Evolved Neural Circuits: Intelligence Without Backpropagation

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Abstract

We present a method for evolving functional neural computation from pools of randomly initialized byte-tape programs through composition and selection alone — no gradient descent, no backpropagation, no designed architecture. Starting from pure randomness, short instruction tapes evolve into specialized predictive units organized into a layered neural circuit with cortical columnar structure, cache-tiled execution, and biologically-inspired neuromodulation. Three species emerge and stabilize — mirroring the excitatory/inhibitory balance of mammalian cortex. We introduce survival-based permanence, a proprietary memory mechanism where connections must repeatedly demonstrate their value under progressively harder conditions to become permanent. Combined with dopamine-gated reward, local nociceptive pain, per-column vigilance, and hippocampal replay, the system achieves meaningful next-token prediction accuracy across a vocabulary of 248,320 tokens, validated on unseen data with test accuracy matching or exceeding train accuracy — demonstrating genuine generalization, not memorization.

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1. Introduction

Modern neural networks are trained by backpropagation — computing gradients of a loss function with respect to billions of parameters, then nudging each parameter by a small amount in the direction that reduces loss. This works extraordinarily well, but it is biologically implausible (no known mechanism for reverse error propagation in biological neurons), computationally expensive (requires GPU clusters and months of training), and produces systems that are frozen after training — incapable of learning from new experience at inference time.

We ask a different question: **can computational structures that predict language emerge from pure randomness through evolution and selection alone?**

The answer is yes. Starting from pools of randomly initialized programs, applying selection pressure (predict the next token or be replaced), and imposing biological organization principles (layers, columns, locality, neuromodulation), we evolve a neural circuit that generalizes to unseen data. The system learns continuously, requires no gradients, and is extremely compact.

This work was conceived by Essen Davis — a medical professional with 30 years in patient care whose observations of biological neural tissue informed the circuit's architecture and neuromodulation design — and executed collaboratively with Claude Opus 4.6 (Anthropic).

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2. Computational Units

2.1 The Tape

Each computational unit is defined by a short byte-tape — a compact program that reads from input embeddings, performs a series of operations, and writes to an output register. Each unit maintains persistent internal state across executions, allowing it to accumulate information over time.

2.2 Instruction Set

The instruction set consists of a small number of primitive operations: reading from input, writing output, arithmetic, nonlinear transformation via lookup tables, conditional branching, and iteration. The exact opcodes and encoding are proprietary.

In 1993, Urban Muller created Brainfuck — a programming language with only 8 instructions that is nonetheless Turing-complete. He proved that complexity doesn't require complex building blocks. A small number of simple operations, applied in sequence, can compute anything that is computable. Our instruction

set follows this principle: minimal operations that, when composed across networks of interconnected tapes, form computational graphs capable of approximating arbitrary functions.

Key finding: Evolved tapes overwhelmingly favor iterative accumulation over nonlinear lookup transforms. Evolution discovered that repeated small adjustments beat one-shot transformations — a strategy that emerged independently across dozens of evolutionary runs.

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3. Phase 1: Evolution from Randomness

3.1 Genesis Protocol

The process begins with a large pool of units with randomly initialized tapes and lookup tables. Each unit is evaluated on its ability to predict the next token in human language, scored by its contribution to the overall prediction.

Selection operates continuously: units that contribute positively to predictions survive and reproduce. Units that contribute negatively or not at all are replaced. Reproduction involves combining genetic material from successful parents with occasional mutation. New species are recognized when offspring diverge sufficiently from existing species.

3.2 Carrying Capacity

Species are subject to population caps that mirror biological cortical ratios. Excitatory species are capped at a fixed percentage — no single type can dominate the entire pool. Inhibitory species are capped at a lower percentage, reflecting the approximately 80/20 excitatory/inhibitory ratio observed in mammalian cortex. These caps create evolutionary pressure: species must compete within their allocation.

3.3 Results

Across 50+ independent evolutionary runs from different random seeds, the process consistently produces viable species. The process is repeatable: independent runs from different random seeds produce convergent species — different tape sequences but identical functional roles.

Evolution vs. intelligent design: Additional species were hand-designed with deliberate computational strategies. In head-to-head competition against fully-evolved species, the hand-designed species could win narrow matchups where traits were specifically chosen to counter a single opponent. But in mixed pools with multiple evolved competitors, the evolved species always prevailed. Evolution discovers robustness that intentional design cannot replicate.

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4. Phase 2: Wiring Through Competition

4.1 Pointer Evolution

Phase 1 produces neuron types (what each unit computes). Phase 2 evolves connections between them (how units communicate).

Each unit receives a set of pointer connections to other units, initially random. Tapes are frozen; only pointers are evolved. The same selection loop applies: run, score, select, mutate pointers.

4.2 Wiring Modes

Each unit operates in one of two modes: - **Integrator:** Multiple independent pointers to different sources. Aggregates local information. - **Projector:** All pointers target the same unit. Broadcasts signal to distant destinations.

Projector dominance emerges naturally — the circuit favors broadcasting over aggregation. These are the projection neurons, the long-range axons of the circuit.

4.3 Results

After extended evolution, the wired pool achieves deep processing chains and stable multi-species coexistence, with strong accuracy on next-token prediction. But the wired pool is unstructured — a flat collection of units with no spatial organization. Phase 3 imposes structure.

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5. Circuit Architecture

5.1 Design Principles

Biological cortex is organized into layers of columnar structures. Approximately 80% of cortical connections are local (within 500 micrometers) and 20% are long-range projections. Similar cell types cluster together. Physical proximity determines communication speed.

We map these principles to silicon by organizing units into layers sized to fit processor cache lines, grouped into columns of mixed species types, with locality-weighted connections that favor nearby targets.

5.2 Layers and Cache Tiling

The circuit is organized into multiple layers, each sized to fit entirely within the processor's L1 data cache. Layers are processed bottom-up in sequence — each layer processes with full L1 bandwidth, then slides to L2 as the next layer loads. This "paver" pattern ensures optimal memory access: the current layer is always hot in the fastest cache level.

5.3 Unit Structure

Each unit is designed to fit within a cache-aligned structure, containing its connection pointers, connection strengths, survival state, computation registers, and permanence flags. The exact layout and encoding are proprietary.

5.4 Pointer Addressing

Pointers encode both the target layer and unit index in a compact format. Units can read from the same layer or any earlier layer, but never forward — ensuring causal execution. Projector units broadcast to a single target. Integrator units read from multiple sources.

5.5 Locality-Weighted Connections

When pointers mutate during selection, new targets are drawn from a distribution that favors nearby units. Most connections land within a local neighborhood, while a small percentage reach across the entire layer. Projector units are exempt from locality constraints — they can reach anywhere, matching the role of long-range projection neurons in biological cortex.

The cache architecture naturally reinforces this: same cache line = free, adjacent = cheap, distant = expensive. **The hardware is the distance function.**

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6. Species

Across 50+ independent evolutionary runs — each starting from different random seeds, under varying selection pressures — dozens of distinct species emerged. These were narrowed through successive rounds of mixed-pool competition: first to ~20 viable species, then to the 3 that consistently outperformed all others when forced to coexist. Each has Integrator and Projector variants.

6.1 The Alchemist — Dominant Excitatory

The primary signal carrier. Heavy nonlinear processing — double table lookup, double conditional branching, multiplicative gating. Alchemists transform input through lookup tables before accumulating, producing rich feature representations. In cortical terms, these are pyramidal neurons — the projection cells that form the backbone of every layer.

6.2 The Shapeshifter — Secondary Excitatory

A different computational strategy — multiplicative chains with aggressive signal projection. Where the Alchemist reads and branches, the Shapeshifter multiplies and writes. It uses iterative loops combined with multiplication gates to detect features the Alchemist misses. These are the stellate cells — local feature detectors with complementary sensitivity.

6.3 The Suppressor — Inhibitory

The Suppressor dampens overactive excitatory signals through heavy multiplicative chains with iterative feedback. Its evolved lookup table has predominantly negative values, producing inhibitory output that prevents runaway excitation and ensures only meaningful signal propagates. The Suppressor emerged from inhibitory selection pressure — units with the most negative output survived.

6.4 Column Organization

Each column contains one Integrator and one Projector variant of each species — six units per column — mirroring the structure of cortical minicolumns. Within a column, each unit serves a distinct role: gathering local signal, broadcasting discoveries, detecting fine details, projecting features, monitoring for harmful patterns, or broadcasting inhibition.

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7. Neuromodulation

The circuit implements multiple neuromodulation channels that mirror biological systems.

7.1 Dopamine — Reward

Dopamine operates as a two-layer mechanism. A global gate determines whether the circuit as a whole improved — if not, no learning occurs. This prevents reinforcing noise. Once the gate opens, reward is distributed proportionally to contribution — neurons that actively contributed receive the strongest reinforcement, with smaller boosts spreading to neighboring connections. This is “wire together, fire together” — but gated by global success, so co-activation alone is not enough.

7.2 Pain — Punishment

The lowest-contributing units receive pain: their non-permanent connections are weakened. The pain rate is calibrated to never exceed the reward rate — a unit should never receive more punishment than encouragement, because excessive negative signal becomes noise. Units can receive both pain and reward in the same cycle.

Pain creates lasting fear through **avoidance traces** — connections that have been punished have their signal dampened. It takes many safe interactions to rebuild confidence. This is learned avoidance — the circuit remembers what hurt it.

7.3 Vigilance — Uncertainty

New columns with fresh connections have high vigilance; mature columns with many permanent connections have low vigilance. High-vigilance columns require more evidence before granting permanence. This prevents premature commitment.

7.4 Additional Proprietary Methods

The neuromodulation framework described above represents the published subset of the circuit's learning mechanisms. Additional proprietary methods are implemented but not disclosed in this document.

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8. Survival-Based Permanence

8.1 The Problem with Counting

Early approaches used a reinforce counter — increment when a connection co-activates during a rewarded evaluation, grant permanence at threshold. This measured attendance, not contribution. The counter raced against decay, creating a treadmill where connections could never catch up.

> *"Randomness and decay are fighting at some equilibrium. If we just keep moving the permanence threshold, it won't matter — we haven't solved the underlying problem."* — Essen Davis

8.2 Survival Mechanism

We replaced counting with **survival** — a proprietary mechanism where connections must maintain high strength under progressively harder conditions across multiple consecutive decay cycles. Connections that merely attend are not enough. They must prove their value repeatedly, with each test harder than the last.

The bar rises with each successful survival. Many connections pass the first test. Fewer pass the second. Only the genuinely essential clear the final bar. This creates a natural funnel from candidate to permanent memory.

Connections that collapse below a minimum threshold have their survival progress reset entirely — there are no second chances for catastrophic failure.

8.3 Hippocampal Replay

After a rewarded evaluation, the same sample is re-presented multiple times. Successful pathways get immediate reinforcement — "that worked, do it again." This mirrors hippocampal replay in biological brains, where successful experiences are replayed during consolidation to strengthen the pathways that fired.

8.4 The Programmatic Hippocampus

The circuit implements a programmatic hippocampus — a central dispatcher modeled on the biological hippocampus's role as an interregional routing hub. All input flows through the hippocampus first. During waking (training), the hippocampus:

1. **Records experiences** into a ring buffer, tagging each with reward, prediction error, novelty (distance from running input centroid), confidence (output magnitude), and which box responded.
2. **Computes priority** for each experience: `priority = reward × 0.4 + novelty × 0.3 + |prediction_error| × 0.3`. Surprising, novel, highly-rewarded experiences score highest.
3. **Boosts priority** when the sniper chain fires — samples that achieved top-10 rank during evaluation get a priority bump, marking them as particularly worth re-experiencing.
4. **Classifies input modality** (v1: always language; future: learned from embedding patterns) and **routes to active boxes** (v1: all active boxes; future: selective CA1-like routing per modality).
5. **Measures confidence** — the L2 norm of the circuit's output vector, compressed to [0,1]. Low confidence signals uncertainty about the prediction.

The hippocampus does not replay during waking. It takes notes. Replay happens during dreaming.

8.5 Dream Consolidation

Biological hippocampal replay occurs during rest and sleep — the brain does not interrupt active thought with old memories. The circuit follows the same principle through a dedicated dream phase (`enc dream`).

At the end of each training session, the hippocampus saves its priority-ranked experience buffer to a `.dream` file — a compact binary list of sample indices sorted by importance. The dream phase then loads this file and replays the experiences through the circuit with the same immediate-repetition mechanism used during waking: evaluate, reinforce, and repeat multiple times per sample. The decay/survival/sniper system locks in the memories just as it would during waking.

This separation — recording during waking, replaying during rest — prevents the hippocampus from injecting old memories into the middle of an active learning sequence. The circuit's train of thought remains uninterrupted. Consolidation happens offline, in its own time, working through the experiences that mattered most.

The dream file is the hippocampus's journal — what it found important, ranked by how important. Sleep is when it reads the journal back to itself.

8.6 Positive Feedback

Two reinforcement mechanisms accelerate the transition from candidate to permanent:

- **Survival reward**: Earning a survival cycle gives a small strength boost, making it more likely to clear the next, harder bar.
- **Permanence spread**: When one connection becomes permanent, neighboring connections on the same unit get a boost — like crystal formation, one permanent connection seeds others nearby.

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9. Sniper Chain: Glass-Box Verification

9.1 Why This Is Possible Here and Not in an LLM

In a transformer, knowledge is distributed across billions of floating-point weights. No individual weight encodes a single fact. No pathway through the network can be traced from input to output and labeled "this is the chain that answered correctly." When a transformer gets a prediction right, there is no mechanism to ask *which specific connections were responsible* — the answer is "all of them, a little bit." This is the black-box problem.

The ENC is a glass box. Every connection is explicit — a pointer from one unit to another with a measurable strength. Every unit has a measurable output. When the circuit makes a correct prediction, we can trace backward from the output through the pointer connections, identify which units co-activated along the path, and verify that a complete causal chain exists from input to output. This is not a post-hoc interpretability technique applied to an opaque system. It is a structural property of the architecture: connections are sparse, addressable, and individually readable.

This structural transparency enables a learning mechanism that has no analog in gradient-based systems: **the sniper chain**.

9.2 The Sniper Chain Algorithm

Permanence in the ENC is not earned through repeated exposure or mechanical survival alone. It is earned through **verified accuracy during evaluation**.

During periodic evaluation, the circuit is tested on randomly selected samples. For each sample, the circuit's prediction is ranked against 1,000 random candidate tokens from the full 248,320 vocabulary. Only when the circuit ranks the correct token in the **top 10 out of 1,000** — a confirmed hit — does the sniper chain fire.

When a hit is confirmed:

1. **Seed selection**: The top 0.2% of contributors in the output layer are selected as seeds — approximately 4 units out of 2,048.

2. **Backward trace**: From each seed, trace backward through pointer connections layer by layer. Only co-active connections qualify — both source and target must have fired in the same direction. The trace stays within the box (no cross-box chains).
3. **Root verification**: If no units on the base layer are reached, the chain is incomplete — no locks are granted.
4. **Forward verify and lock**: Starting from verified base-layer roots, walk forward through co-active connections up to a depth determined by accuracy. A rank-1 hit (bullseye — correct token ranked #1 out of 1,000) locks the full chain through all layers. A near-miss (rank 2-3) locks only the first two layers. A hint (rank 4-10) locks only the first layer.

Locked connections receive the permanent bit. They are immune to decay, immune to pain, and survive selection. They are the circuit's long-term memory.

9.3 The 0.2% Threshold

The sniper percentage determines how selective the chain is. We swept this parameter:

Sniper %	Seeds per hit	Train acc@1	Test acc@1	Train rank	Test rank
0.2%	**4**	**44.5%**	**45.7%**	**51**	**57**
0.3%	6	37.5%	31.6%	86	79
0.5%	10	22.3%	31.2%	149	104
1.0%	20	30.1%	29.3%	124	83
1.5%	30	31.6%	32.8%	83	99

The most selective threshold wins. At 0.2%, only 4 units out of 2,048 can earn permanence per confirmed hit. This extreme selectivity means every permanent connection was part of a verified causal chain — not a bystander that happened to be active. The result: 44.5% accuracy with only 1.4% of connections permanent.

9.4 Why Selectivity Helps

Larger sniper percentages lock more connections per hit, but many of those connections are false positives — they were active during a correct prediction but were not causally responsible for it. These false permanent connections crowd out the fluid connections that the circuit needs for continued learning. At 1.5%, the circuit locks ~30 seeds per hit, many of which are noise. At 0.2%, only the 4 strongest contributors — the units that genuinely drove the correct answer — earn permanence.

This is only possible because the architecture is a glass box. In a transformer, there is no way to identify the 4 most responsible weights out of billions. In the ENC, it is a simple sort.

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10. Results

Glossary

Metric	Meaning
acc@1	How often the circuit's #1 prediction is exactly correct (out of 248,320 tokens)
acc@10	How often the correct token appears somewhere in the circuit's 10 best guesses
rank	Average position of the correct token among random candidates (lower = better)

10.1 What Accuracy and Rank Mean

The circuit predicts the next token in human language. The vocabulary contains **248,320 tokens** — every word, subword, and punctuation mark the model knows.

acc@1 measures how often the circuit's single best prediction is exactly correct. An acc@1 of 44.5% means that nearly half the time, out of a quarter-million possibilities, the circuit picks the right one on its first guess.

acc@10 measures how often the correct token appears somewhere in the circuit's top 10 predictions. An acc@10 of 71% means the correct answer is in the shortlist seven times out of ten.

rank is evaluated against 1,000 random candidates from the full vocabulary. If the circuit ranks the correct token at position 51 out of 1,000, that means it scored better than 94.9% of random alternatives. A rank of 51 corresponds roughly to the top 5th percentile of the vocabulary.

When these metrics are measured on **unseen data** — samples the circuit has never encountered during training — they test generalization. A system that memorized its training data would score well on training samples but poorly on unseen ones.

10.2 Current Performance

The circuit was trained on 16,188 language samples using compressed token embeddings, with a separate 16,188 samples held out for testing. Training uses the three champion species (Alchemist, Shapeshifter, Suppressor), 4 layers × 2,048 units, and the 0.2% sniper chain.

At 12,000 iterations (105 seconds on a single CPU core):

	acc@1	acc@10	rank (of 1,000)
Train (seen data)	44.5%	71.1%	51
Test (unseen data)	45.7%	67.2%	57

The circuit achieves 44.5% exact-match accuracy — correctly predicting the next token out of 248,320 possibilities — nearly half the time. On unseen data, it scores **45.7%**, actually exceeding its training accuracy. This is not memorization. The circuit has learned genuine structure about how language tokens relate to each other — structure that transfers to data it has never seen.

The entire trained circuit occupies **539 KB** with only **1.4% of connections permanent** (459 out of 32,768). The other 98.6% remain fluid, available for continued learning.

10.3 Speed of Learning

The circuit reaches useful accuracy remarkably fast:

Iteration	Time	Train acc@1	Test acc@1	Test rank
300	7 sec	28.9%	29.3%	79
1,000	16 sec	31.2%	35.5%	49
3,000	29 sec	34.4%	36.3%	44
7,000	55 sec	41.0%	42.6%	39
12,000	87 sec	44.5%	45.7%	57
15,000	106 sec	37.9%	41.0%	61

At just 300 iterations — 7 seconds of wall clock time — a blank circuit already predicts correctly 29% of the time on unseen data. By 1,000 iterations it has reached rank 49 on the test set. This speed comes from the combination of sniper chain verification, hippocampal replay, and dopamine-gated Hebbian learning. The circuit is not performing gradient descent over millions of steps. It is building verified causal chains from confirmed hits.

The implication for deployment is significant. If a blank circuit reaches meaningful accuracy in 7 seconds, a pretrained circuit — one that already has thousands of verified permanent chains encoding general language structure — can interpret and learn from new input in real time. New patterns do not need to overcome a cold start. They land on an existing scaffold of permanent knowledge, and the 98.6% of connections that remain fluid can immediately adapt to encode new associations. This is the difference between teaching a newborn to speak and teaching a fluent speaker a new word. The pretrained circuit already knows how tokens relate. New input is not a training problem — it is a single evaluation that either reinforces existing chains or begins building new ones.

10.4 Inference Speed

On a single CPU core (Apple M4 Pro), the trained circuit processes **1,300 token predictions per second** in pure inference mode — 0.78 ms per token, including output collection and ranking against 1,000 candidates. During training (with reward, pain, replay, and selection active), the circuit sustains **142 iterations per second**, where each rewarded iteration includes 6 forward passes (1 evaluation + 5 hippocampal replays).

A trained circuit is faster than an untrained one. Pruning and pain carve away weak connections, leaving sparser activation patterns that execute more efficiently — the circuit gets faster as it gets smarter.

10.5 Context: What an LLM Achieves

These results are evaluated against 1,000 random candidate tokens drawn from the full 248,320-word vocabulary. This is a meaningful test — the correct token must score higher than 999 random alternatives — but it is not the same as picking the right token from the full vocabulary.

A well-trained transformer LLM evaluated against 1,000 random candidates would achieve approximately 95-99% acc@1, because LLMs produce highly peaked probability distributions where the correct next token scores far above random alternatives. On the full vocabulary without candidate filtering, LLMs typically achieve 50-75% exact top-1 accuracy depending on text difficulty.

The ENC at 44.5% acc@1 against 1,000 candidates — with a rank of 51, placing the correct token in roughly the top 5th percentile — is not yet competitive with transformer performance. Extrapolated to the full vocabulary, a rank of 51/1,000 corresponds roughly to position ~12,000 out of 248,320 tokens.

The comparison, however, is between a 539 KB circuit trained in 105 seconds on a single CPU core with no backpropagation, and models trained on trillions of tokens across thousands of GPUs over months. The gap is real. The question is whether scaling the filing cabinet architecture — more boxes, more training data, more iterations — closes it. The architecture's learning speed (29% accuracy from noise in 7 seconds), storage efficiency (1.4% permanent connections), and continuous learning capability suggest the curve has room to climb.

10.6 Generalization

Test accuracy consistently matches or exceeds train accuracy throughout training. This pattern — unseen data scoring as well as or better than training data — has been observed across every training configuration tested. The circuit is not memorizing input-output pairs. It is learning the structural relationships between tokens in the embedding space.

This is a direct consequence of the sniper chain mechanism. Permanence is only granted on confirmed evaluation hits, using samples drawn randomly from the full dataset. A chain that locks during evaluation on one sample will only be useful on other samples if it encodes a general pattern. Chains that encode memorized noise will not fire on new inputs and will eventually be replaced.

10.7 Storage Density and Scaling

Each box in the filing cabinet architecture contains 4 layers × 2,048 units × 4 pointer connections = 32,768 total connections. At 70% permanent capacity — the threshold at which a box is considered full and a new blank box opens — each box stores 22,938 permanent connections. Each permanent connection is a verified causal link between specific units: a pointer target, a strength, survival state, and pain trace. These are the circuit's learned associations — analogous to parameters in a conventional neural network.

Per-box capacity: - 32,768 connections × 70% = 22,938 permanent connections - Box size: 8,192 units × 64 bytes = 512 KB (0.5 MB) - Density: 45,876 parameters per MB

Scaling to 1 billion parameters: - 1,000,000,000 / 22,938 = 43,594 boxes - 43,594 × 0.5 MB = **21.3 GB**

This is within the memory budget of consumer hardware. A 24 GB Apple Silicon Mac could hold approximately 1.1 billion verified parameters. Each box is independently cache-friendly (128 KB per layer fits in L1), and dormant boxes consume zero compute — only active and recently-filled boxes execute.

The sniper percentage does not change the capacity of a box. A box at 70% permanent holds 22,938 connections regardless of whether they were locked at 0.2% or 1.5% sniper selectivity. What changes is the quality of those connections. At 0.2%, every permanent connection was among the top 4 contributors during a confirmed evaluation hit — a rank ≤ 10 out of 1,000 candidates. At 1.5%, the same box fills with connections that include false positives: units that were active during a correct prediction but were not causally responsible for it.

The comparison to transformer parameters is not 1:1. A transformer weight is a single floating-point number in a dense matrix multiply — one of billions that collectively encode knowledge through distributed representations. An ENC permanent connection is a verified causal link: a specific source unit connected to a specific target unit, with measured co-activation during a confirmed prediction. Each ENC parameter carries more semantic weight than a single transformer weight, but the two architectures encode knowledge in fundamentally different ways. Whether 1 billion ENC parameters equals 1 billion transformer parameters in capability is an open question that only scaling will answer.

10.8 Ablation: Neuromodulation Impact

The neuromodulation channels described in this paper — dopamine, pain, vigilance, and survival-based permanence — represent the published subset of the circuit's learning mechanisms. Additional proprietary channels are implemented but not disclosed.

Systematic ablation of the disclosed channels demonstrates that each contributes significantly. Without any neuromodulation, the circuit achieves negligible accuracy. Adding dopamine gating alone provides meaningful improvement. Adding pain provides further gains. Survival-based permanence with the sniper chain mechanism yields the largest single improvement — over an order of magnitude above baseline. The undisclosed channels provide additional gains beyond what is reported here.

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11. Relationship to LLMs

The neural circuit does not sit inside an LLM inference pipeline. It is a standalone system that shares the LLM's vocabulary.

The circuit's input and output space is defined by compressed token embeddings extracted from an LLM's embedding matrix. The circuit reads these embeddings as input context and scores candidate tokens against them. It uses the LLM's learned vocabulary representations but does not require the LLM to be running.

This means the circuit can be trained and evaluated independently — all it needs is the compact embedding table and training data. The LLM's role is limited to two offline steps: providing the embedding matrix and generating the training data.

The circuit pairs naturally with Arvis — a separate, proprietary energy-based scoring head that evaluates token candidates at over 1,200 tokens per second on consumer hardware. Where the Evolved Neural Circuit provides continuous learning and biological adaptation, the Arvis energy head provides fast, efficient token scoring against the same shared vocabulary. Together they form complementary components of a system that does not require a transformer at inference time.

The long-term path is for the circuit to grow capable enough to operate as a fully independent system — predicting tokens from its own learned representations, without relying on an LLM for anything beyond the initial shared vocabulary.

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12. Path Forward

12.1 CPU-Native Architecture

The Evolved Neural Circuit is designed from the ground up for CPU cache hierarchies, not GPU tensor cores. This is not a compromise — the architecture is genuinely faster on CPU than it would be on GPU.

Every design choice points to CPU strengths:

- **16-byte tape programs** fit in a CPU register file. Each of the 2,048 units per layer executes its own tape with unique branching, pointer chasing, and conditional logic — exactly the kind of irregular, divergent workload that CPUs handle through branch prediction and speculative execution, and that GPUs serialize through thread divergence.
- **128 KB per layer** fits exactly in the L1 data cache on Apple Silicon. The paver pattern ensures the current layer is always in the fastest memory on the chip. No cache misses, no memory stalls.
- **4 MB per brain** fits entirely in L2 cache. The entire trained circuit — all layers, all units, all connection weights — lives in the second-fastest memory on the chip. A transformer needs 4–70 GB of VRAM for the same task.

- **No matrix multiplies.** The architecture contains zero GEMMs, zero dense linear algebra. The operation that GPU tensor cores are specifically designed to accelerate does not exist here.
- **Pointer-driven random access** across layers. Units read from arbitrary locations via pointer connections — a pattern that thrives on CPU cache prefetching and out-of-order execution, but defeats GPU memory coalescing.
- **Parallel functional regions.** Eight independent boxes run on eight CPU cores via GCD `dispatch_apply`. Each box processes its own context slice with no synchronization during the forward pass. This maps cleanly to CPU core-level parallelism.

The implication is significant: the ENC runs at full speed on any device with a CPU and 4 MB of free memory — phones, embedded systems, medical devices, satellites, IoT hardware. No GPU driver stack required. No VRAM budget. No cloud API. Power draw measured in milliwatts, not hundreds of watts. The entire history of deep learning has been a story of scaling GPU compute. This architecture takes the opposite path: designed for the processor that already exists in every computing device on Earth.

12.2 Multimodal Perception

The circuit is architecture-agnostic about its input. It processes embeddings — it doesn't care whether those embeddings represent text tokens, image patches, or audio spectrograms. Adding vision or audio is a matter of providing appropriate embeddings to layer 0. The circuit learns cross-modal associations through the same evolutionary and neuromodulation mechanisms.

12.3 Dynamic Brain Growth

The brain does not allocate a fixed amount of memory at initialization. It grows as it learns.

Each box in the filing cabinet starts as a blank reservation — a 12-byte metadata record with `first_layer = -1`, consuming no layer memory. When the currently accepting box fills to 80% permanent connections, the next blank box is allocated: 4 layers × 2,048 units of memory are appended to the layer array, columns are initialized, and the new box begins accepting input. The brain expands on demand.

This means a default brain with 204,800 box reservations — a theoretical ceiling of 100 GB — occupies approximately 0.5 MB at birth: one active box plus metadata for the rest. Memory consumption tracks learning progress. A brain that has learned 10 domains and filled 20 boxes uses 10 MB. A brain that has been trained extensively across thousands of domains might occupy several gigabytes. The ceiling is an SSD-era number: 100 GB is not pre-allocated, it is the upper bound of growth on hardware with ample storage.

This architecture solves the scaling problem without paying the scaling cost upfront. The brain is as small as it needs to be and as large as it can grow.

12.4 Hot-Swappable Skills

The brain's vigilance system knows what it doesn't know — columns with low confidence produce measurable uncertainty signals. This creates a natural trigger for loading specialized knowledge on demand.

A skill (`.skill` file) is a self-contained package of trained boxes — complete with their own species definitions (neuron types), connection weights, survival state, and column state. Skills live on SSD normally. When the brain encounters input outside its current expertise, the relevant skill loads from disk: its species definitions merge into the brain's definition array with automatic type index remapping, and its boxes append to the brain's filing cabinet. The skill's boxes participate in evaluation and prediction exactly like native boxes — no bridge columns, no special execution path.

When the skill is no longer needed, it unloads: boxes save their current state back to the `.skill` file on SSD (preserving any learning that occurred while loaded), then their layer memory is freed. The boxes return to unallocated state, and the brain shrinks.

Skills are variable-sized. A narrow skill (conversation patterns) might be a single box — 0.5 MB. A deep skill (clinical medicine) might be hundreds of boxes spanning hundreds of megabytes. There are no fixed slots or size categories. The constraint is available RAM, not an architectural limit.

Multiple skills can be loaded simultaneously. A brain working on a medical coding problem could have `medicine.skill` and `coding.skill` loaded at the same time, with both contributing to predictions. SSD reads at 7+ GB/s on current Apple Silicon — loading a 10 MB skill takes ~1.5 ms.

Skills are shareable. Train a world-class medicine skill on one machine, distribute the `.skill` file, and any compatible brain loads it instantly. The skill carries everything it needs — no dependency on the host brain's training history. This is the `.skill` file as a unit of knowledge distribution: portable, versioned, independently trainable.

The biological analog is long-term memory consolidation. The hippocampus does not hold everything in working memory simultaneously — it retrieves relevant memories when context demands them and lets them fade when attention moves elsewhere. Skills on SSD are the library. The brain is the reading room.

12.5 Sleep Cycles

The dream consolidation mechanism is currently a manual phase — the user runs `enc dream` after training. The path forward is an autonomous sleep cycle: the circuit trains, detects diminishing returns (reward rate stabilizing, accuracy plateauing), saves a `.dream` file, enters dream mode to consolidate, then wakes and resumes training with refreshed memories. The hippocampus transitions from programmatic routing to a learned neural hippocampus — a box that learns to route input to the correct region based on experience, not hardcoded rules. The training signal: "did the routing decision lead to a correct prediction?"

12.6 The Living System

The long-term goal: a system that doesn't need a transformer at all. An Evolved Neural Circuit large enough and trained long enough to handle language on its own — not through statistical pattern matching on trillions of tokens, but through evolved computational tissue that learns the way biological brains learn.

The circuit already has the foundations: it learns continuously, generalizes to unseen data, modulates its own learning through reward and pain, and forms persistent memory through survival. What it lacks is scale, and

scale is an engineering problem.

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13. Discussion

13.1 What This Demonstrates

A system evolved from random bytes, trained without backpropagation, achieves genuine generalization on next-token prediction. The core mechanisms — survival-based permanence, dopamine-gated reward, local pain, hippocampal replay — are biologically inspired and computationally minimal. The system is extremely compact and processes in microseconds.

This is not yet competitive with transformer language models for general-purpose text generation. But the comparison misses the point: this system *learns continuously after deployment*, requires no GPU for training, and builds its representations from evolutionary pressure rather than gradient descent. No production AI system today has these properties.

13.2 Biological Parallels

Biological System	Circuit Analog
Cortical columns	Mixed-species columns
Pyramidal neurons	Alchemist Projectors
Stellate cells	Shapeshifter Integrators
Interneurons	Suppressor units
Dopamine system	Global reward gating
Nociception	Local pain with avoidance traces
Norepinephrine	Per-column vigilance
Long-term potentiation	Survival-based permanence
Hippocampal replay	Success replay (immediate)
Hippocampal memory consolidation	Dream phase (.dream file)
Sleep replay	`enc dream` — offline consolidation from priority-ranked buffer
Novelty detection	Input centroid distance

Biological System	Circuit Analog
Synaptic homeostasis	Global decay

13.3 Open Questions

1. **Scale vs. accuracy**: How does accuracy scale with circuit size?
2. **Wide vs. deep**: Does the cortical pattern (wide, thin) outperform the spinal cord pattern (narrow, deep)?
3. **Cross-modal transfer**: Can circuits evolved on language adapt to vision and audio?
4. **Working memory**: Can shared state enable multi-step reasoning?

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