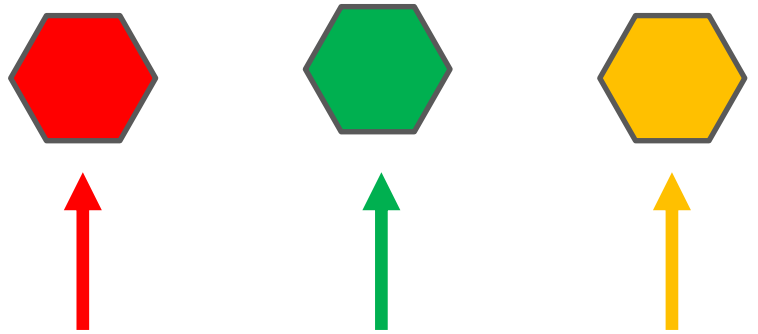
Perth Machine Learning Group

Current state of AI and where we are going with PMLG

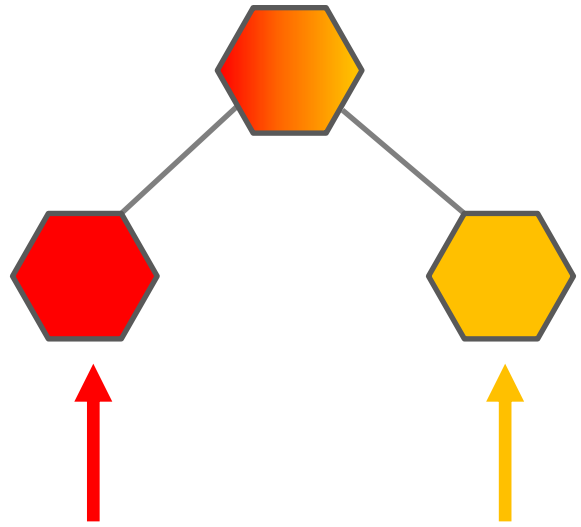
2023

AI ..
where are
we currently

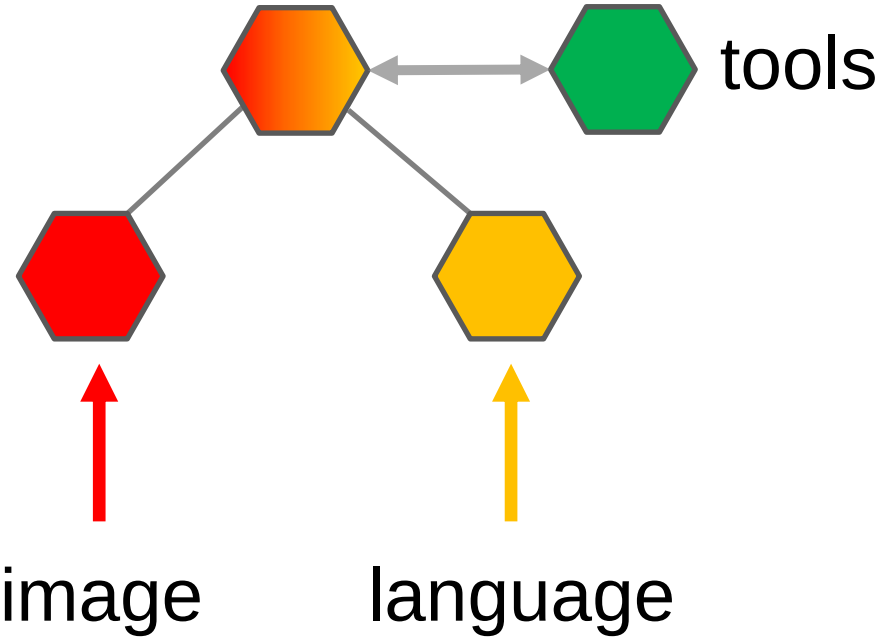
Unimodal

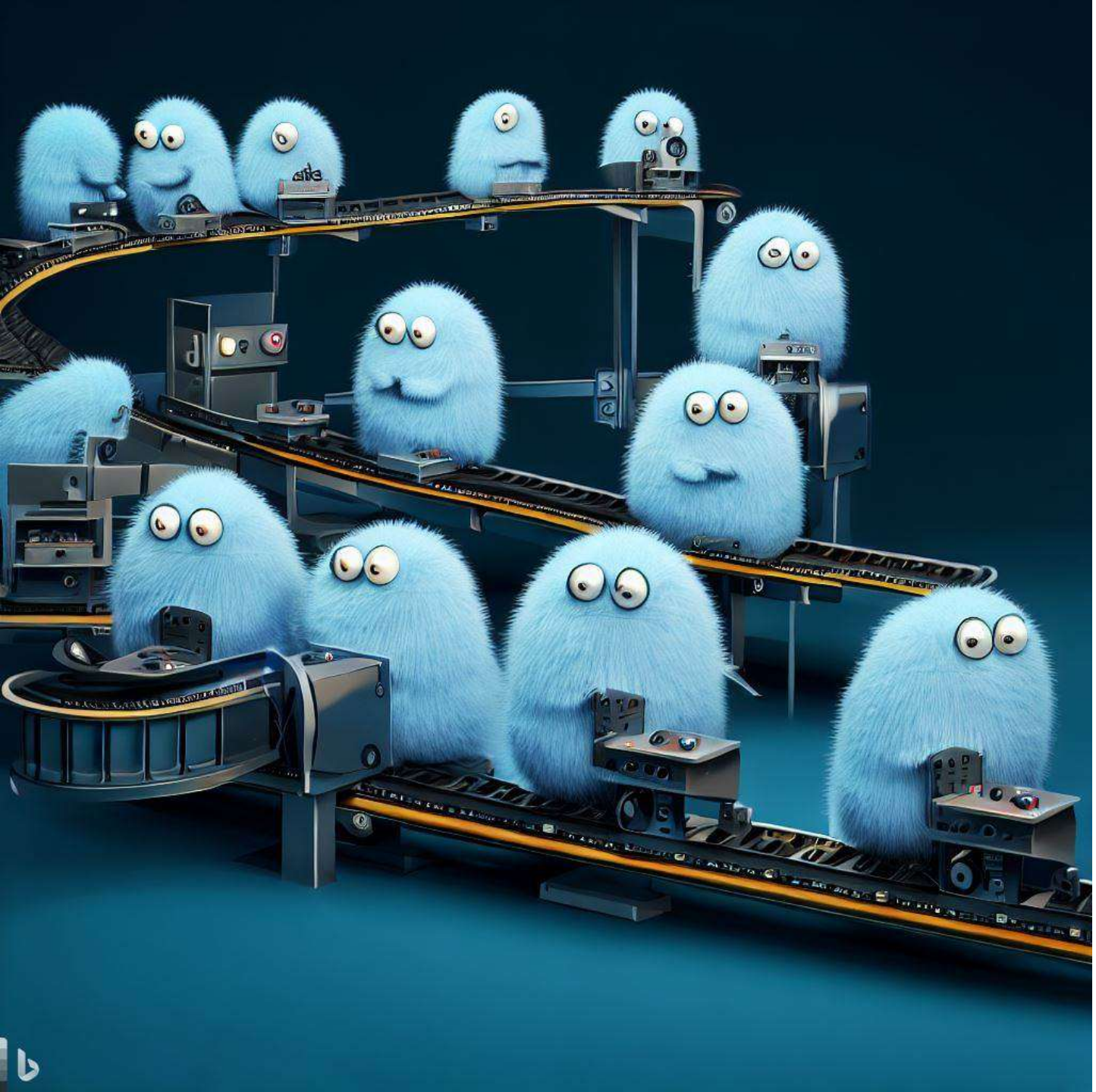


multimodal



Tool use





knowledge based

AI automation

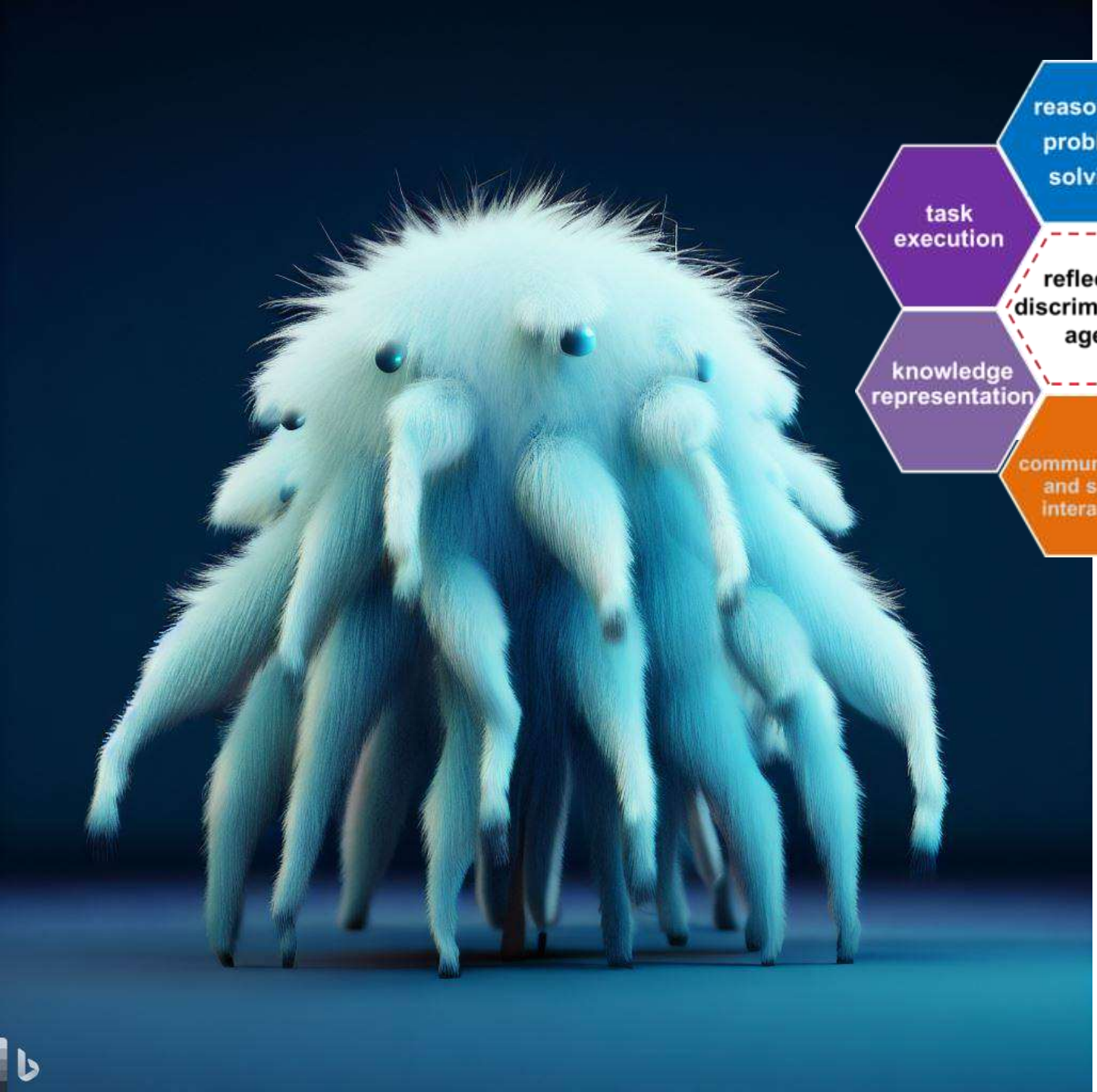
expanding memory, tasks management, and planning

..to make agents

systems of systems cognitive architecture

Executive planning

how to connect them is still an open question



Differentiable Neural Computer,
Recursive RvNN,
Neural Theorem Provers

Monte Carlo Tree Search,
World Models, etc.

Convolutional Networks (CNs),
Transformer-based LLM, etc.

Temporal Convolution networks,
Transformer-based LLM

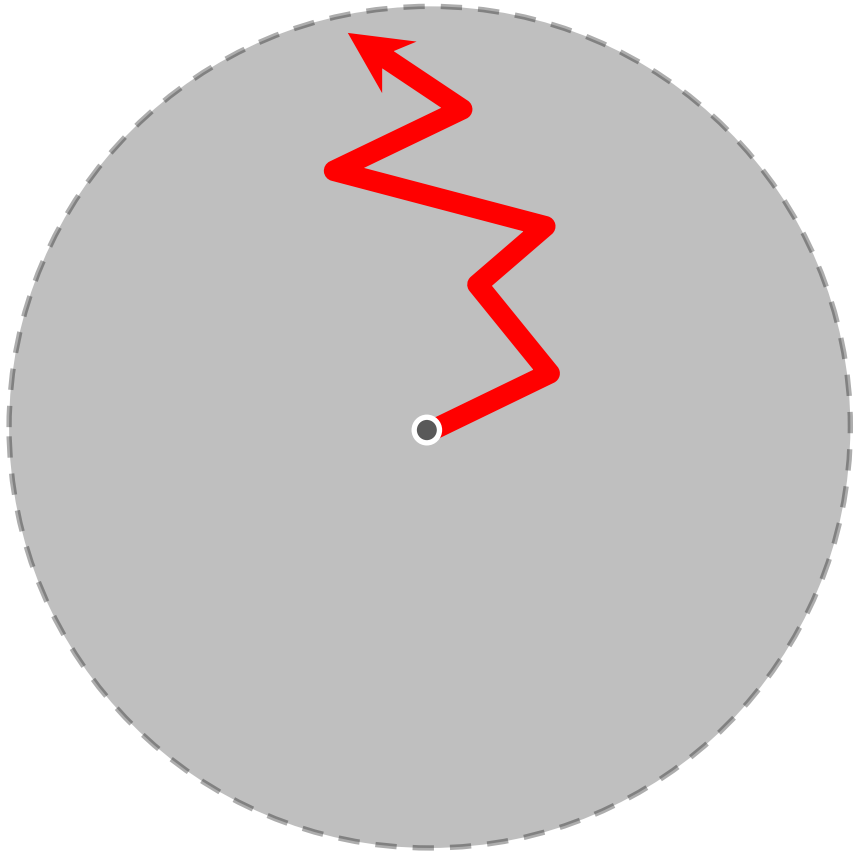
Graph Convolutional Networks,
Knowledge Graph Embeddings,
Transformer-based LLM

Hierarchical Deep RL,
Dynamic Skill Acquisition

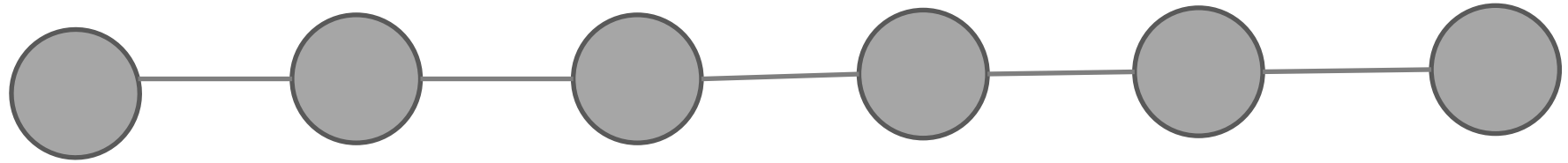
language models

Transformers

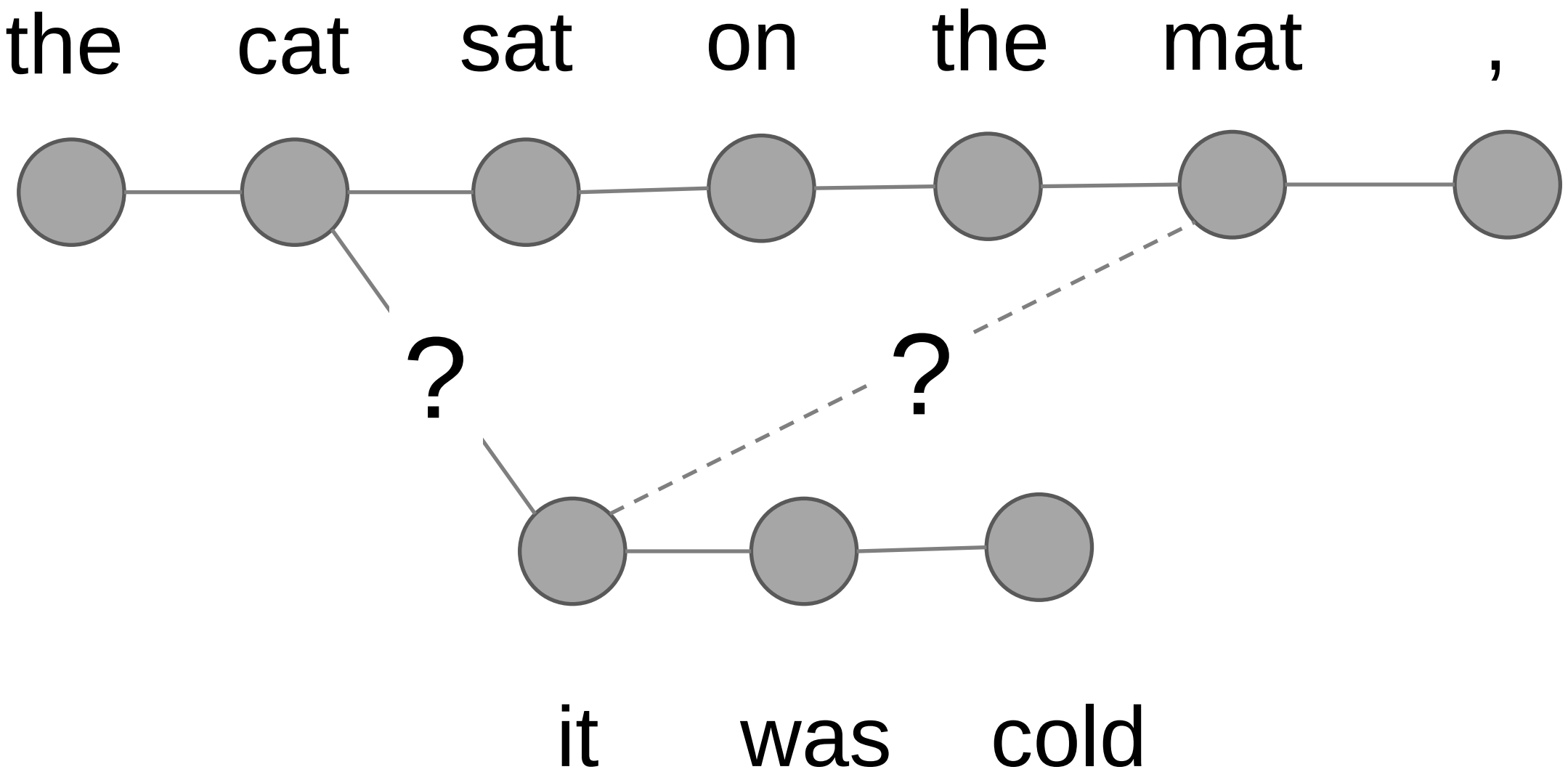
Hallucination



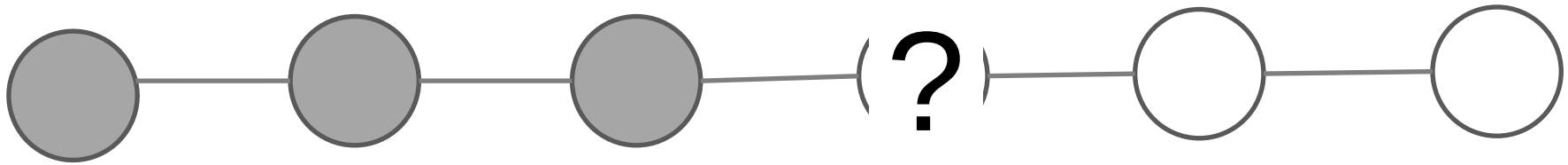
Language as a graph



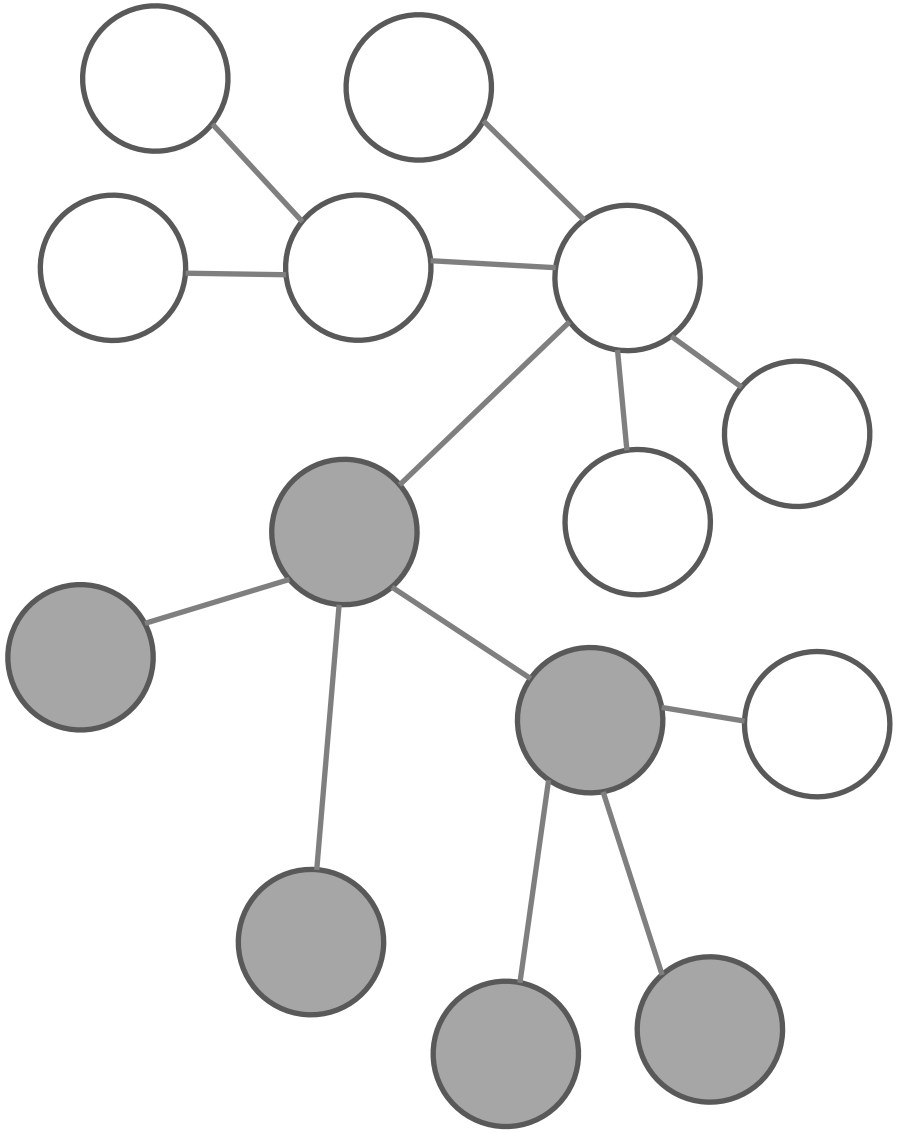
the cat sat on the mat


the
cat
sat
on
the
mat
,
?
?
it
was
cold

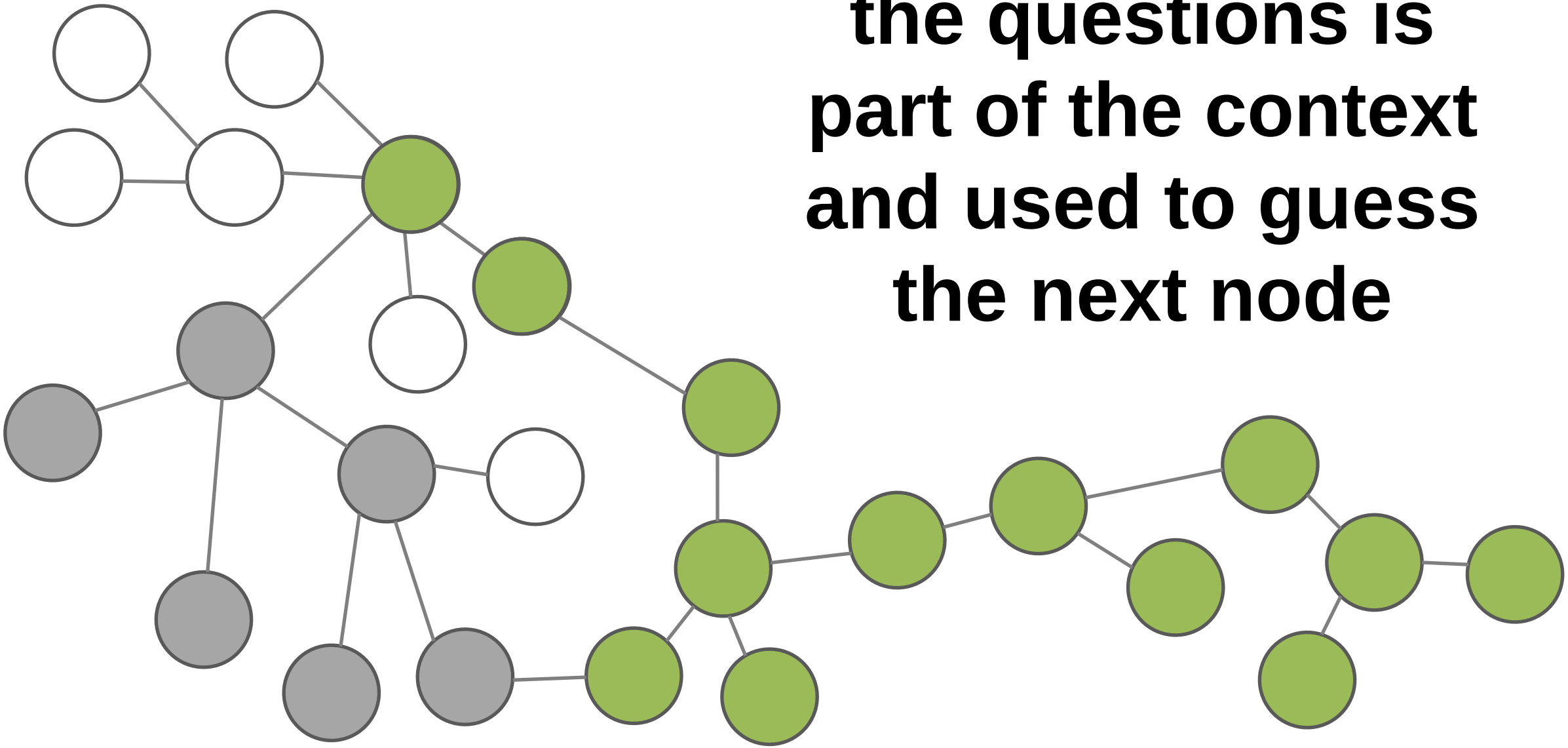
Language models trained to guess next node in graph



the cat sat the mat

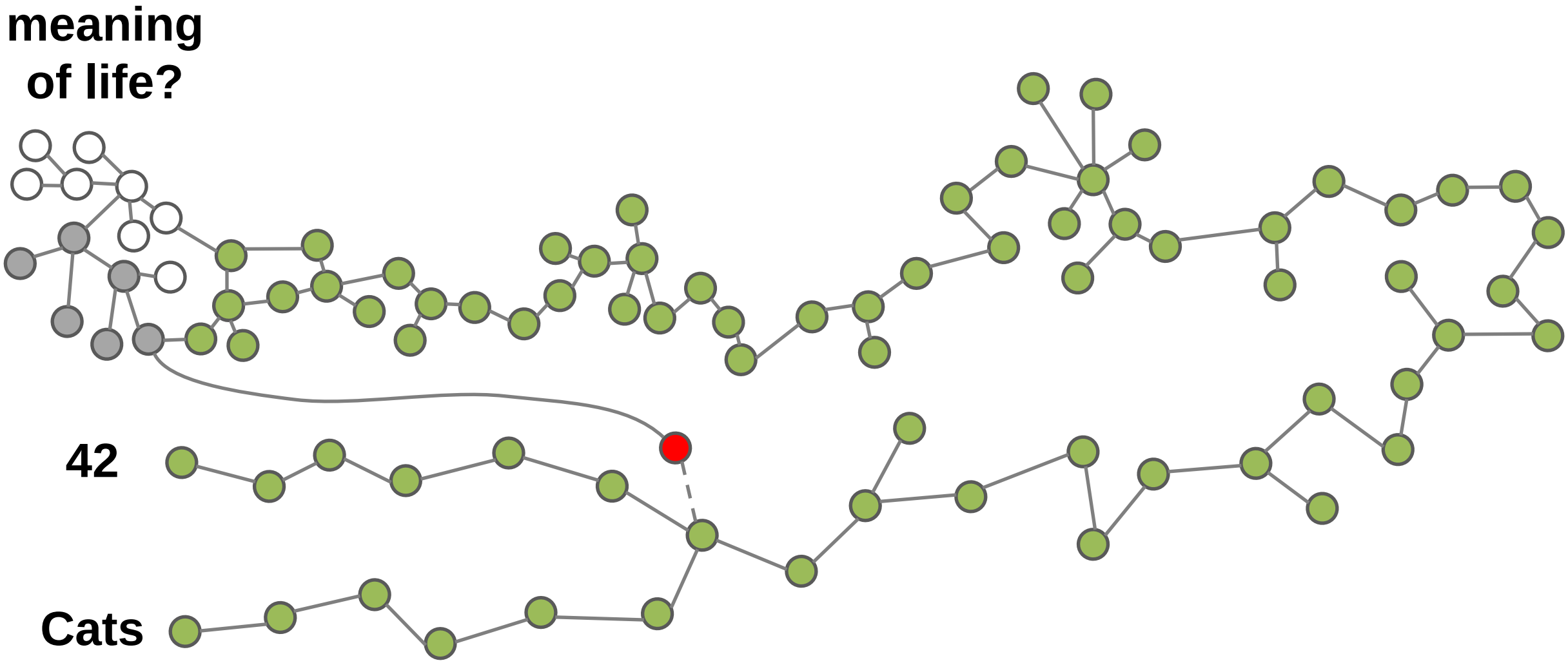


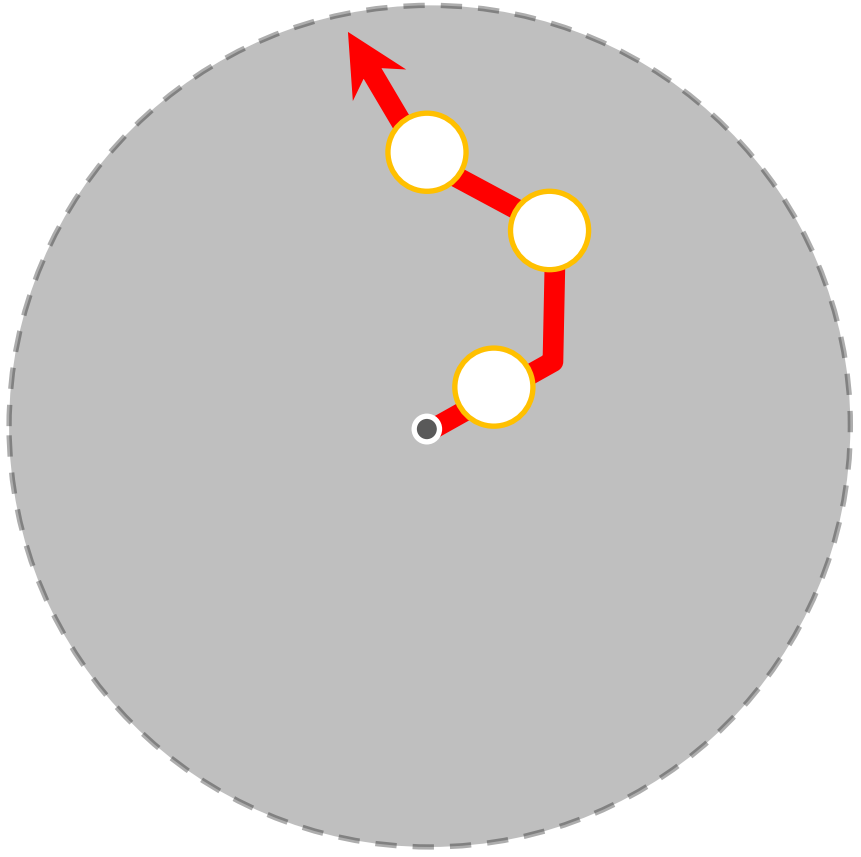
Questions are partially observed graphs



the questions is part of the context and used to guess the next node

….and extrapolates





Where do Language models store their data?

Locating and Editing Factual Associations in GPT

Locating and Editing Factual Associations in GPT

Kevin Meng[*] MIT CSAIL
David Bau[*] Northeastern University
Alex Andonian MIT CSAIL
Yonatan Belinkov[†] Technion – IIT

Abstract

We analyze the storage and recall of factual associations in autoregressive transformer language models, finding evidence that these associations correspond to localized, directly-editable computations. We first develop a causal intervention for identifying neuron *activations* that are decisive in a model's factual predictions. This reveals a distinct set of steps in middle-layer feed-forward modules that mediate factual predictions while processing subject tokens. To test our hypothesis that these computations correspond to factual association recall, we modify feed-forward *weights* to update specific factual associations using Rank-One Model Editing (ROME). We find that ROME is effective on a standard zero-shot relation extraction (zsRE) model-editing task. We also evaluate ROME on a new dataset of difficult counterfactual assertions, on which it simultaneously maintains both specificity and generalization, whereas other methods sacrifice one or another. Our results confirm an important role for mid-layer feed-forward modules in storing factual associations and suggest that direct manipulation of computational mechanisms may be a feasible approach for model editing. The code, dataset, visualizations, and an interactive demo notebook are available at https://rome.baulab.info/.

Source: https://arxiv.org/abs/2202.05262

Mass-Editing Memory in A Transformer

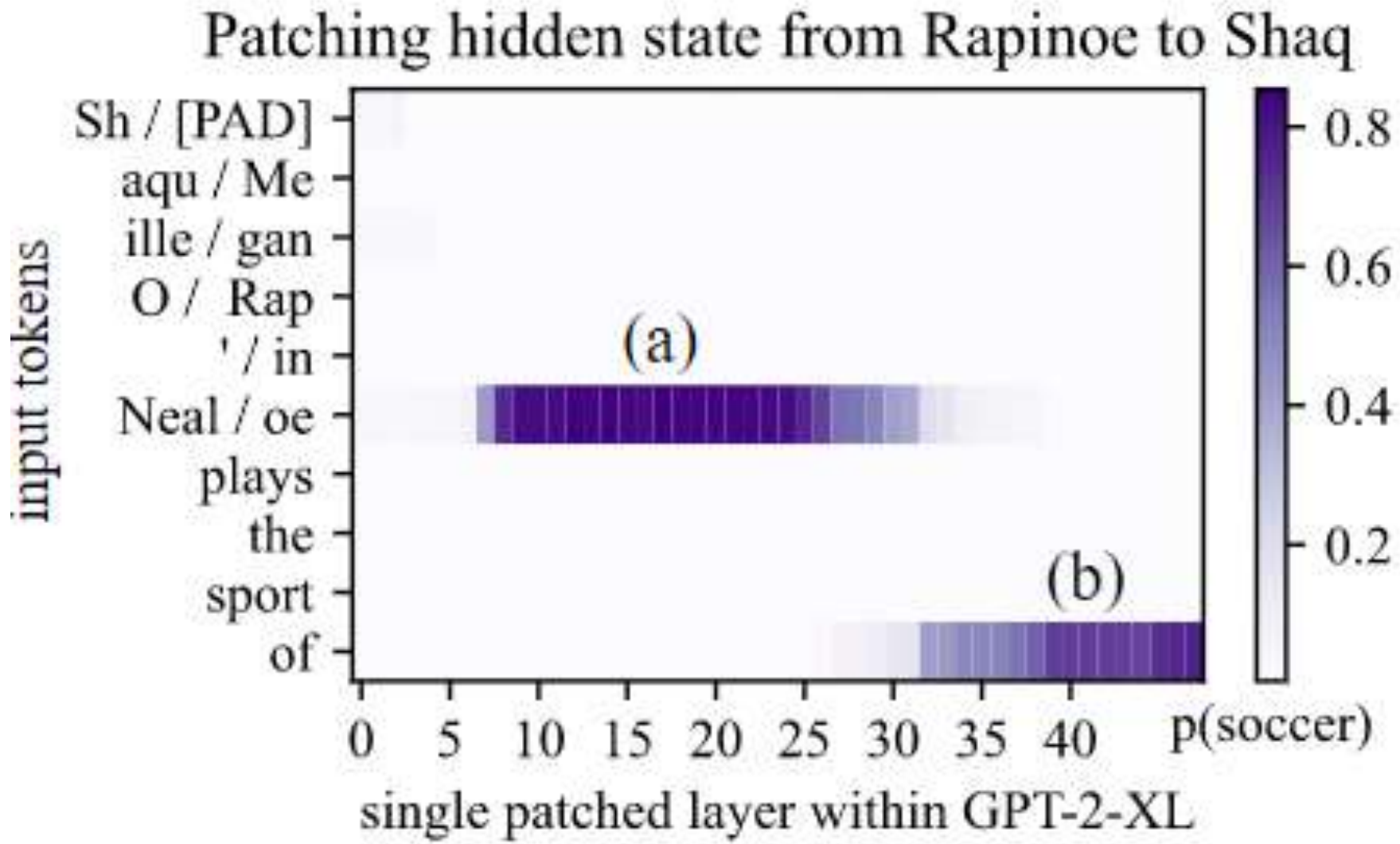
MASS-EDITING MEMORY IN A TRANSFORMER

Kevin Meng[1,2] **Arnab Sen Sharma**[2] **Alex Andonian**[1] **Yonatan Belinkov**[1,3] **David Bau**[2]
[1]MIT CSAIL [2]Northeastern University [3]Technion – IIT

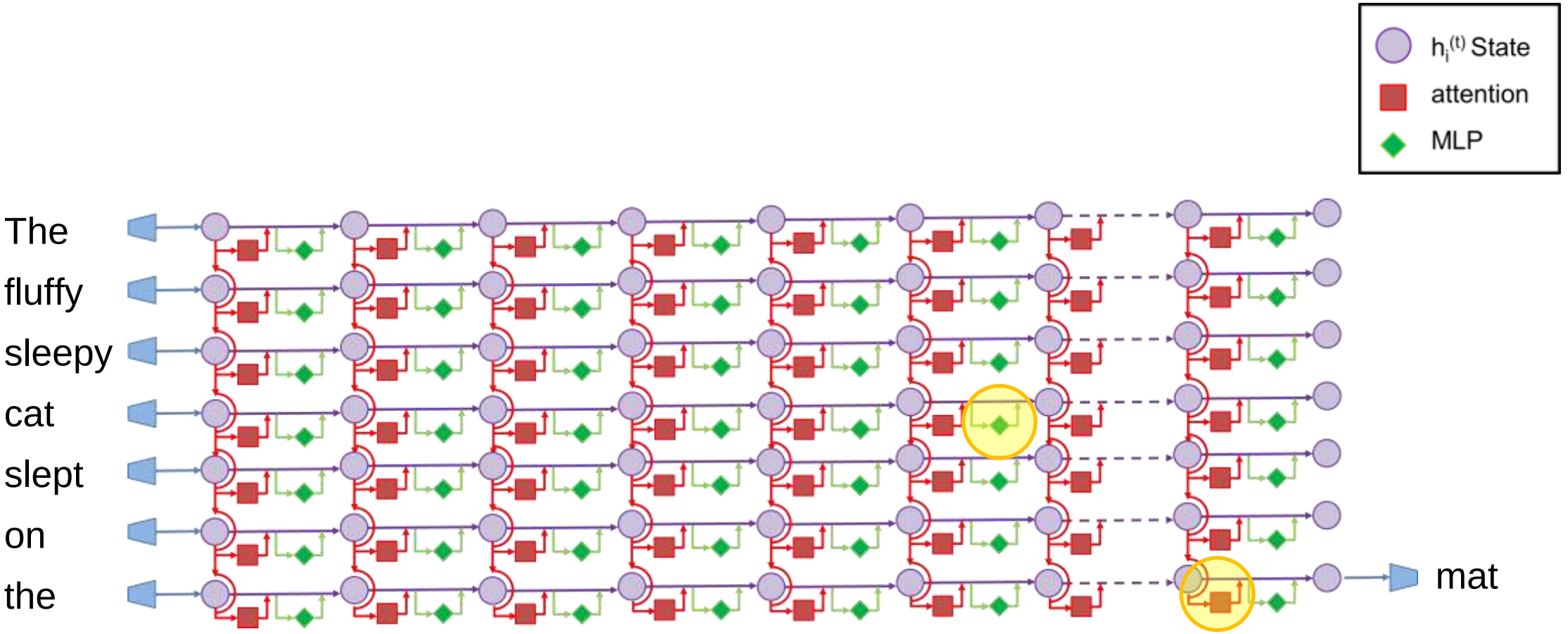
ABSTRACT

Recent work has shown exciting promise in updating large language models with new memories, so as to replace obsolete information or add specialized knowledge. However, this line of work is predominantly limited to updating single associations. We develop MEMIT, a method for directly updating a language model with many memories, demonstrating experimentally that it can scale up to *thousands of associations* for GPT-J (6B) and GPT-NeoX (20B), exceeding prior work by orders of magnitude. Our code and data are at memit.baulab.info.

Source: https://arxiv.org/abs/2210.07229



a) Knowledge retrieval in MLP b) Attention mechanism at the late site bring information to the end of the network for next word prediction



- Knowledge retrieval in mid layer MLP (Objects - nouns?)
- Attention mechanism at the late site bring information to the end of the network for next word prediction

The Tolman-Eichenbaum Machine: Unifying Space and Relational Memory through Generalization in the Hippocampal Formation

Source: https://doi.org/10.1016/j.cell.2020.10.024

Article

The Tolman-Eichenbaum Machine: Unifying Space and Relational Memory through Generalization in the Hippocampal Formation

James C.R. Whittington,[1,8,9,*] Timothy H. Muller,[1,2,8] Shirley Mark,[3] Guifen Chen,[4,5] Caswell Barry,[6,7] Neil Burgess,[2,3,4,6] and Timothy E.J. Behrens[1,3,6]

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https://doi.org/10.1016/j.cell.2020.10.024

SUMMARY

The hippocampal-entorhinal system is important for spatial and relational memory tasks. We formally link these domains, provide a mechanistic understanding of the hippocampal role in generalization, and offer unifying principles underlying many entorhinal and hippocampal cell types. We propose medial entorhinal cells form a basis describing structural knowledge, and hippocampal cells link this basis with sensory representations. Adopting these principles, we introduce the Tolman-Eichenbaum machine (TEM). After learning, TEM entorhinal cells display diverse properties resembling apparently bespoke spatial responses, such as grid, band, border, and object-vector cells. TEM hippocampal cells include place and landmark cells that remap between environments. Crucially, TEM also aligns with empirically recorded representations in complex non-spatial tasks. TEM also generates predictions that hippocampal remapping is not random as previously believed; rather, structural knowledge is preserved across environments. We confirm this structural transfer over remapping in simultaneously recorded place and grid cells.

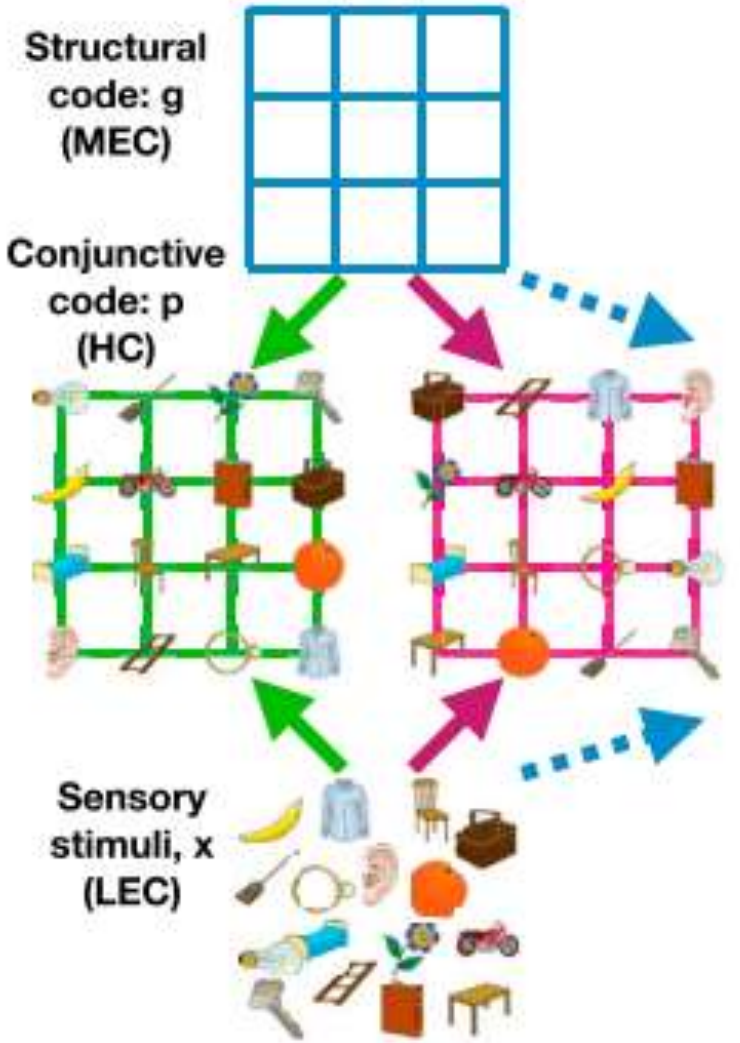
Spatial knowledge

&

Sensory representation

Abstract location Medial EC

Structural knowledge



Sensory input Lateral EC

Sensory representation

Relating Transformers to Models and Neural Representations of the Hippocampal Formation

Published as a conference paper at ICLR 2022

RELATING TRANSFORMERS TO MODELS AND NEURAL REPRESENTATIONS OF THE HIPPOCAMPAL FORMATION

James C.R. Whittington*
University of Oxford & Stanford University

Joseph Warren, Timothy E.J. Behrens
University of Oxford & University College London

ABSTRACT

Many deep neural network architectures loosely based on brain networks have recently been shown to replicate neural firing patterns observed in the brain. One of the most exciting and promising novel architectures, the Transformer neural network, was developed without the brain in mind. In this work, we show that transformers, when equipped with recurrent position encodings, replicate the precisely tuned spatial representations of the hippocampal formation; most notably place and grid cells. Furthermore, we show that this result is no surprise since it is closely related to current hippocampal models from neuroscience. We additionally show the transformer version offers dramatic performance gains over the neuroscience version. This work continues to bind computations of artificial and brain networks, offers a novel understanding of the hippocampal-cortical interaction, and suggests how wider cortical areas may perform complex tasks beyond current neuroscience models such as language comprehension.

Source: https://arxiv.org/abs/2112.04035

Associative Memory

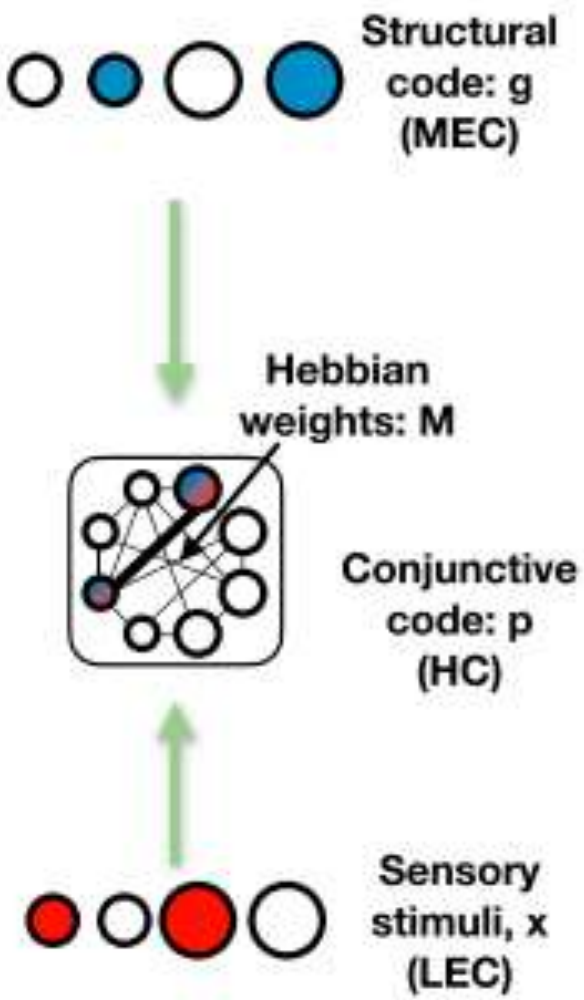
Associative Memory

Associative Memory

Associative Memory

Abstract location Medial EC

Structural knowledge



Sensory input Lateral EC

Sensory representation

Hopfield Networks is All You Need

HOPFIELD NETWORKS IS ALL YOU NEED

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Michael Widrich* **Thomas Adler*** **Lukas Gruber*** **Markus Holzleitner***
Milena Pavlović[‡,§] **Geir Kjetil Sandve[§]** **Victor Greiff[‡]** **David Kreil[†]**
Michael Kopp[†] **Günter Klambauer*** **Johannes Brandstetter*** **Sepp Hochreiter*[,†]**

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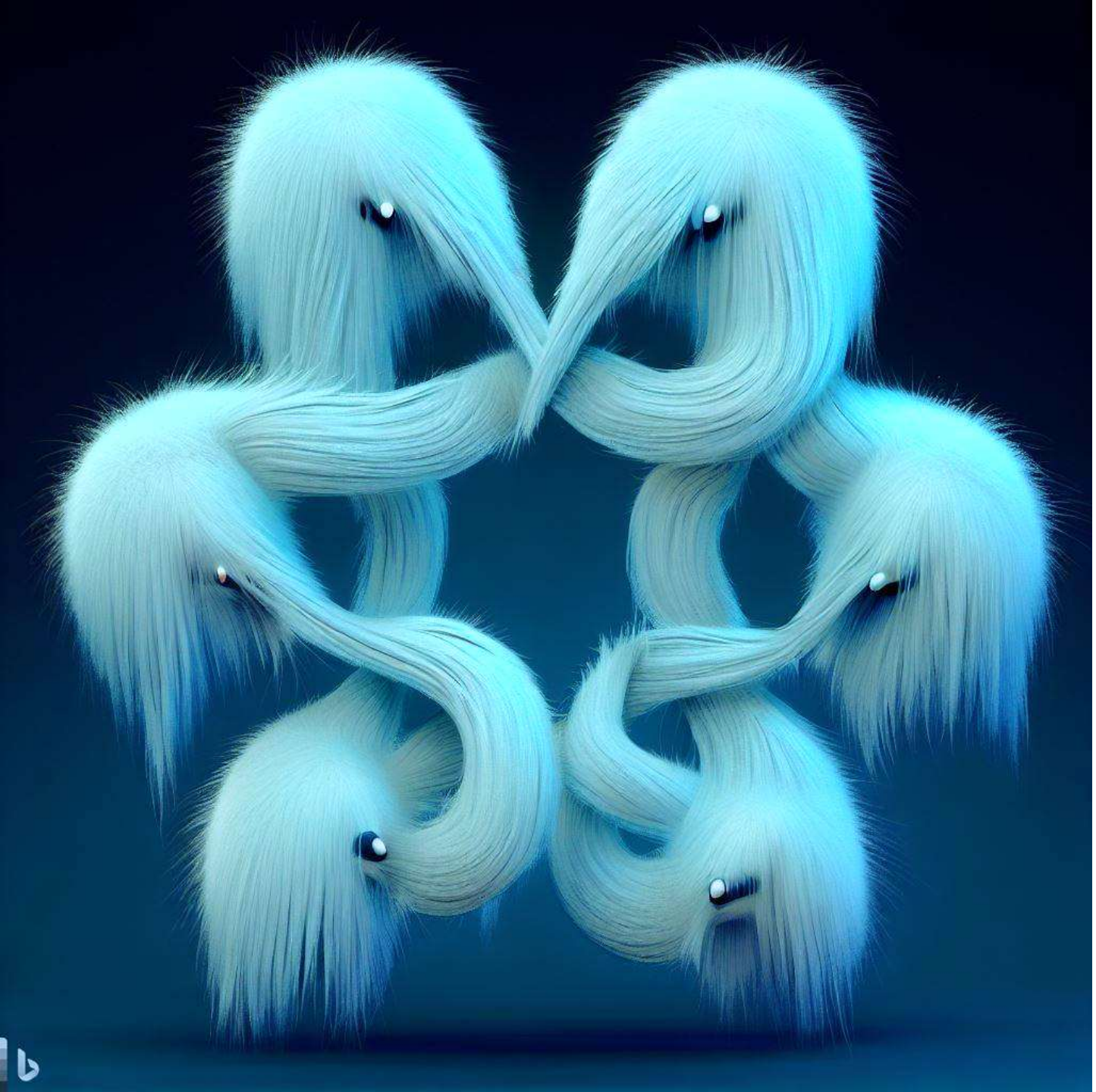
[‡]Department of Immunology, University of Oslo, Norway
[§]Department of Informatics, University of Oslo, Norway

ABSTRACT

We introduce a modern Hopfield network with continuous states and a corresponding update rule. The new Hopfield network can store exponentially (with the dimension of the associative space) many patterns, retrieves the pattern with one update, and has exponentially small retrieval errors. It has three types of energy minima (fixed points of the update): (1) global fixed point averaging over all patterns, (2) metastable states averaging over a subset of patterns, and (3) fixed points which store a single pattern. The new update rule is equivalent to the attention mechanism used in transformers. This equivalence enables a characterization of the heads of transformer models. These heads perform in the first layers preferably global averaging and in higher layers partial averaging via metastable states. The new modern Hopfield network can be integrated into deep learning architectures as layers to allow the storage of and access to raw input data, intermediate results, or learned prototypes. These Hopfield layers enable new ways of deep learning, beyond fully-connected, convolutional, or recurrent networks, and provide pooling, memory, association, and attention mechanisms. We demonstrate the broad applicability of the Hopfield layers across various domains. Hopfield layers improved state-of-the-art on three out of four considered multiple instance learning problems as well as on immune repertoire classification with several hundreds of thousands of instances. On the UCI benchmark collections of small classification tasks, where deep learning methods typically struggle, Hopfield layers yielded a new state-of-the-art when compared to different machine learning methods. Finally, Hopfield layers achieved state-of-the-art on two drug design datasets. The implementation is available at: https://github.com/ml-jku/hopfield-layers

Source: https://arxiv.org/pdf/2008.02217.pdf



Source: https://arxiv.org/pdf/2008.02217.pdf

Modern Hopfield Networks

Memory scales exponential with number of nodes

Energy Transformer

Energy Transformer

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Abstract

Transformers have become the de facto models of choice in machine learning, typically leading to impressive performance on many applications. At the same time, the architectural development in the transformer world is mostly driven by empirical findings, and the theoretical understanding of their architectural building blocks is rather limited. In contrast, Dense Associative Memory models or Modern Hopfield Networks have a well-established theoretical foundation, but have not yet demonstrated truly impressive practical results. We propose a transformer architecture that replaces the sequence of feedforward transformer blocks with a single large Associative Memory model. Our novel architecture, called Energy Transformer (or ET for short), has many of the familiar architectural primitives that are often used in the current generation of transformers. However, it is not identical to the existing architectures. The sequence of transformer layers in ET is purposely designed to minimize a specifically engineered energy function, which is responsible for representing the relationships between the tokens. As a consequence of this computational principle, the attention in ET is different from the conventional attention mechanism. In this work, we introduce the theoretical foundations of ET, explore it's empirical capabilities using the image completion task, and obtain strong quantitative results on the graph anomaly detection task.

Source: https://arxiv.org/abs/2302.07253

https://www.youtube.com/watch?v=5LXiQUsnHrI

Backprop?

Fine Tuning Language Models with Just Forward Passes

Fine-Tuning Language Models with Just Forward Passes

Sadhika Malladi* Tianyu Gao* Eshaan Nichani Alex Damian

Jason D. Lee Danqi Chen Sanjeev Arora

Princeton University

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Abstract

Fine-tuning language models (LMs) has yielded success on diverse downstream tasks, but as LMs grow in size, backpropagation requires a prohibitively large amount of memory. Zeroth-order (ZO) methods can in principle estimate gradients using only two forward passes but are theorized to be catastrophically slow for optimizing large models. In this work, we propose a memory-efficient zeroth-order optimizer (**MeZO**), adapting the classical ZO-SGD method to operate in-place, thereby fine-tuning LMs with *the same memory footprint as inference*. For example, with a single A100 80GB GPU, MeZO can train a 30-billion parameter model, whereas fine-tuning with backpropagation can train only a 2.7B LM with the same budget. We conduct comprehensive experiments across model types (masked and autoregressive LMs), model scales (up to 66B), and downstream tasks (classification, multiple-choice, and generation). Our results demonstrate that (1) MeZO significantly outperforms in-context learning and linear probing; (2) MeZO achieves comparable performance to fine-tuning with backpropagation across multiple tasks, with up to 12× memory reduction; (3) MeZO is compatible with both full-parameter and parameter-efficient tuning techniques such as LoRA and prefix tuning; (4) MeZO can effectively optimize non-differentiable objectives (e.g., maximizing accuracy or F1). We support our empirical findings with theoretical insights, highlighting how adequate pre-training and task prompts enable MeZO to fine-tune huge models, despite classical ZO analyses suggesting otherwise.[2]

Source: https://arxiv.org/abs/2305.17333

Forward-Forward Training of an Optical Neural Network

Forward-Forward Training of an Optical Neural Network

Ilker Oguz[1,*], Junjie Ke[2], Qifei Wang[2], Feng Yang[2], Mustafa Yildirim[1], Niyazi Ulas Dinc[1], Jih-Liang Hsieh[1], Christophe Moser[1] and Demetri Psaltis[1]

[1] IEM, EPFL, Switzerland

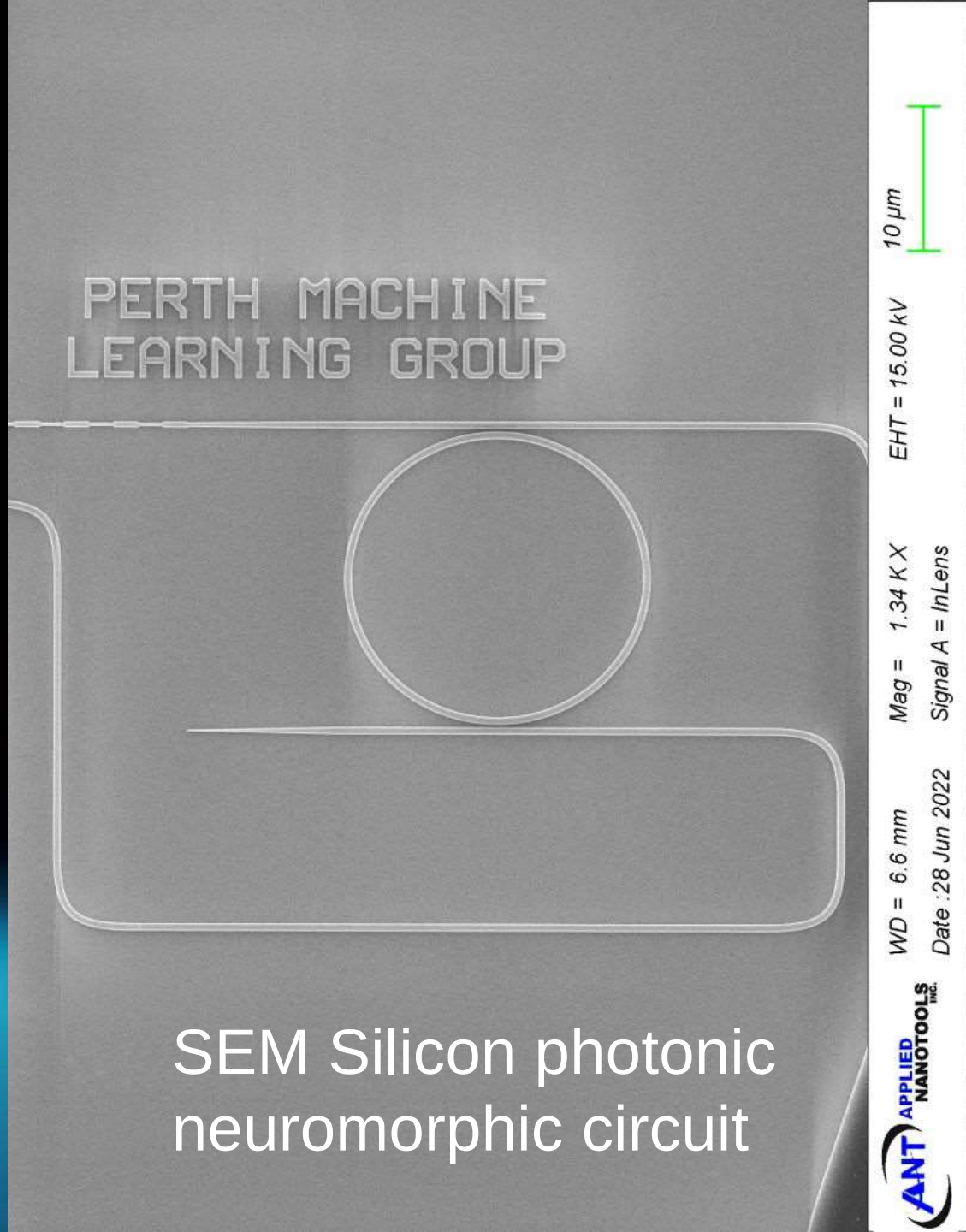
[2] Google Research, USA

*ilker.oguz@epfl.ch

Abstract

Neural networks (NN) have demonstrated remarkable capabilities in various tasks, but their computation-intensive nature demands faster and more energy-efficient hardware implementations. Optics-based platforms, using technologies such as silicon photonics and spatial light modulators, offer promising avenues for achieving this goal. However, training multiple trainable layers in tandem with these physical systems poses challenges, as they are difficult to fully characterize and describe with differentiable functions, hindering the use of error backpropagation algorithm. The recently introduced Forward-Forward Algorithm (FFA) eliminates the need for perfect characterization of the learning system and shows promise for efficient training with large numbers of programmable parameters. The FFA does not require backpropagating an error signal to update the weights, rather the weights are updated by only sending information in one direction. The local loss function for each set of trainable weights enables low-power analog hardware implementations without resorting to metaheuristic algorithms or reinforcement learning. In this paper, we present an experiment utilizing multimode nonlinear wave propagation in an optical fiber demonstrating the feasibility of the FFA approach using an optical system. The results show that incorporating optical transforms in multilayer NN architectures trained with the FFA, can lead to performance improvements, even with a relatively small number of trainable weights. The proposed method offers a new path to the challenge of training optical NNs and provides insights into leveraging physical transformations for enhancing NN performance.

Source: https://arxiv.org/abs/2305.19170



SEM Silicon photonic neuromorphic circuit

Frozen Graphs

Plasticity

Continual learning

Compositionality

Topological Deep Learning: Going Beyond Graph Data

Topological Deep Learning: Going Beyond Graph Data

Abstract

Topological deep learning is a rapidly growing field that pertains to the development of deep learning models for data supported on topological domains such as simplicial complexes, cell complexes, and hypergraphs, which generalize many domains encountered in scientific computations. In this paper, we present a unifying deep learning framework built upon a richer data structure that includes widely adopted topological domains.

Specifically, we first introduce *combinatorial complexes*, a novel type of topological domain. Combinatorial complexes can be seen as generalizations of graphs that maintain certain desirable properties. Similar to hypergraphs, combinatorial complexes impose no constraints on the set of relations. In addition, combinatorial complexes permit the construction of hierarchical higher-order relations, analogous to those found in simplicial and cell complexes. Thus, combinatorial complexes generalize and combine useful traits of both hypergraphs and cell complexes, which have emerged as two promising abstractions that facilitate the generalization of graph neural networks to topological spaces.

Second, building upon combinatorial complexes and their rich combinatorial and algebraic structure, we develop a general class of message-passing *combinatorial complex neural networks (CCNNs)*, focusing primarily on attention-based CCNNs. We characterize permutation and orientation equivariances of CCNNs, and discuss pooling and unpooling operations within CCNNs in detail.

Third, we evaluate the performance of CCNNs on tasks related to mesh shape analysis and graph learning. Our experiments demonstrate that CCNNs have competitive performance as compared to state-of-the-art deep learning models specifically tailored to the same tasks. Our findings demonstrate the advantages of incorporating higher-order relations into deep learning models in different applications.

Source: https://arxiv.org/abs/2206.00606

what might change in the future

A Path Towards Autonomous Machine Intelligence

A Path Towards Autonomous Machine Intelligence
Version 0.9.2, 2022-06-27

Yann LeCun
Courant Institute of Mathematical Sciences, New York University yann@cs.nyu.edu
Meta - Fundamental AI Research yann@fb.com

June 27, 2022

Abstract

How could machines learn as efficiently as humans and animals? How could machines learn to reason and plan? How could machines learn representations of percepts and action plans at multiple levels of abstraction, enabling them to reason, predict, and plan at multiple time horizons? This position paper proposes an architecture and training paradigms with which to construct autonomous intelligent agents. It combines concepts such as configurable predictive world model, behavior driven through intrinsic motivation, and hierarchical joint embedding architectures trained with self-supervised learning.

Keywords: Artificial Intelligence, Machine Common Sense, Cognitive Architecture, Deep Learning, Self-Supervised Learning, Energy-Based Model, World Models, Joint Embedding Architecture, Intrinsic Motivation.

Source: https://openreview.net/pdf?id=BZ5a1r-kVsf

But doing something like the Brain in an unexpected way

- Memory plasticity not frozen models
- Continual learning
- Better spatial and subject representation
- Larger contexts?
- Compositional graphs

- Transformers are working on graphs and nodes
- Function is very similar to parts of the brain
- The models of these parts of the brain blend spatial/structural and sensory inputs
- The division of spatial and structural input may also seen in transformers
- This knowledge could guide us on how we can better train transformers
- Transformers layers behave as a special case of Modern Hopfield networks
- Modern Hopfield networks are capable of continuous learning and don’t need backprop
- You can train regular Transformers without backprop too
- Modern Hopfield networks storage capability scales exponentially with nodes
- Hopfield networks are energy based models, potentially keys in well with JEPA style architectures

- My guess this is what is being worked on now for the next generation of models.
- Capabilities, continual learning, not frozen graph
- May see large improvements in small models, as we address learning.
- Potential for planning capability
- Orientation to more executive coordinating role in cognitive architectures

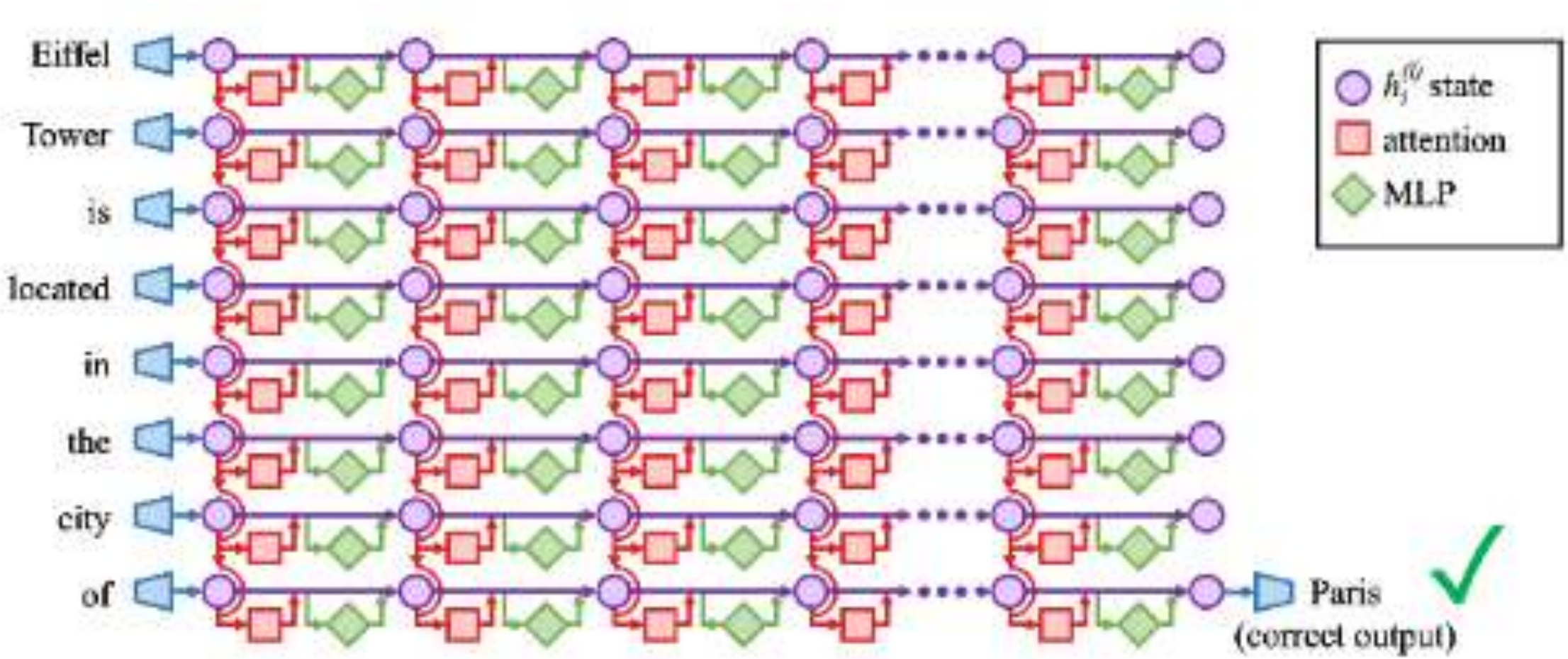
RELATING TRANSFORMERS TO MODELS AND NEURAL REPRESENTATIONS OF THE HIPPOCAMPAL FORMATION

James C.R. Whittington*
University of Oxford & Stanford University

Joseph Warren, Timothy E.J. Behrens
University of Oxford & University College London

ABSTRACT

Many deep neural network architectures loosely based on brain networks have recently been shown to replicate neural firing patterns observed in the brain. One of the most exciting and promising novel architectures, the Transformer neural network, was developed without the brain in mind. In this work, we show that transformers, when equipped with recurrent position encodings, replicate the precisely tuned spatial representations of the hippocampal formation; most notably place and grid cells. Furthermore, we show that this result is no surprise since it is closely related to current hippocampal models from neuroscience. We additionally show the transformer version offers dramatic performance gains over the neuroscience version. This work continues to bind computations of artificial and brain networks, offers a novel understanding of the hippocampal-cortical interaction, and suggests how wider cortical areas may perform complex tasks beyond current neuroscience models such as language comprehension.



a) Knowledge retrieval in MLP b) Attention mechanism at the late site bring information to the end of the network for next word prediction

Find out more about PMLG

Collaboration

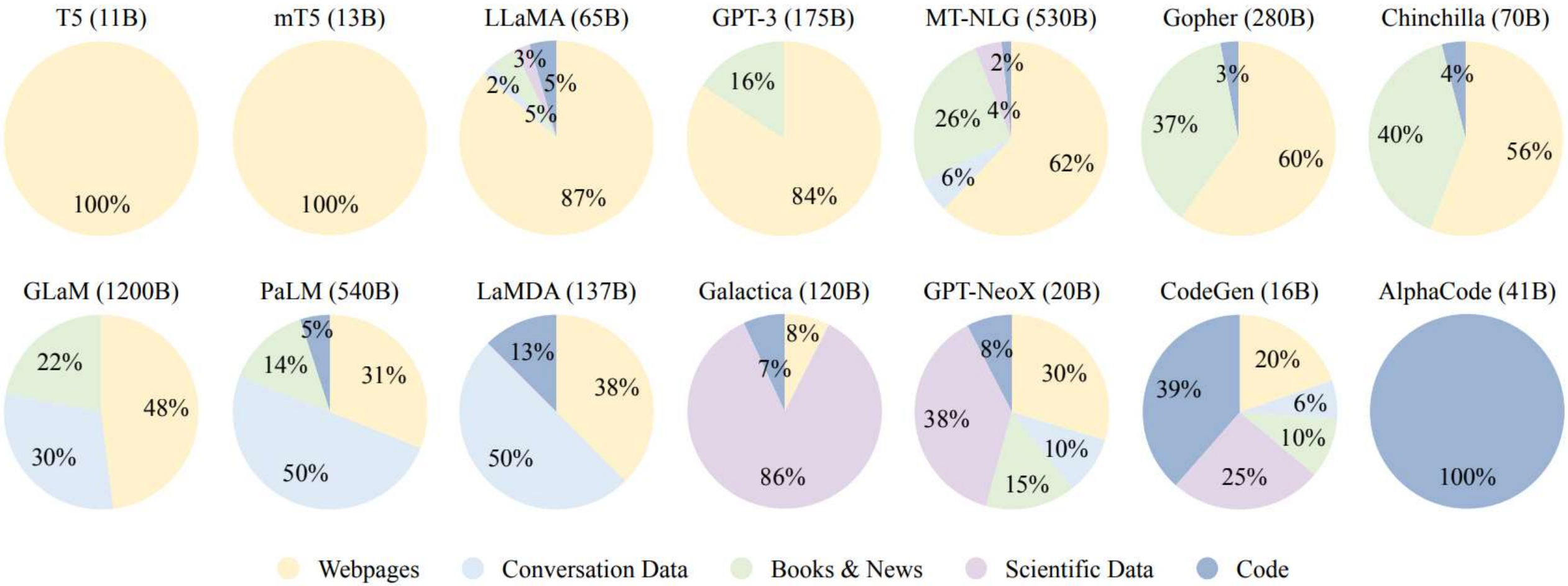
www.pmlg.com.au/about
pmlg@assistedevolution.net

Events

www.meetup.com/perth-machine-learning-group/

Spares / odds and sods

Ratios of various data sources in the pre-training data for existing LLMs



Source: https://arxiv.org/pdf/2303.18223.pdf

Energy Based

Energy Based

Energy Based

DOGMA

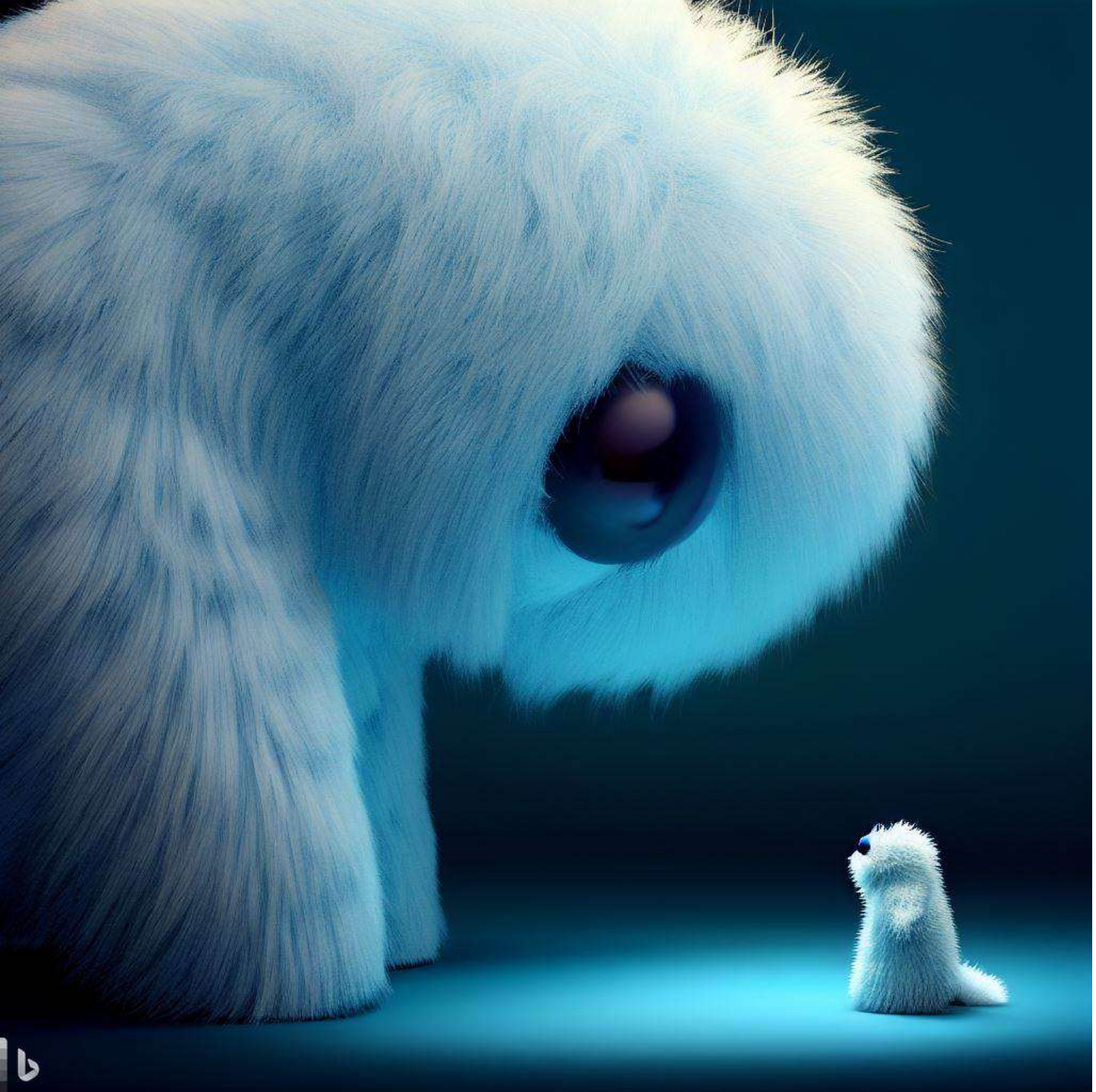
DOGMA

trained to follow instructions and tasks

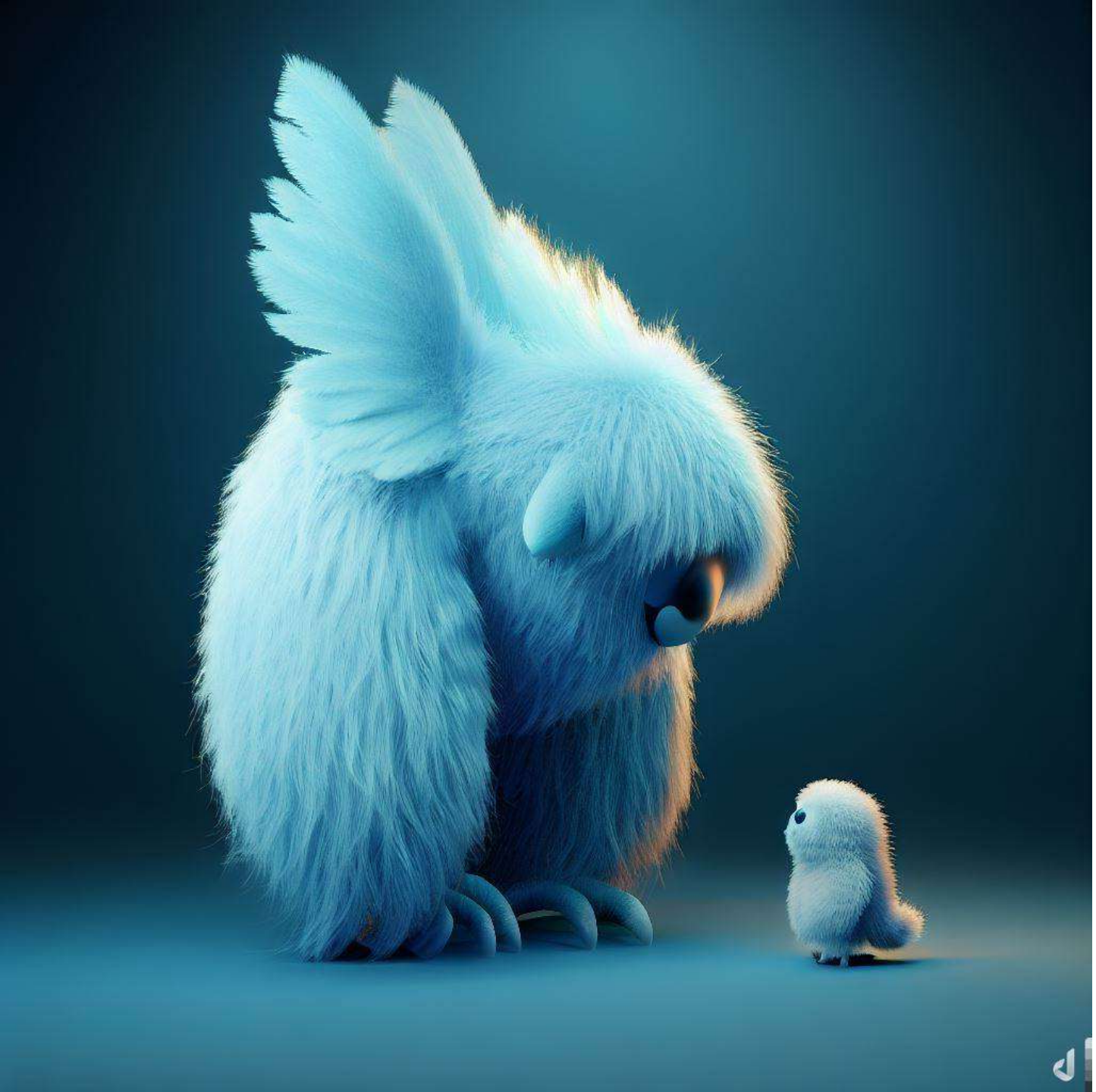
https://arxiv.org/pdf/2211.04325.pdf

trained with human feedback

https://arxiv.org/pdf/2211.04325.pdf



scaling



emergent capabilities with scaling

slow to train

expensive to train

Consume a lot of power

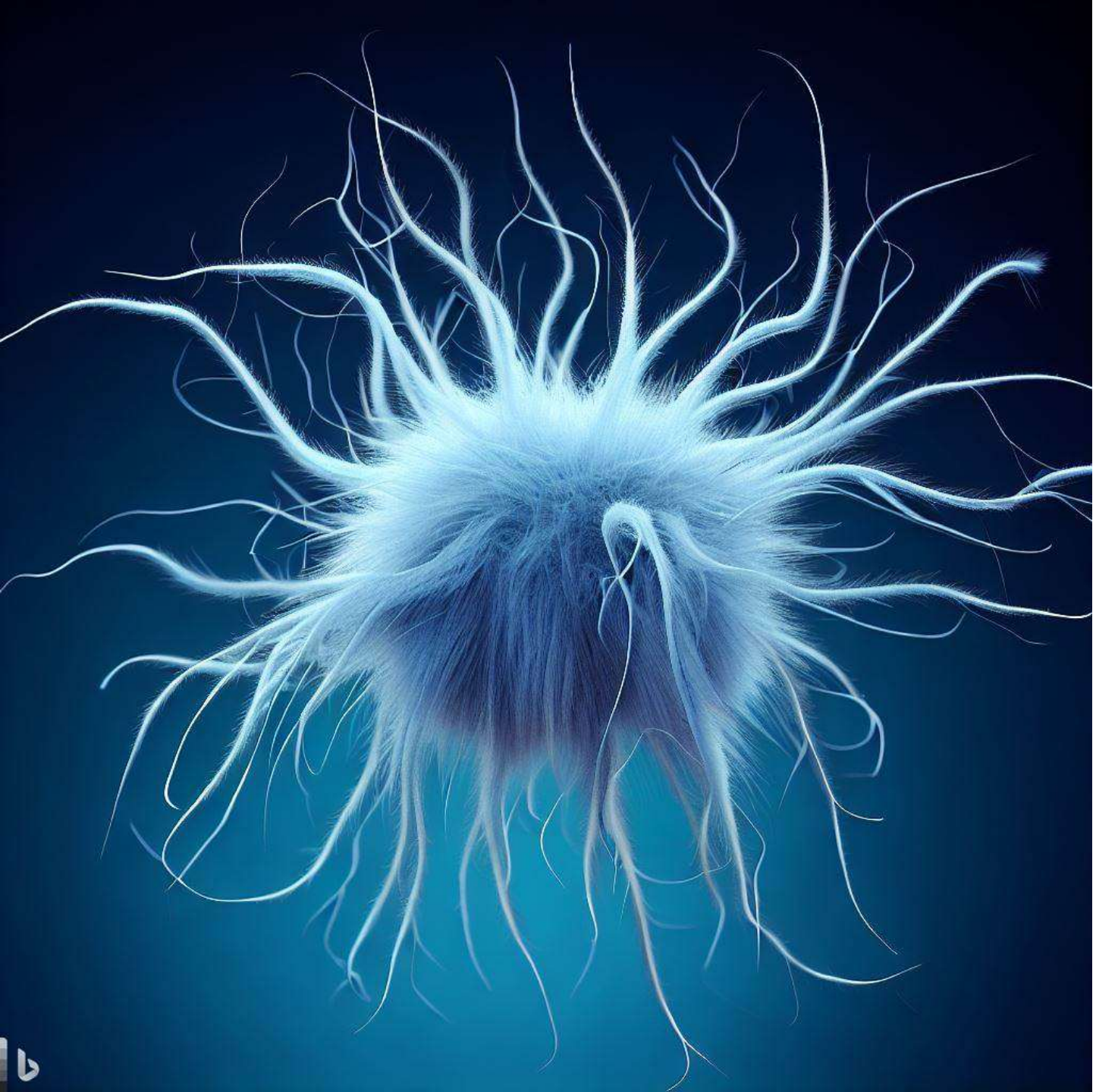
expensive to run

Is this the future or is there a better way?

smaller

1000 x faster

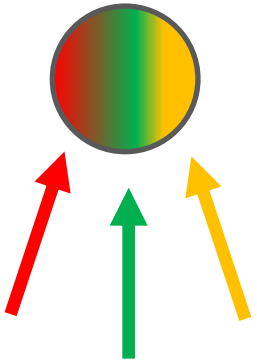
1000 x energy efficient



and maybe work more like the brain

and organic electronics

early fusion multimodal



joint representation

To stand on the shoulders of giants

You must first climb their backs, traversing thick forests of hairy IP and slippery scales of non reproduceable results

SEM Silicon photonic neuromorphic circuit

PMLG

Community (3k members in 5 years)

Research and Development

Research Collaborations