

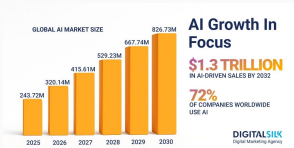
# **A Better Path Forward: Reconciling AI's Drive for Scale With the Reality of Its Energy Costs**

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William Fishell

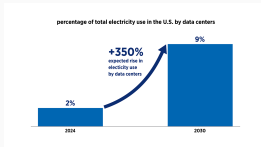
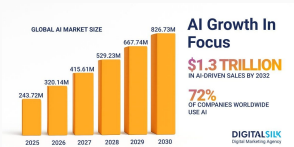
October 20th 2025

# Overview



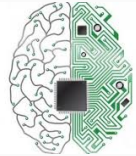
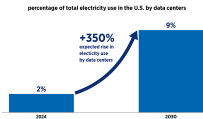
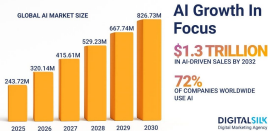
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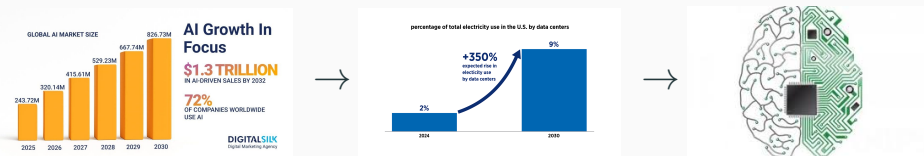
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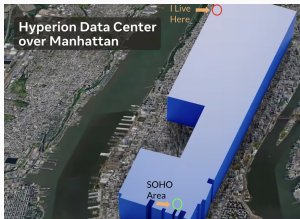
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# Scaling Energy Infrastructure Today for AI Tomorrow



*Meta's proposed \$30B data center in Louisiana vs. the size of Manhattan*



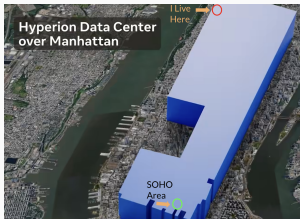
*Microsoft secures nuclear power from the Three Mile Island reactor*



*\$500B U.S. backed 'Stargate' data center initiative*

- Demand from AI is **delaying modernization of the U.S. power grid**, forcing utilities to keep coal-fired plants online rather than retire them [1].

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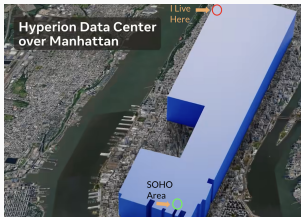
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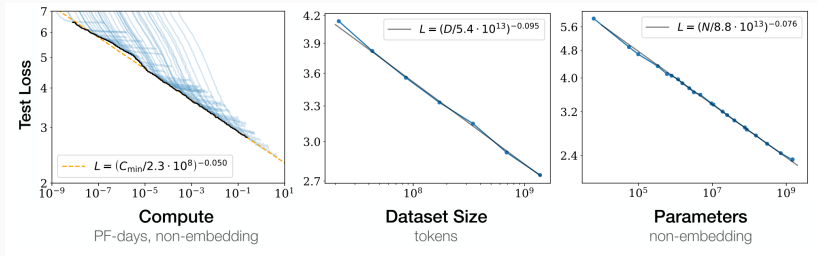
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**Why is all of this power even necessary?**

# Bigger Models Get Better Results

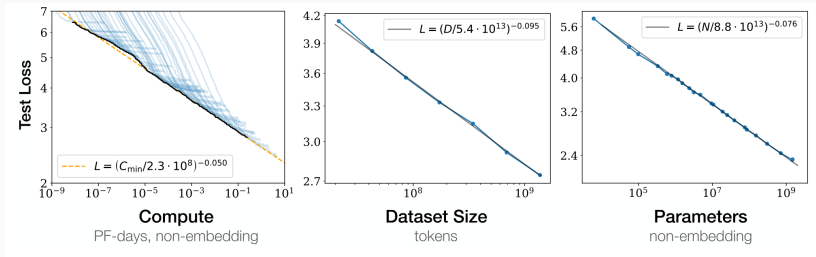
Models performance **scales logarithmically** with compute, dataset size and model-size



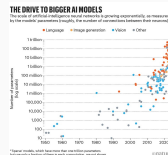
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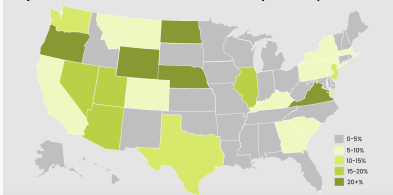
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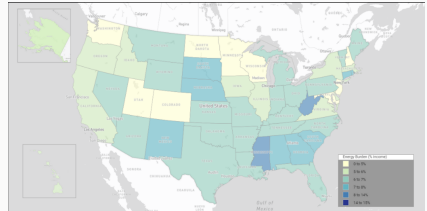
Companies exponentially increasing the the size of these models and the compute used to train them to keep up with scaling laws [4]

# The burdens of AI Energy Demand Disproportionally Hurt Low Income Areas

Projected Data Center Share of State Electricity Consumption in 2030



Share of Electricity Going to Data Centers by State

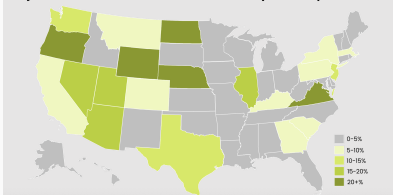


Share of Income per Household going to electricity

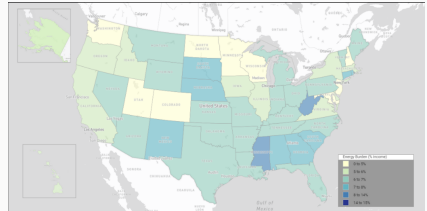
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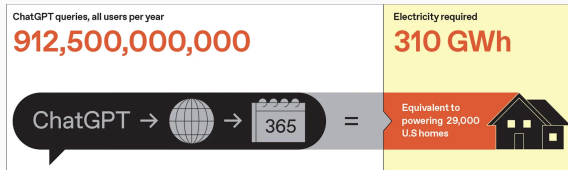
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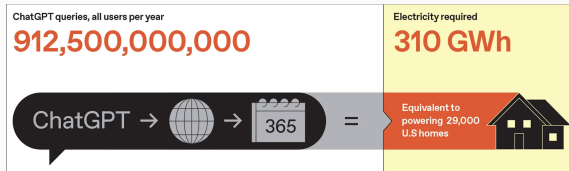
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- Data center investment and energy consumption is **primarily concentrated in rural areas causing rising utilities prices**
- **Rising prices are not coupled with positive investment** for these local communities

# What is Being Done To Address the Externalities of the AI Boom?

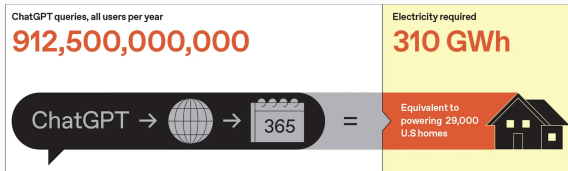


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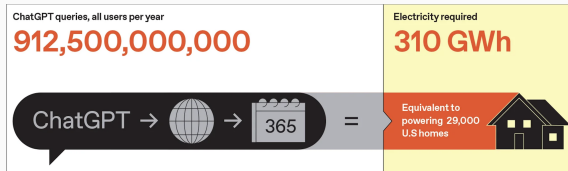
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2. The Trump administration's EPA is actively rekindling U.S. fossil fuel production to fuel an "AI arms race with China" [5].

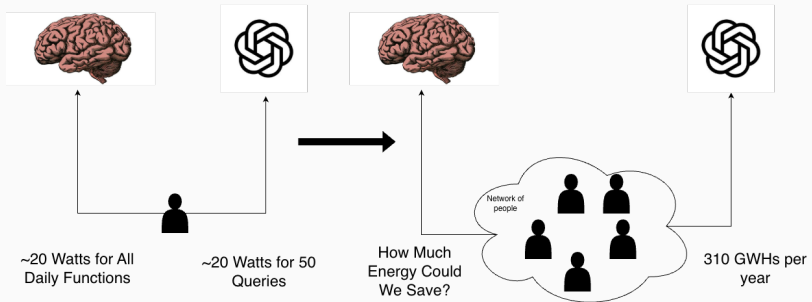
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These LLMs are a poor imitation of human thinking. Can we take advantage of this fact?



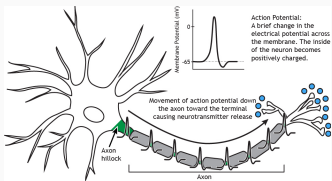
Can **biology** guide an answer to the side-effects of **the AI revolution**?

# What Can Neuroscience Tell Us About Computation?

**Neuromorphic Computing** imitates 3 aspects of our brains **for more efficient computation**

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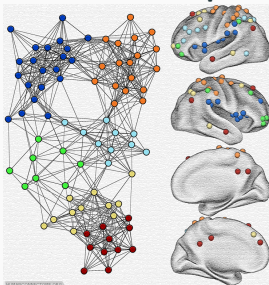
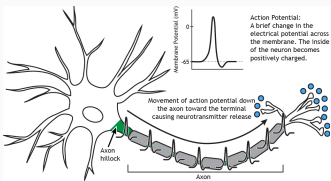
**Neuromorphic Computing** imitates 3 aspects of our brains for more efficient computation



- **Action potential:** A way for encoding complex computation with a sparse set of signals

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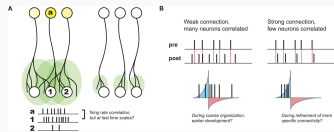
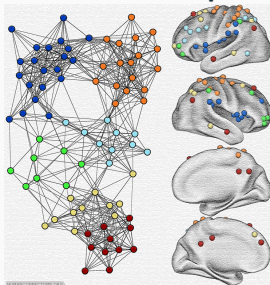
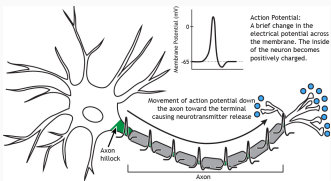
## Neuromorphic Computing imitates 3 aspects of our brains for more efficient computation



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- **Massive Parallelization:** The connection of multiple neural pathways enabling for a large amount of multi tasking

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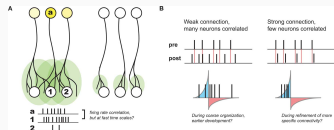
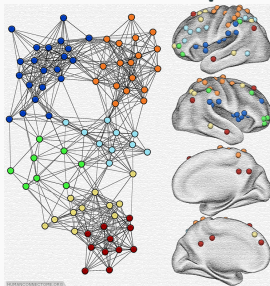
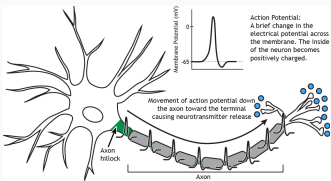
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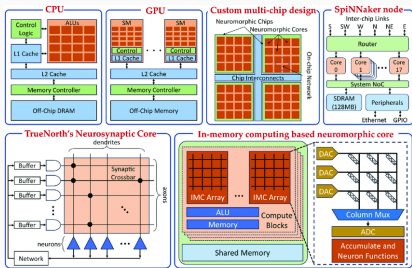
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## What happens when we build software and Hardware Based on these Processes?

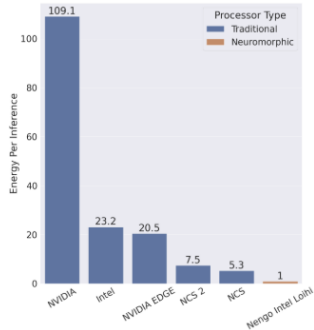
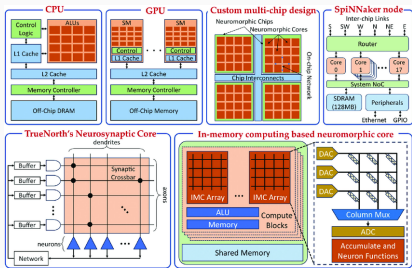
# Neuromorphic Computing is an Ultra-Efficient, Brain-Inspired Approach for Building Hardware and Software



- **CPUs are not used for machine learning** because they do things in series, making learning very slow
- **GPUs are the backbone of machine learning** because of their **parallelized architecture**; the dominance of GPUs is why NVIDIA is worth so much money
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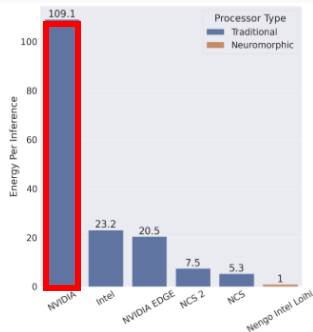
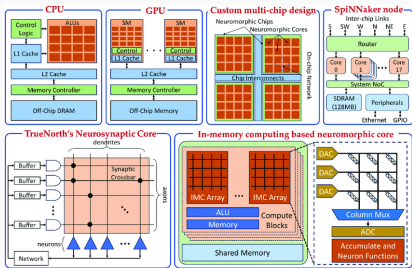
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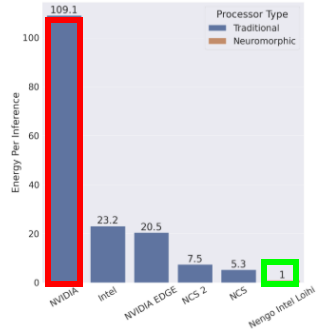
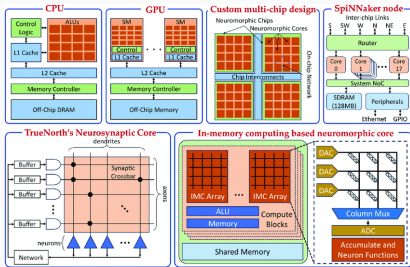
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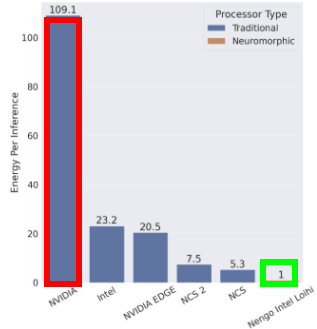
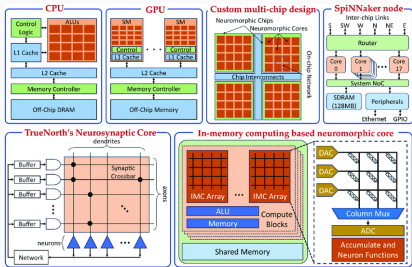
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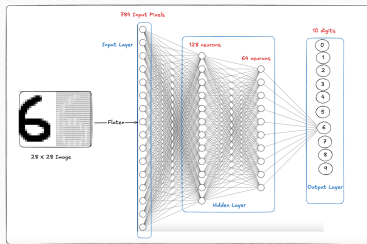
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If neuromorphic hardware is so **much more power efficient while maintaining performance**, what obstacles are preventing widespread adoption of this technology?

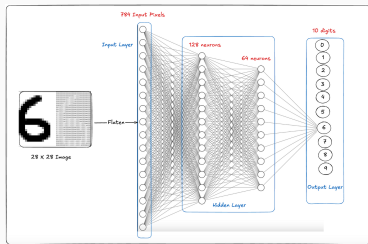
# Neuromorphic Hardware Delivers its Energy Efficiency Only When Paired With Biologically Inspired Algorithms



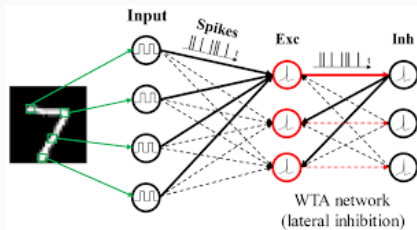
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*Handwritten Digits*

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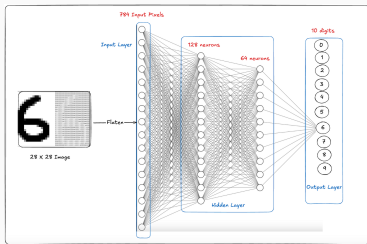


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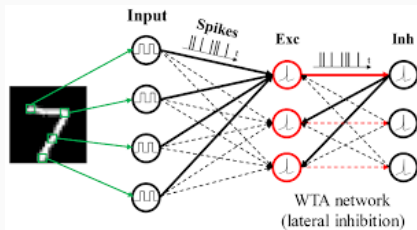
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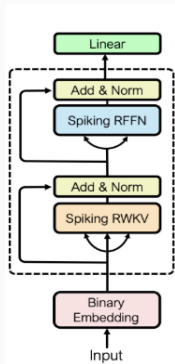
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- A normal neural network treats **each pixel as an input neuron**
- Spiking neural networks, inspired by biology, use **rate encoding schemes to represent the same information**

# Despite Limited Use, Spiking Neural Networks Have Demonstrated Promising Results in LLMs

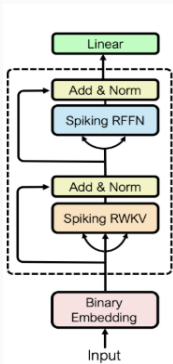
## SpikeGPT



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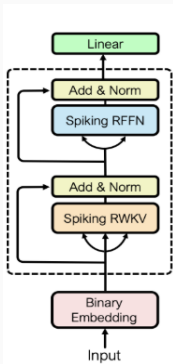
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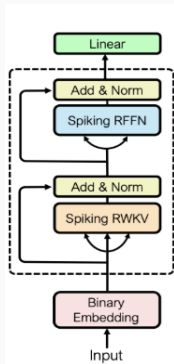


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These neuromorphic language models struggle at modeling long-range dependencies **without a lot** of training data

# Traditional Language Models (Transformers) Are Able to Model Long-Range Dependencies With Few Examples

*Long-Range Dependencies* are relationships in sequential data where predictions are **dependent** on earlier points

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## Dependency Parsing in Language Modeling

John saw the dog

PropN

Verb

Det

Noun

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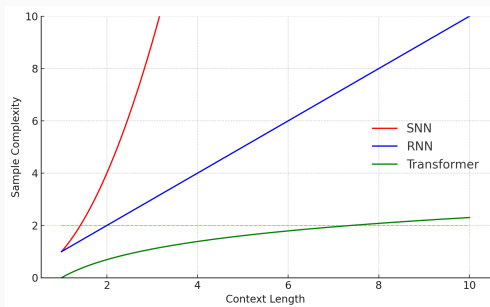


## Word Associations in Harry Potter Learned by LLM

<START>Mr and Mrs Dursley, of number four, Privet Drive, were proud to say that they were perfectly normal, thank you very much. They were the last people you'd expect to be involved in anything strange or mysterious, because they just didn't hold with such nonsense. Mr Dursley was the director of a firm called Grunnings, which made drills. He was a big, beefy man with hardly any neck, although he did have a very large moustache. Mrs Dursley was thin and blonde and had nearly twice the usual amount of neck, which came in very useful as she spent so much of her time craning over garden fences, spying on the neighbours. The Dursleys had a small son called Dudley and in their opinion there was no finer boy anywhere. The Dursleys had everything they wanted, but they also had a secret, and their greatest fear was that somebody would discover it. They didn't think they could bear it if anyone found out about the Potters. Mrs Potter was Mrs Dursley's sister, but they hadn't met for several years; in fact, Mrs Dursley pretended she didn't have a sister, because her sister and her good-for-nothing husband were as unDursleyish as it was possible to be. The Dursleys shuddered to think what the neighbours would say if the Potters arrived in the street. The Dursleys knew that the Potters had a small son, too, but they had never even seen him. This boy was another good reason for keeping the Potters away; they didn't want Dudley mixing with a child like that.

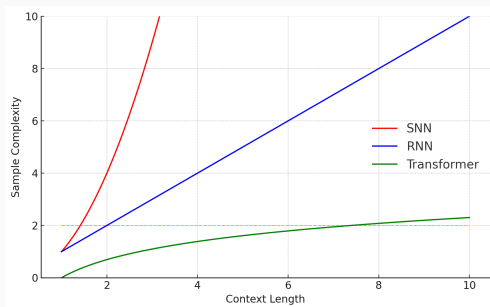
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## Samples Needed For PAC Learnability For Popular Language Modeling Architectures



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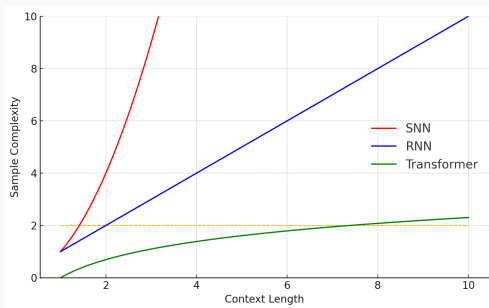
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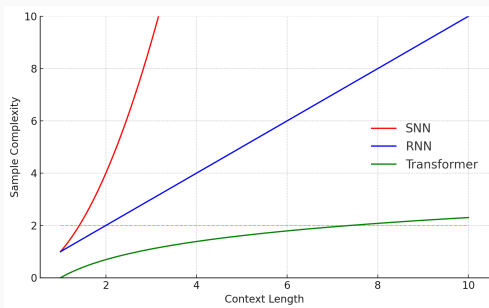
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**Biology can save the day once again!**

*This work was recently submitted to BioRxiv and presented at the SHDA Workshop at the International Conference on Supercomputing (ICS 2025).*

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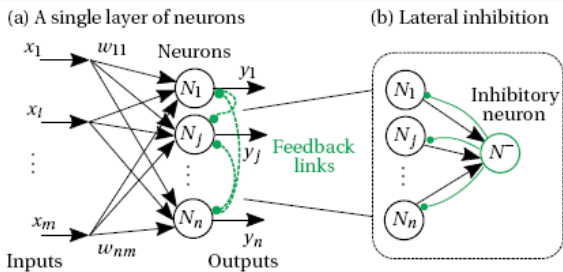
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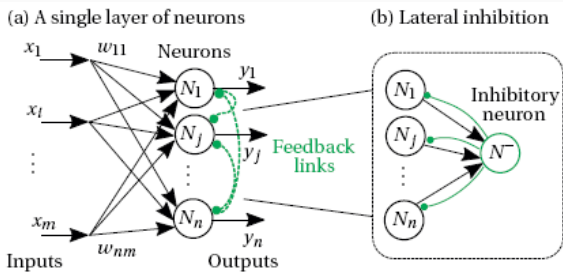


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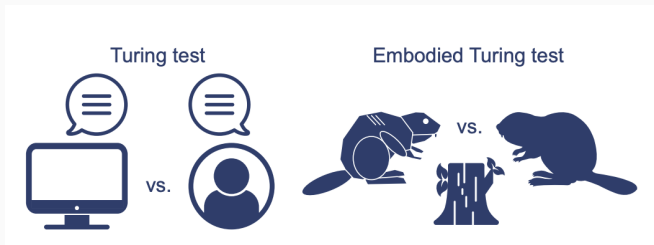


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Where else does Neuromorphic computing fit into the AI revolution?

# Artificial Intelligence Exists Beyond Just Language Models

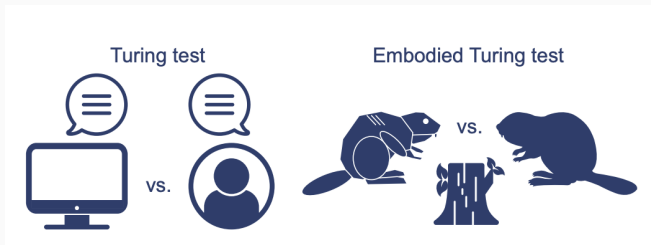
**Embodied Intelligence** is the next frontier for Machine Learning



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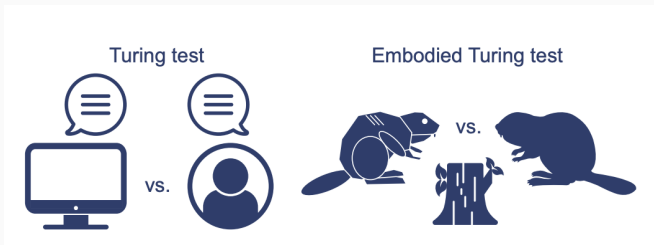
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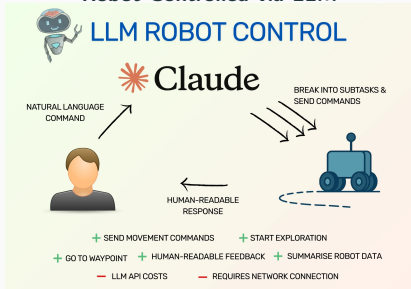


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For our purposes we will focus on **autonomous driving** for our Embodied Turing test

# Current Machine Learning Methods are Either Unsuitable for Robotics or not Scalable due to their Energy Demands

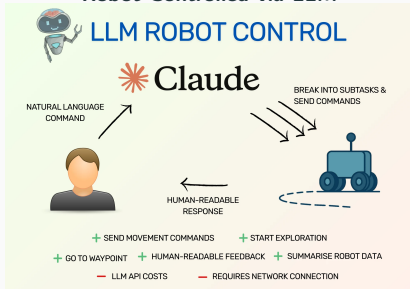
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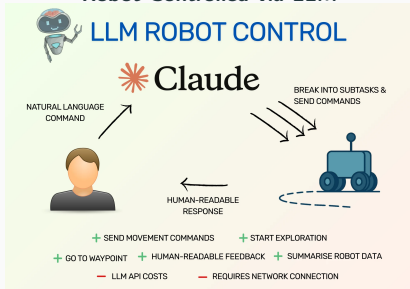
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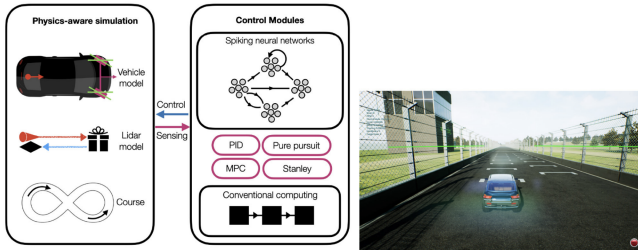


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- **Neuromorphic computing is a perfect substitute** for these types of embodied intelligence

# Autonomous Driving is Already Turning to Neuromorphic Computing For Better Performance on Power Constrained Systems

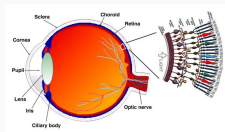


*SNN architecture for autonomous driving*

- Large automotive companies such as **Mercedes** are actively researching **Neuromorphic** setups for the **future of self-driving** [9]
- **Neuromorphic computing** scales exceptionally well for **vision tasks** — delivering performance comparable to classical vision models, but at only a fraction of the energy cost
- Autonomous driving is a leading example of how **neuromorphic systems** are **beginning to rival traditional architectures in embodied intelligence** [10]

# Emulating Convolution Still Demands Many Synapses, Making Neuromorphic Models Computationally Expensive at Scale

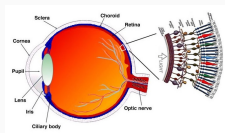
## Neuronal Model of Eye



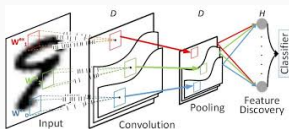
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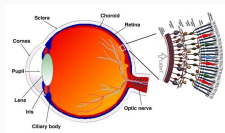
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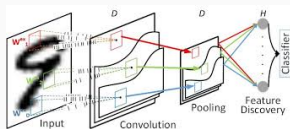
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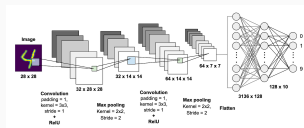
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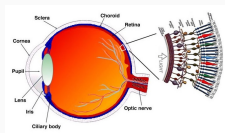
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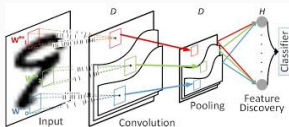
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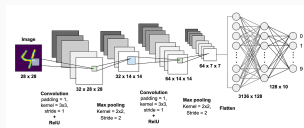
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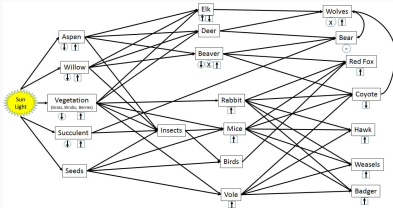
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**Biological plausibility** offers powerful tools for designing more efficient machine learning architectures, but it **shouldn't be followed blindly**

# Inspired by complex adaptive systems, we simulate neural circuits while reproducing convolution-like computation



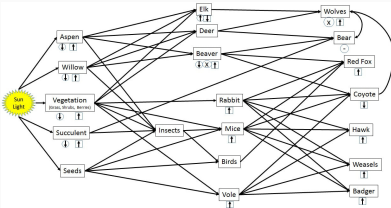
*Agent based simulation software for modeling complex  
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*Wolf Introduction To Yellow Stone National Park*

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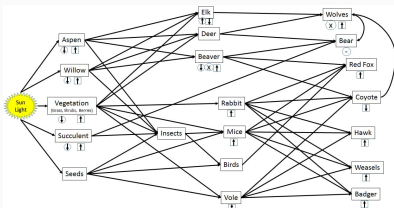
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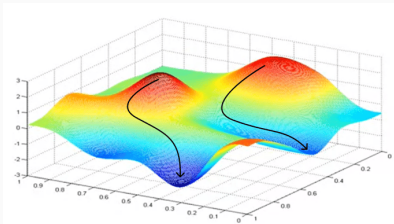
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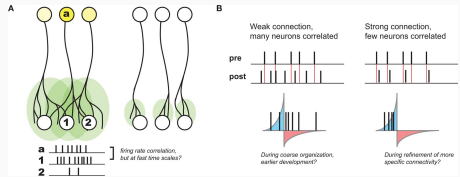
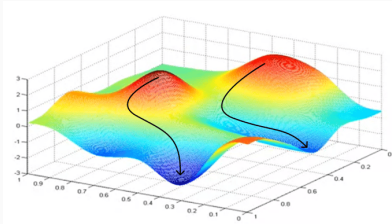
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# This Neuromorphic Convolution Architecture Enables Biologically Realistic Learning



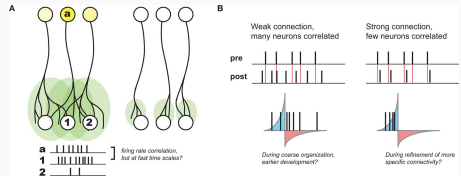
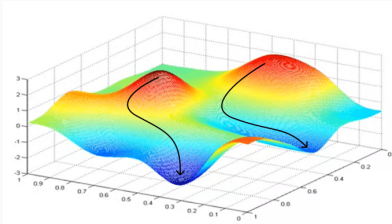
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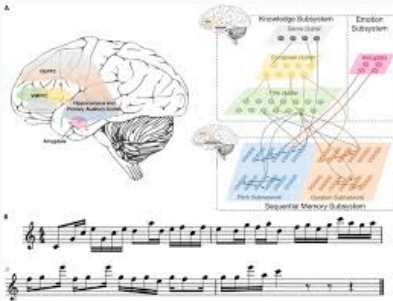
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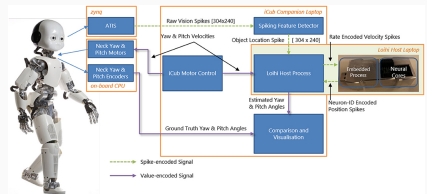
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# Neuromorphic Computing: A Promising but Not Yet Scalable Solution to AI's Energy Crisis

Neuromorphic computing presents a **better** path forward through biology as **current LLMs and robots power demands are unsustainable**



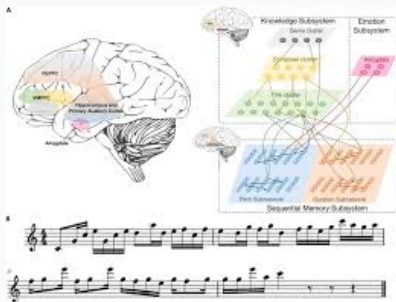
*Biological representation of an SNN learning compositional language*



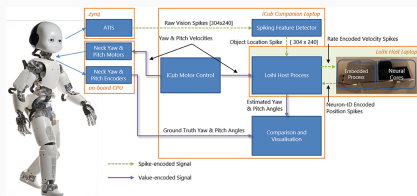
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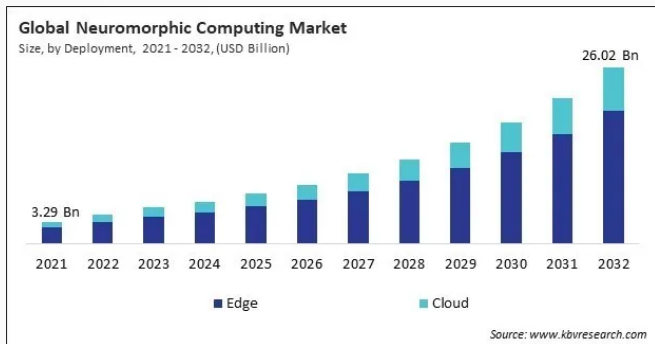


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Despite all this hype, **Neuromorphic computing** is considered the nuclear fusion of computer science: it **over promises and under delivers**

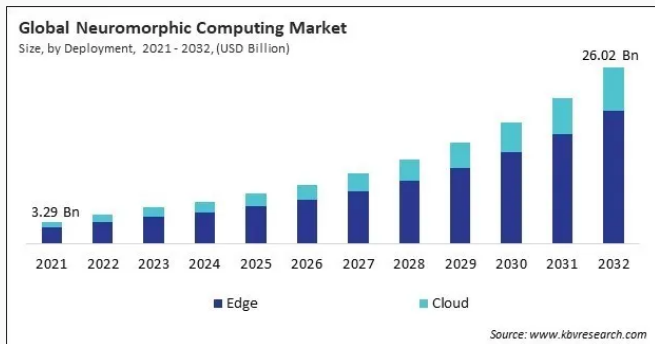
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Neuromorphic computing still has **significant ground to cover** before it can become a viable competitor to **today's SOTA AI models and infrastructure**

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Let's open this up to a **broader discussion** — not just questions **about the work itself**, **but also your thoughts on the societal, technical, and policy implications of neuromorphic computing**, and whether this is truly a direction we want to pursue and accelerate

**Thank You For Listening!**





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