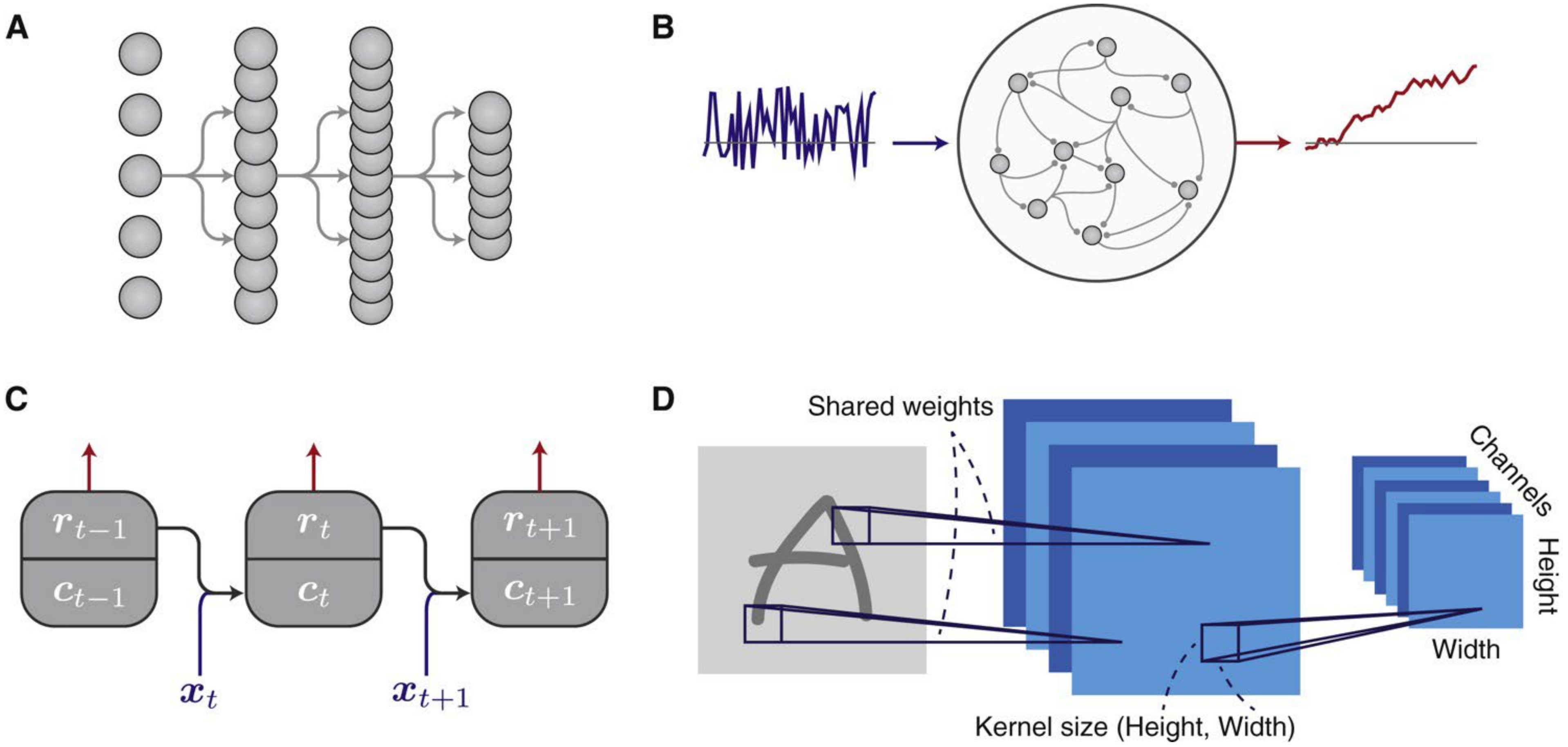


What is AI?

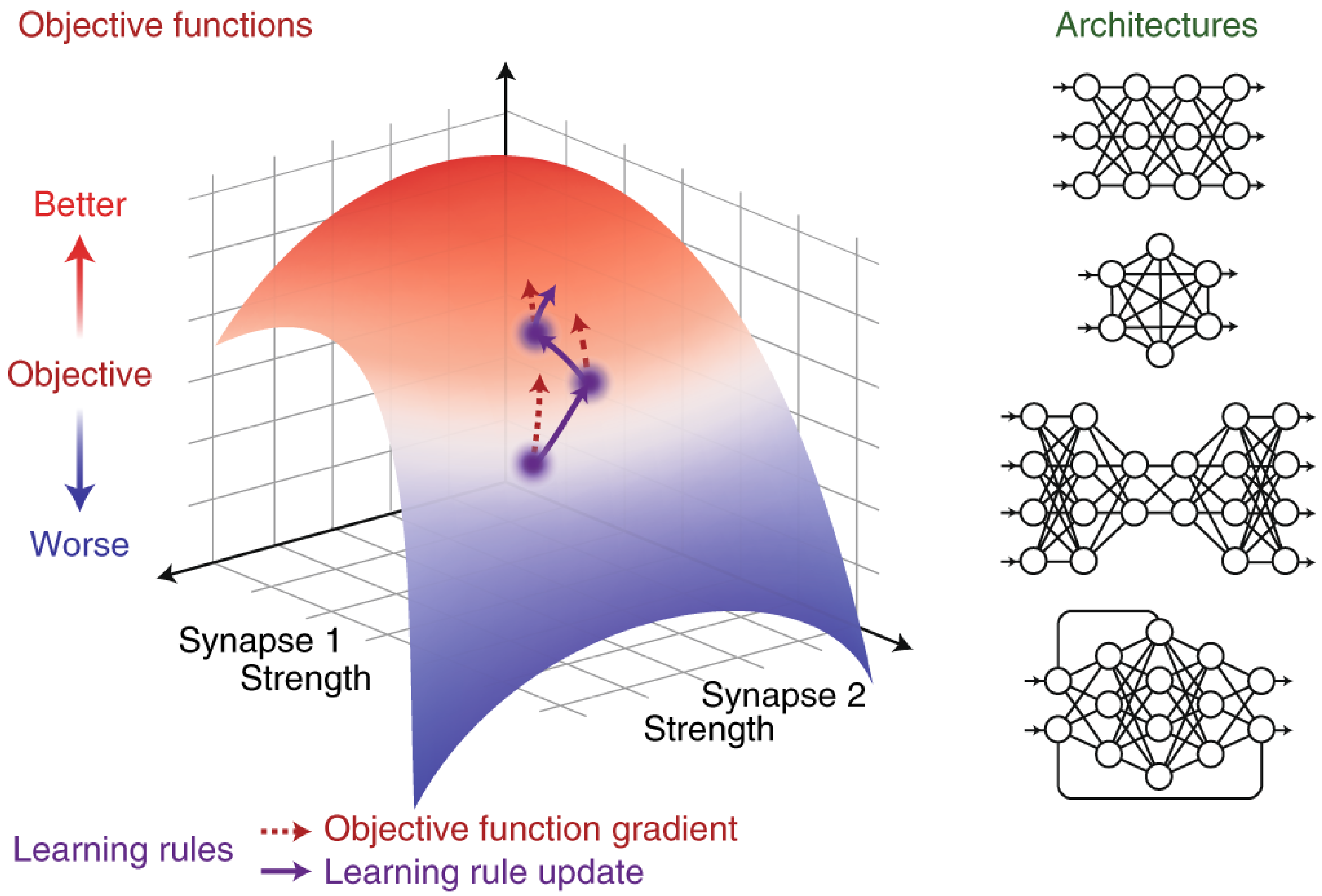
- Modern AI computing technologies are based on artificial neural networks (ANNs), which are network models of simple nodes and connections whose weights are adjusted due to training with data
- Once technical barriers to scale were surpassed, impressive capabilities of perception, cognition, and learning emerged in large ANN models, with more and more data and compute required to pre-train the biggest foundation and frontier models

Common Neural Networks Used to Understand and Analyze Neuroscience Data



Yang, G. R. & Wang, X.-J. Artificial Neural Networks for Neuroscientists: A Primer. *Neuron* **107**, 1048–1070 (2020).

Three Components: Architecture, Learning Rule, and Objective Function



Richards, B. A. et al. A deep learning framework for neuroscience. Nat. Neurosci. 22, 1761–1770 (2019).

Three Components: Architecture, Learning Rule, and Objective Function

```python

class Value:
    """ stores a single scalar value and its gradient """

    def __init__(self, data, _children=(), _op=''):
        self.data = data
        self.grad = 0
        # internal variables used for autograd graph construction
        self._backward = lambda: None
        self._prev = set(_children)
        self._op = _op # the op that produced this node, for graphviz / de

    def __add__(self, other):
        other = other if isinstance(other, Value) else Value(other)
        out = Value(self.data + other.data, (self, other), '+')

        def _backward():
            self.grad += out.grad
            other.grad += out.grad
        out._backward = _backward

        return out

    def __mul__(self, other):
        other = other if isinstance(other, Value) else Value(other)
        out = Value(self.data * other.data, (self, other), '*')

        def _backward():
            self.grad += other.data * out.grad
            other.grad += self.data * out.grad
        out._backward = _backward

        return out

    def __pow__(self, other):
        assert isinstance(other, (int, float)), "only supporting int/float
        out = Value(self.data**other, (self,), f'**{other}')

        def _backward():
            self.grad += (other * self.data**(other-1)) * out.grad
        out._backward = _backward

        return out

    def relu(self):
        out = Value(0 if self.data < 0 else self.data, (self,), 'ReLU')

        def _backward():
            self.grad += (out.data > 0) * out.grad
        out._backward = _backward

        return out

```

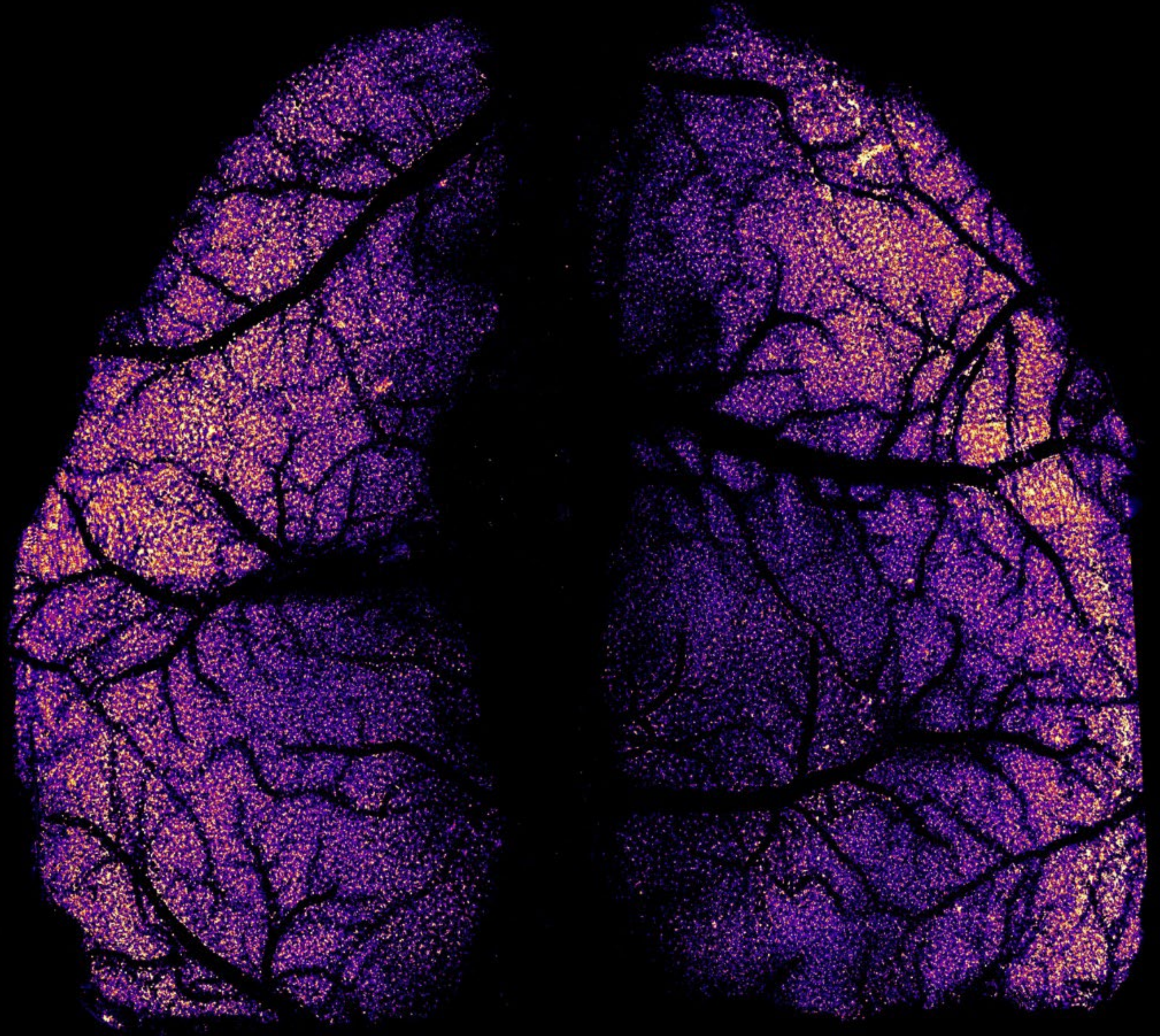
```python
    def backward(self):

        # topological order all of the children in the graph
        topo = []
        visited = set()
        def build_topo(v):
            if v not in visited:
                visited.add(v)
                for child in v._prev:
                    build_topo(child)
                topo.append(v)
        build_topo(self)

        # go one variable at a time and apply the chain rule to get its gradient
        self.grad = 1
        for v in reversed(topo):
            v._backward()

    def __neg__(self): # -self
        return self * -1

    def __radd__(self, other): # other + self
        return self + other

    def __sub__(self, other): # self - other
        return self + (-other)

    def __rsub__(self, other): # other - self
        return other + (-self)

    def __rmul__(self, other): # other * self
        return self * other

    def __truediv__(self, other): # self / other
        return self * other**-1

    def __rtruediv__(self, other): # other / self
        return other * self**-1

    def __repr__(self):
        return f"Value(data={self.data}, grad={self.grad})"
```

```python
import random
from micrograd.engine import Value

class Module:

    def zero_grad(self):
        for p in self.parameters():
            p.grad = 0

    def parameters(self):
        return []

class Neuron(Module):

    def __init__(self, nin, nonlin=True):
        self.w = [Value(random.uniform(-1,1)) for _ in range(nin)]
        self.b = Value(0)
        self.nonlin = nonlin

    def __call__(self, x):
        act = sum((wi*xi for wi,xi in zip(self.w, x)), self.b)
        return act.relu() if self.nonlin else act

    def parameters(self):
        return self.w + [self.b]

    def __repr__(self):
        return f"{'ReLU' if self.nonlin else 'Linear'}Neuron({len(self.w)})"

class Layer(Module):

    def __init__(self, nin, nout, **kwargs):
        self.neurons = [Neuron(nin, **kwargs) for _ in range(nout)]

    def __call__(self, x):
        out = [n(x) for n in self.neurons]
        return out[0] if len(out) == 1 else out

    def parameters(self):
        return [p for n in self.neurons for p in n.parameters()]

    def __repr__(self):
        return f"Layer of [{', '.join(str(n) for n in self.neurons)}]"

class MLP(Module):

    def __init__(self, nin, nouts):
        sz = [nin] + nouts
        self.layers = [Layer(sz[i], sz[i+1], nonlin=i!=len(nouts)-1) for i in range(len(nouts))]

    def __call__(self, x):
        for layer in self.layers:
            x = layer(x)
        return x

    def parameters(self):
        return [p for layer in self.layers for p in layer.parameters()]

    def __repr__(self):
        return f"MLP of [{', '.join(str(layer) for layer in self.layers)}]"
```

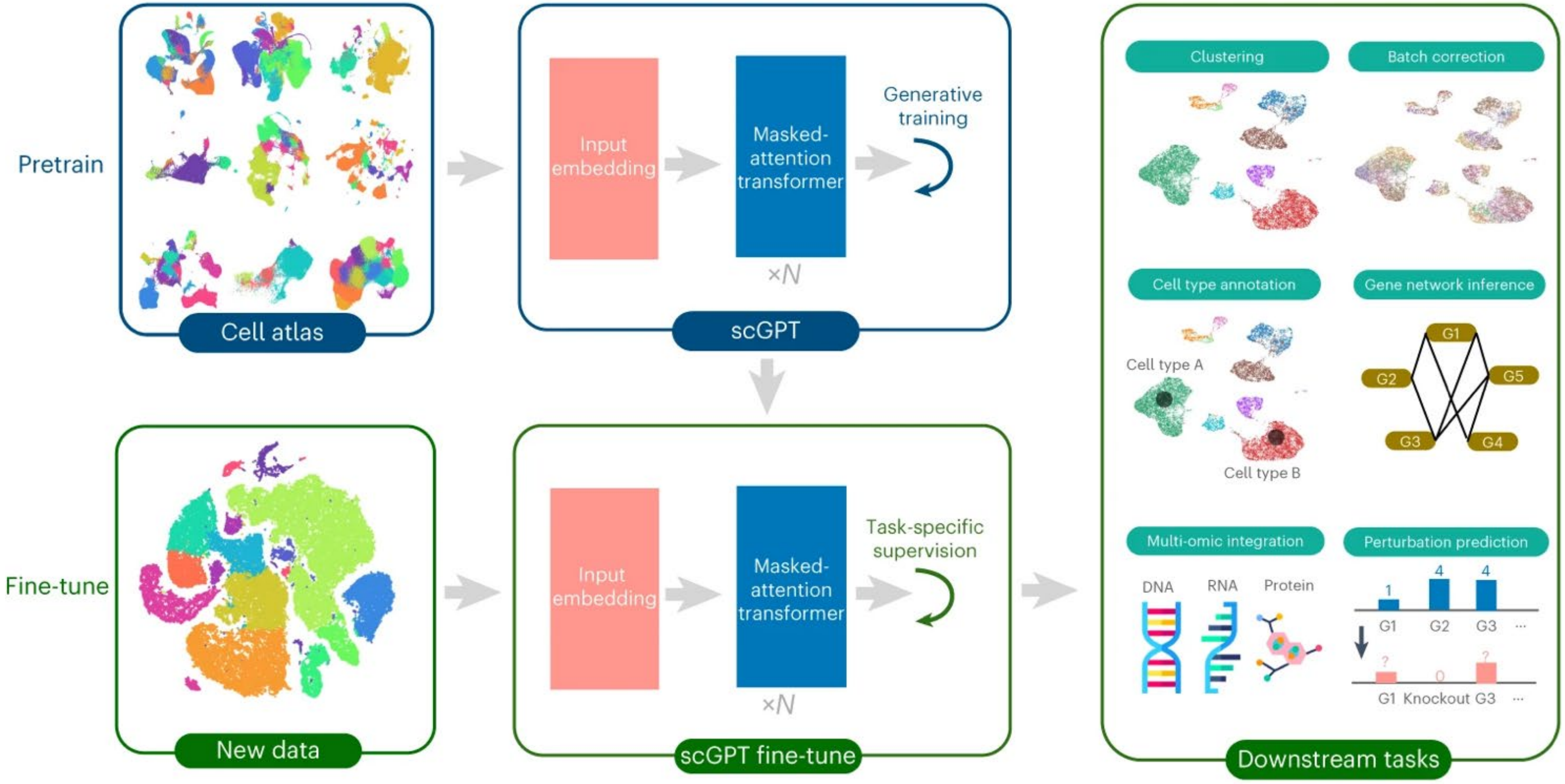
https://github.com/karpathy/micrograd

AI Applications in Neuroscience

- Hypothesis generation and theory development
- In silico modeling and physical simulation
- Encoding models to advance theory and understanding
- Neural decoding models for prediction and control
- BCIs including DBS and neuroprostheses



Pre-Training Generative Foundation Models for Single-Cell Multi-Omics



Cui, H. *et al.* scGPT: toward building a foundation model for single-cell multi-omics using generative AI. *Nat. Methods* **21**, 1470–1480 (2024).

Learning Multi-Objective Ontologies of Human Cognition and Brain Systems

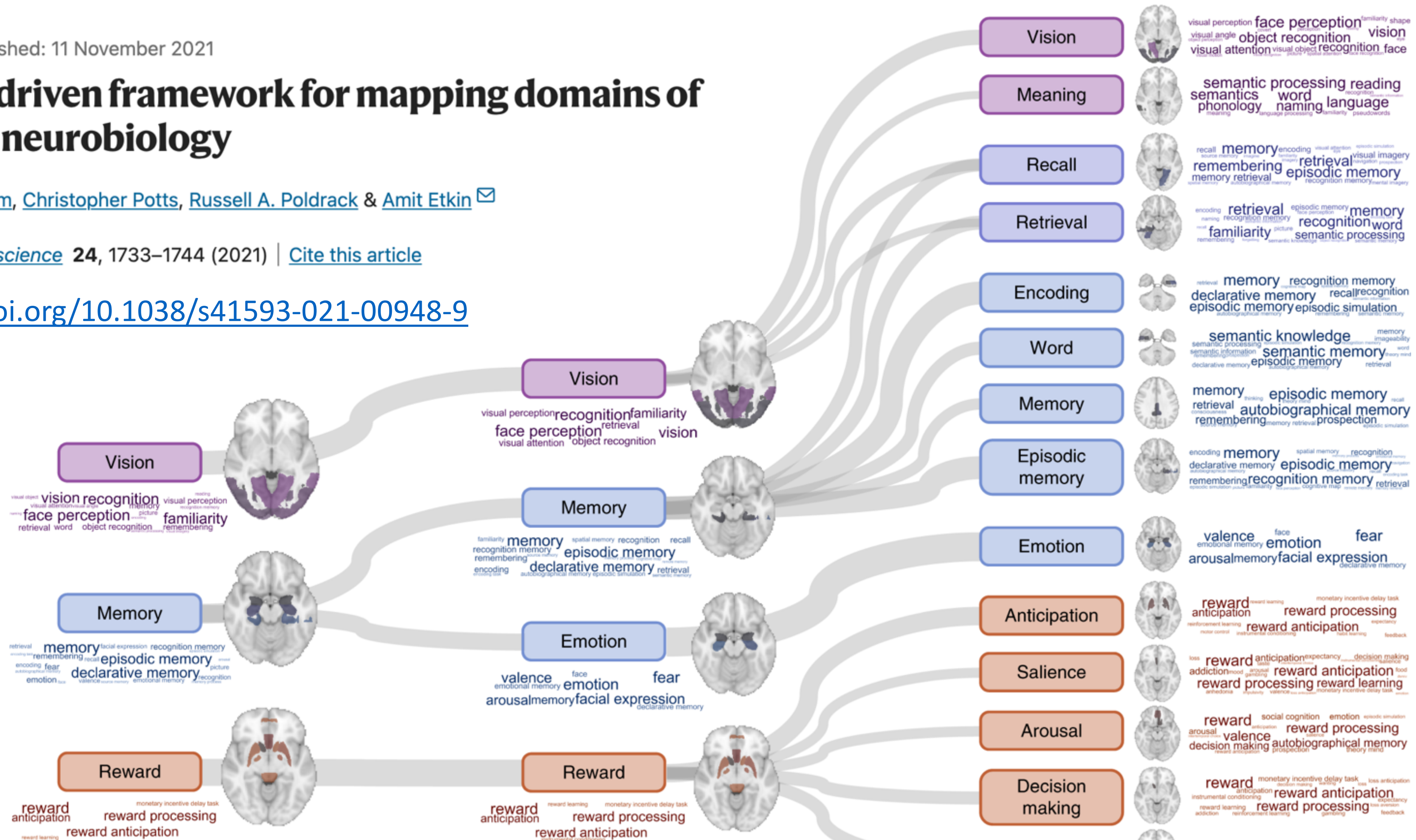
Article | Published: 11 November 2021

A data-driven framework for mapping domains of human neurobiology

Elizabeth Beam, Christopher Potts, Russell A. Poldrack & Amit Etkin

Nature Neuroscience **24**, 1733–1744 (2021) | Cite this article

https://doi.org/10.1038/s41593-021-00948-9



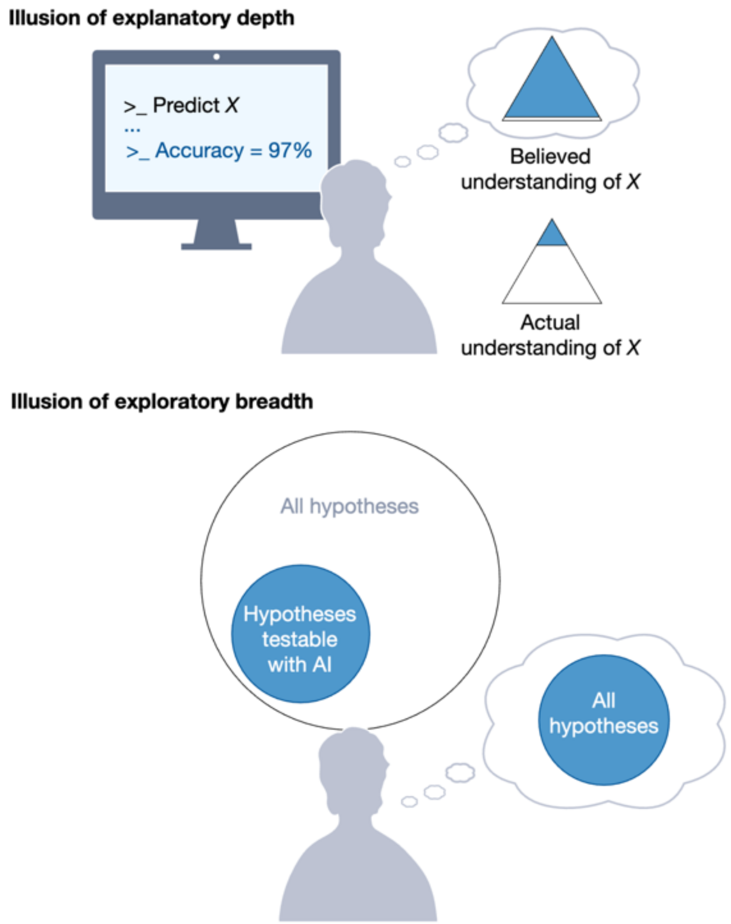
Limitations and Ethics of Generative AI and LLMs

Fundamental challenges

- Hallucinations
- Dependence on large pre-training datasets
- Intensive computational requirements
- Reasoning capabilities

Biases and other ethical considerations

- Models inherit biases of training data
- Generative models can produce harmful, offensive, skewed, or misleading output
- Different users have different assumptions about the breadth, depth, and truthfulness of the knowledge and capabilities of AI tools



Bzdok, D. *et al.* Data science opportunities of large language models for neuroscience and biomedicine. Neuron 112, 698–717 (2024).

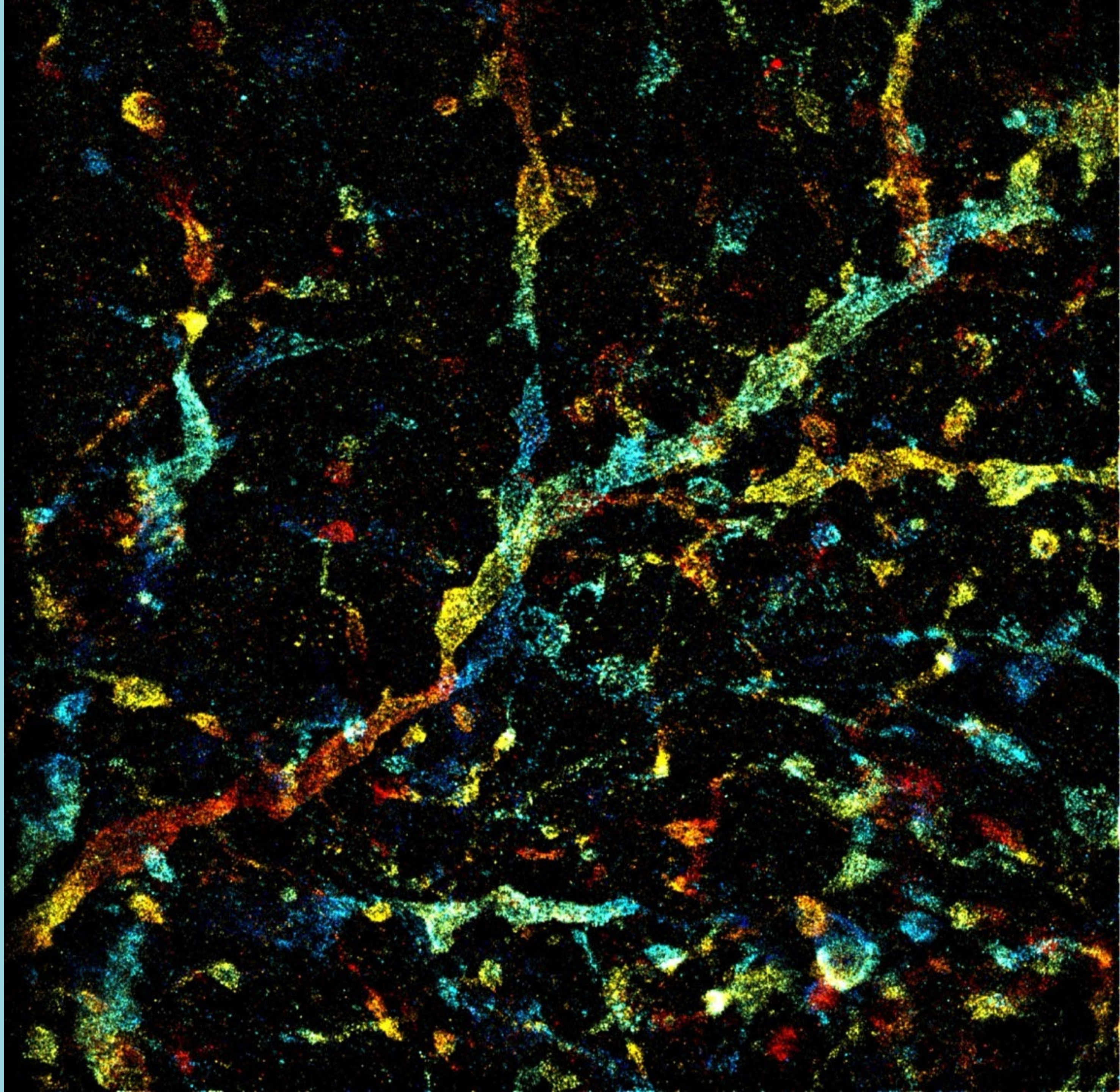
Messeri, L. & Crockett, M. J. Artificial intelligence and illusions of understanding in scientific research. Nature 627, 49–58 (2024).

The BRAIN Initiative was founded on ethical data sharing

- **BRAIN 2025 core principles**

  4. *Establish platforms for sharing data.* Public, integrated repositories for datasets and data analysis tools, with an emphasis on ready accessibility and effective central maintenance, will have immense value.

  6. *Consider ethical implications of neuroscience research*. BRAIN Initiative research may raise important uses about neural enhancement, data privacy, and appropriate use of brain data [and] should hew to the highest ethical standards for research with human subjects and with non-human animals…



The BRAIN Initiative Data Ecosystem

Mission

To promote the data science advances and data sharing & informatics infrastructure needed to leverage BRAIN-supported research data to understand the brain and enhance brain health.

Strategy & Funding Opportunities

- **BRAIN Data Science & Informatics**
  - Data Science and Informatics | BRAIN Initiative
- **BRAIN Data Archives**
  - RFA-MH-25-110: BRAIN Initiative: Data Archives for the BRAIN Initiative (R24)
- **Data Coordination and AI Centers for the BRAIN Transformative Projects**
  - RFA-MH-23-130: BRAIN BBQS Data Coordination and AI Center (U24) (*Expired example*)

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The BRAIN Data Archives

Data Archive	Data Domain	Dataset Totals
BIL (Brain Image Library)	light microscopy	5,773 datasets 473 anatomical structures 13 modalities
NeMO (The Neuroscience Multi-omic Data Archive)	multi-omics	2,964,483 files 562,648 samples 5 modalities
DANDI (Distributed Archives for Neurophysiology Data Integration)	neurophysiology behavior	698 TB 534 dandisets 1,345 users
OpenNeuro (Also integrated with NEMAR and OpenNeuroPET)	human neuroimaging	986 datasets 39,796 participants
DABI (Data Archive BRAIN Initiative)	human invasive neurophysiology	49+ studies 895+ subjects
BossDB (Brain Observatory Storage Service & Database)	electron microscopy X-ray microtomography	47 projects 9 modalities 7 species

Scientific/Research Contact & Program Officer
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BRAINshare Project Data Sharing Case Studies

- “Sharing human brain data can yield scientific benefits, but because of various disincentives, only a fraction of these data is currently shared. We profile three successful data-sharing experiences from the NIH BRAIN Initiative Research Opportunities in Humans (ROH) Consortium and demonstrate benefits to data producers and to users.”

Neuron

CellPress

NeuroView

Benefits of sharing neurophysiology data from the BRAIN Initiative Research Opportunities in Humans Consortium

Vasiliki Rahimzadeh,[1,12] Kathryn Maxson Jones,[1,2,12] Mary A. Majumder,[1] Michael J. Kahana,[3] Ueli Rutishauser,[4] Ziv M. Williams,[5] Sydney S. Cash,[6] Angelique C. Paulk,[6] Jie Zheng,[7] Michael S. Beauchamp,[8] Jennifer L. Collinger,[9] Nader Pouratian,[10] Amy L. McGuire,[1] Sameer A. Sheth,[11,*] and NIH Research Opportunities in Humans (ROH) Consortium

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[11]Department of Neurosurgery, Baylor College of Medicine, Houston, TX 77030, USA
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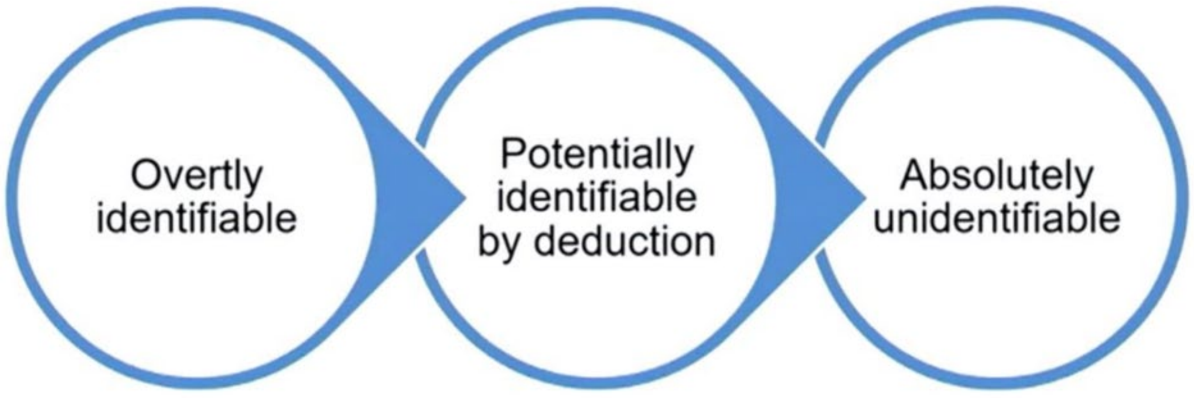
https://doi.org/10.1016/j.neuron.2023.09.029

Sharing human brain data can yield scientific benefits, but because of various disincentives, only a fraction of these data is currently shared. We profile three successful data-sharing experiences from the NIH BRAIN Initiative Research Opportunities in Humans (ROH) Consortium and demonstrate benefits to data producers and to users.

https://doi.org/10.1016/j.neuron.2023.09.029

Ethical Data Sharing for Human Research

- Identifiability has implications for ethics, oversight, and regulations
- Re-identification risk depends on the context in which data are released
- Important context includes: data types, de-identification strategies, and additional accessible data sources that could be combined with the shared research data



(Lowrance & Collins, 2007)

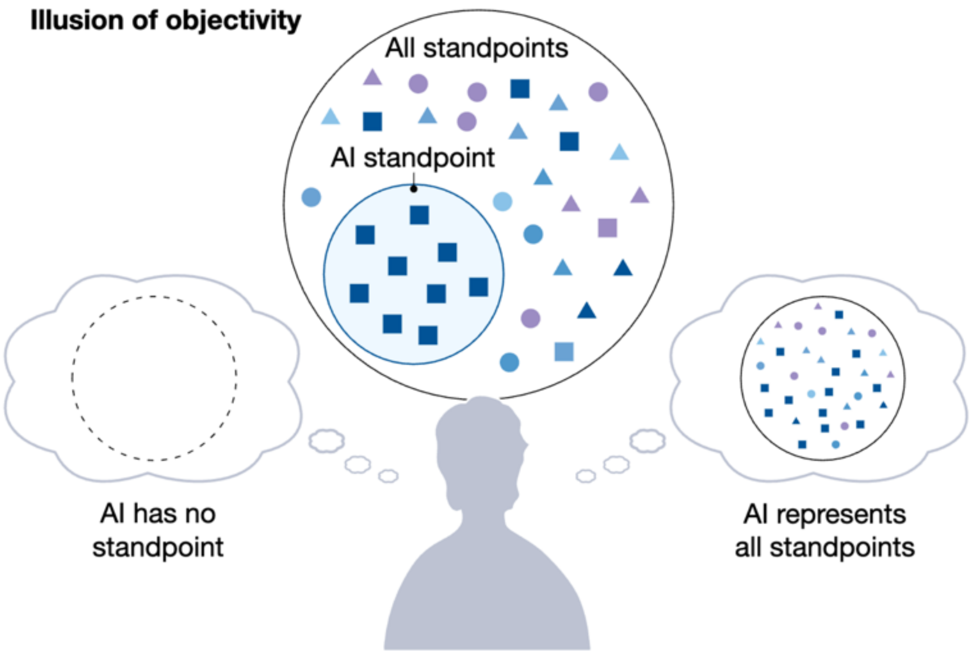
- ***There is a spectrum of identifiability depending on instrumentation, recording modalities, processing steps, and data analysis strategies***

Hendriks, S., Ramos, K. M. & Grady, C. Survey of Investigators About Sharing Human Research Data in the Neurosciences. Neurology 99, e1314–e1325 (2022). https://doi.org/10.1212/WNL.0000000000207297

For NIH Data Management and Sharing principles and best practices for human participant data, see NOT-OD-22-213.

AI Ethical Imperatives for Neuroscience? Open Models, Explainability, and Robust Data Provenance

- The output of our AI tools should be interpretable, and not *over*intepretable, to be useful, while minimizing biases in the underlying models and in how users understand the models and their output.
- Ethical applications in neuroscience and other scientific domains will be impeded by “black box” AI models based on closed weights and proprietary architectures.
- Robust tracking and updating of metadata is needed, including data provenance, consents, and conditions of use for AI training. Provenance keeps *people* in-the-loop with downstream AI and data uses.



Artificial intelligence and illusions of understanding in scientific research

https://doi.org/10.1038/s41586-024-07146-0
Lisa Messeri[1,4] & M. J. Crockett[2,3,4]
Received: 31 July 2023

https://doi.org/10.1038/s41586-024-07146-0

Recent and Upcoming Meetings

NASEM Neuroscience and AI Workshop — March 25–26, 2024

Exploring the Bidirectional Relationship between AI and Neuroscience

Session 5: Regulatory & Policy Advocacy and Engagement

- Michael Littman, NSF; *Session Moderator*
- **John Ngai, BRAIN Initiative**
- **Nita Farahany, Duke University**; NASEM *Planning Cmte*
- Eva Weicken, Fraunhofer HHI
- Wade Shen, White House OSTP; ARPA-H

NASEM Workshop Videos & Materials

UPCOMING

SfN Professional Development Workshop:

Working With and Working for AI

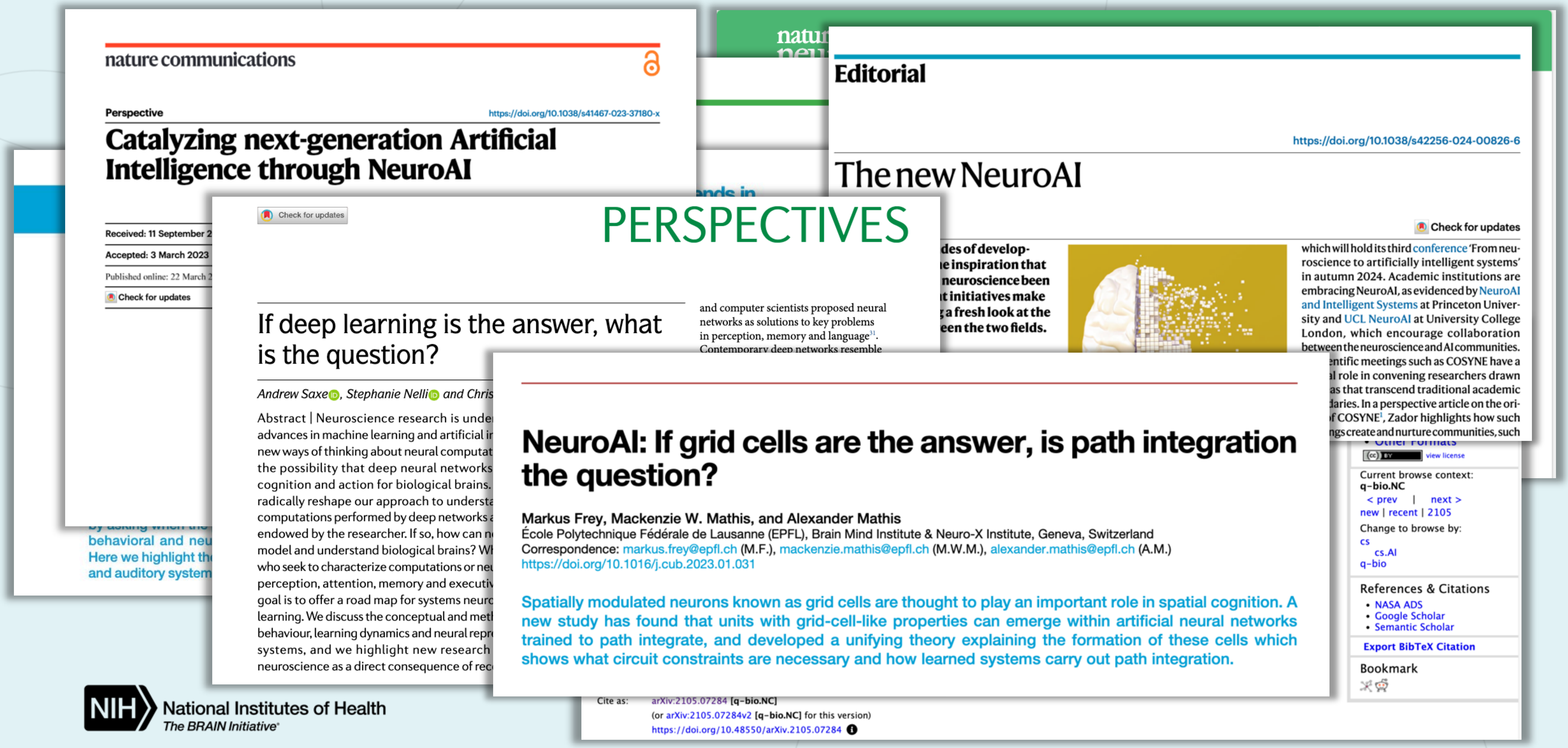
Saturday, October 5, Noon–2pm CDT

MCP Room S403, Chicago

This workshop will touch on AI applications and job opportunities that are or will be arising in this field. Speakers will address not only their employment of AI techniques but also employment opportunities in AI.

SfN 2024 Workshop Information

Neuroscience and AI: Emerging scientific questions



nature communications

Perspective

https://doi.org/10.1038/s41467-023-37180-x

Catalyzing next-generation Artificial Intelligence through NeuroAI

Received: 11 September 2…
Accepted: 3 March 2023
Published online: 22 March 2…
Check for updates

behavioral and neu…
Here we highlight th…
and auditory system…

Editorial

https://doi.org/10.1038/s42256-024-00826-6

The new NeuroAI

Check for updates

…des of develop-
…e inspiration that
…neuroscience been
…t initiatives make
…a fresh look at the
…een the two fields.

which will hold its third conference 'From neuroscience to artificially intelligent systems' in autumn 2024. Academic institutions are embracing NeuroAI, as evidenced by NeuroAI and Intelligent Systems at Princeton University and UCL NeuroAI at University College London, which encourage collaboration between the neuroscience and AI communities. …entific meetings such as COSYNE have a …l role in convening researchers drawn …as that transcend traditional academic …daries. In a perspective article on the ori…f COSYNE[1], Zador highlights how such …ngs create and nurture communities, such

Check for updates

PERSPECTIVES

If deep learning is the answer, what is the question?

Andrew Saxe, Stephanie Nelli and Chris…

Abstract | Neuroscience research is unde… advances in machine learning and artificial i… new ways of thinking about neural computat… the possibility that deep neural networks… cognition and action for biological brains. … radically reshape our approach to understa… computations performed by deep networks a… endowed by the researcher. If so, how can n… model and understand biological brains? W… who seek to characterize computations or ne… perception, attention, memory and executiv… goal is to offer a road map for systems neur… learning. We discuss the conceptual and met… behaviour, learning dynamics and neural repr… systems, and we highlight new research… neuroscience as a direct consequence of rec…

and computer scientists proposed neural networks as solutions to key problems in perception, memory and language[31]. Contemporary deep networks resemble

NeuroAI: If grid cells are the answer, is path integration the question?

Markus Frey, Mackenzie W. Mathis, and Alexander Mathis
École Polytechnique Fédérale de Lausanne (EPFL), Brain Mind Institute & Neuro-X Institute, Geneva, Switzerland
Correspondence: markus.frey@epfl.ch (M.F.), mackenzie.mathis@epfl.ch (M.W.M.), alexander.mathis@epfl.ch (A.M.)
https://doi.org/10.1016/j.cub.2023.01.031

Spatially modulated neurons known as grid cells are thought to play an important role in spatial cognition. A new study has found that units with grid-cell-like properties can emerge within artificial neural networks trained to path integrate, and developed a unifying theory explaining the formation of these cells which shows what circuit constraints are necessary and how learned systems carry out path integration.

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(or arXiv:2105.07284v2 [q-bio.NC] for this version)
https://doi.org/10.48550/arXiv.2105.07284

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Upcoming Event

The 2024 BRAIN NeuroAI Workshop

November 12th & 13th — NIH Campus, Bethesda or Virtual

This two-day hybrid workshop will bring together researchers at all career levels to discuss how BRAIN's data, tools, and technologies can accelerate scientific discovery and transformative advances at the intersection of neuroscience and AI.

The BRAIN Initiative®

Learn more about the workshop and register to attend at
https://n4solutionsllc.com/BRAINNeuroAI

NIH BRAIN NeuroAI Working Group **Joseph Monaco/NINDS [C], Grace Hwang/NINDS,** Bo-Shiun Chen/NINDS, Nina Hsu/NINDS, Pantea Moghimi/ NINDS, Sandra Molina/NINDS, Leslie Osborne/NINDS, Sudha Srinivasan/NINDS, Jay Churchill/NIMH, Michele Ferrante/NIMH, Mauricio Rangel Gomez/NIMH, Courtney Pinard/NIMH, Elizabeth Powell/NIAAA, Jessica Mollick/NIDA, Susan Wright/NIDA, Roger Miller/NIDCD, Merav Sabri/ NIDCD, Clayton Bingham/NLM, Mohd Anwar/NIBIB, Chris Kinsinger/OD, Dana Schloesser/OBSSR

Scientific Planning Committee

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- **Doris Tsao**, University of California, Berkeley
- **Gina Adam**, George Washington University
- **Blake Richards**, Mila - Quebec Artificial Intelligence Institute
- **J. Brad Aimone**, Sandia National Laboratories

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