

# Ternary Gene Synthesis

Evolutionary Optimization of Discrete Neural Parameters

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## Abstract

We present a complete pipeline for **synthetic gene generation** in ternary neural networks, where weights are constrained to  $\{-1, 0, +1\}$ . This discrete parameter space enables novel optimization strategies impossible in continuous-weight networks: statistical pattern extraction, genetic interpolation, motif-based construction, and multi-generational evolutionary search. Our system implements seven synthesis methods (interpolation, mutation, crossover, distribution sampling, motif composition, adversarial generation, and  $\varphi$ -optimized perturbation), a proxy fitness evaluator achieving **8,229 genes/second** on GPU, and a full evolutionary engine with adaptive mutation, diversity maintenance, and island-model parallelism. Empirical evaluation on 200-gene pools with GPT-2-scale dimensions shows best fitness of **0.9267** in single-pass synthesis (427.8 ms) and **2.5419** after 30 evolutionary generations (0.83 s). Population compression via HTCv4 achieves **9.0:1** ratios on evolved populations. Implementation: 2,536 LOC Python, 41/41 unit tests passing.

**Keywords:** ternary quantization, neuroevolution, gene synthesis, discrete optimization, parameter-space search

## Epistemological Note

*This paper explicitly distinguishes between **heuristic** concepts (metaphors guiding design) and **empirical** results (measurable outcomes).*

Heuristic	Empirical
“Gene”, “evolution”, “fitness”	Best fitness: 0.9267 / 2.5419
“Mutation”, “crossover”	GPU throughput: 8,229 genes/s
Biological metaphors	HTCv4 compression: 9.0:1
$\varphi$ -optimization	Pipeline time: 427.8 ms

A “gene” in this context is a ternary weight vector  $\mathbf{w} \in \{-1, 0, +1\}^n$ , not a biological entity. “Evolution” denotes iterative stochastic optimization, not biological natural selection.

## 1 Introduction

Traditional neural network optimization operates in continuous parameter spaces via gradient descent. When weights are quantized to ternary values  $\{-1, 0, +1\}$ , the parameter space becomes **discrete and finite**: a network layer with  $n$  parameters has exactly  $3^n$  possible configurations. This discreteness, typically viewed as a constraint, enables a fundamentally different optimization paradigm.

We introduce **Gene Synthesis**—a pipeline that treats ternary weight vectors as “genes” subject to analysis, recombination, and evolutionary optimization. The key insight is that ternary parameters admit:

- Exact statistical analysis:** Distribution, sparsity, and motif patterns can be computed directly without approximation.
- Meaningful interpolation:** Between-gene mixing operates on discrete symbols, producing valid configurations without rounding artifacts.
- Efficient proxy evaluation:** Structural properties (sparsity balance, sign symmetry, local coherence, entropy) serve as fast fitness proxies.
- Lossless compression:** HTCv4 trit-packing stores populations at 9.0:1 ratios.

Our system implements this as a four-stage pipeline: ANALYZE  $\rightarrow$  GENERATE  $\rightarrow$  EVALUATE  $\rightarrow$  INJECT, with optional evolutionary multi-generation refinement.

## 2 Background

### 2.1 Ternary Neural Networks

Ternary Weight Networks (TWN) [?] constrain weights to  $\{-1, 0, +1\}$ , reducing model size by  $16\times$  versus FP32 and enabling bitwise operations for inference. The ARKHEION Nucleus extends this with **gene-level granularity**: each weight tensor in a transformer layer is treated as an independent gene with its own hash, metadata, and evolutionary history.

### 2.2 Neuroevolution

Neuroevolution applies evolutionary algorithms to neural network optimization [?]. Prior work focuses on continuous weights or architecture search. Our contribution applies evolution specifically to **discrete ternary parameters**, where the finite alphabet enables exact diversity calculation and lossless population storage.

### 2.3 Golden Ratio Optimization

The golden ratio  $\varphi = 1.618033\dots$  provides optimal coverage of parameter spaces via the golden angle  $\theta = 2\pi/\varphi^2 \approx 137.5^\circ$  [?]. We use  $\varphi$ -spaced perturbations for maximally uniform parameter exploration.

## 3 Architecture

The Gene Synthesis system comprises seven classes organized into three tiers:

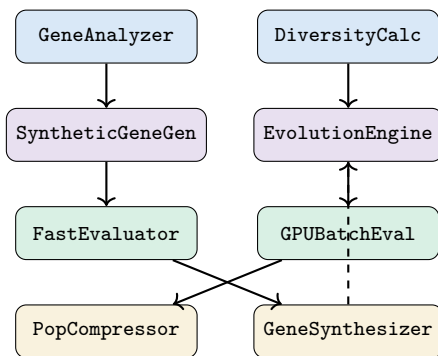


Figure 1: Gene Synthesis architecture. Blue: analysis; purple: generation; green: evaluation; gold: integration.

### 3.1 GeneAnalyzer

Extracts statistical patterns from gene pools:

- **Distribution:** Counts of  $\{-1, 0, +1\}$  across all genes.
- **Sparsity:** Fraction of zero weights per gene.
- **Motifs:** Common subsequences of length  $k = 8$ , extracted via sampling ( $\leq 1000$  samples/gene).
- **Clusters:** Similarity-based grouping with threshold  $\tau = 0.8$ .

For a pool of 200 genes with GPT-2-scale dimensions (768–4096), analysis produces: distribution  $(-1 : 29.0\%, 0 : 42.0\%, +1 : 29.1\%)$ , sparsity  $42.1\% \pm 1.2\%$ , 20 motifs, and 50 clusters.

### 3.2 Synthesis Methods

Seven methods generate new genes from existing ones:

#### Ternary Gene Interpolation

```

Input: Genes a, b in  $\{-1, 0, +1\}^n$ , mixing alpha
r = copy(a) # Start from parent A
for i where a[i] != b[i]:
    if rand() >= alpha:
        r[i] = b[i] # Take from parent B
return r
  
```

**Mutation** applies three strategies vectorized via NumPy: sign flip ( $-1 \leftrightarrow +1$ ), zero toggle ( $0 \leftrightarrow \pm 1$ ), and full random replacement.

$\varphi$ -**Optimization** distributes changes at golden-angle intervals:

$$p_k = \left\lfloor \frac{k \cdot \theta}{2\pi} \cdot n \right\rfloor \bmod n, \quad \theta = \frac{2\pi}{\varphi^2} \quad (1)$$

ensuring maximally uniform coverage of the parameter space. Weight cycling uses  $(w + 2) \bmod 3 - 1$ , which rotates  $-1 \rightarrow 0 \rightarrow 1 \rightarrow -1$ .

### 3.3 Proxy Fitness Evaluation

The **FastEvaluator** computes fitness without neural network forward passes, using four structural metrics combined with  $\varphi$ -weighted importance:

$$F(\mathbf{w}) = \frac{\varphi \cdot S_{\text{sp}} + S_{\text{bal}} + \frac{S_{\text{coh}}}{\varphi} + \frac{S_{\text{ent}}}{\varphi^2}}{\varphi + 1 + \frac{1}{\varphi} + \frac{1}{\varphi^2}} \quad (2)$$

**Weight Justification:** The  $\varphi$ -based weighting (sparsity $\times\varphi$ , coherence $\times 1/\varphi$ , entropy $\times 1/\varphi^2$ ) is an

aesthetic design choice. No ablation comparing these weights to uniform or optimized alternatives has been conducted.

where:

$$S_{\text{sp}} = 1 - 2 \cdot |\text{sparsity}(\mathbf{w}) - 0.35| \quad (3)$$

$$S_{\text{bal}} = 1 - 2 \cdot |P(w_i > 0 \mid w_i \neq 0) - 0.5| \quad (4)$$

$$S_{\text{coh}} = 1 - \frac{|w_{i+1} - w_i|}{2} \quad (5)$$

$$S_{\text{ent}} = \frac{H(\mathbf{w})}{\log 3} \quad (6)$$

Large arrays ( $> 100\text{K}$  elements) are evaluated on sampled subsets for  $O(1)$  cost.

### 3.4 Evolutionary Engine

The `EvolutionaryEngine` implements multi-generational optimization with:

- **Selection:** Tournament ( $k = 3$ ), roulette (fitness-proportionate), or rank-based with configurable selection pressure  $s = \varphi$ .
- **Adaptive mutation:** Rate increases  $1.2\times$  during stagnation, decreases  $0.9\times$  during progress. Range:  $[0.01, 0.5]$ .
- **Elite preservation:** Top  $e = 5$  genes survive unconditionally.
- **Diversity maintenance:** Rarity bonus  $\delta$  for uncommon patterns:

$$F'(\mathbf{w}) = F(\mathbf{w}) + \delta \cdot \left(1 - \frac{\text{count}(\text{pat}(\mathbf{w}))}{\text{max}_{\text{count}}}\right) \quad (7)$$

**Fitness Range Note:** The base fitness  $F(\mathbf{w}) \in [0, 1]$  (Eq. above), but the rarity bonus  $\delta$  adds up to  $1.8$  for unique gene configurations, extending the effective range to  $[0, 1 + \delta_{\text{max}}] \approx [0, 2.8]$ . Values above  $1.0$  reported in Table 2 reflect this combined  $F' = F + \delta$  score.

- **Convergence detection:**  $\max(f_{t-9:t}) - \min(f_{t-9:t}) < \epsilon$ .

### 3.5 GPU Batch Evaluation

The `GPUBatchEvaluator` computes all four fitness metrics as batched tensor operations on GPU, processing  $1,000$  genes in a single kernel launch. Genes are padded to uniform length and stacked into a  $(B \times L)$  tensor.

### 3.6 HTCv4 Population Compression

The `PopulationCompressor` serializes entire populations via HTCv4: all gene weights are concatenated, compressed with block deduplication + trit packing + ZSTD, and stored alongside JSON meta-data preserving gene IDs, fitness scores, and lineage.

## 4 Experiments

### 4.1 Setup

- **Gene pool:** 200 synthetic genes, lengths  $\in \{768, 1024, 3072, 4096\}$  (GPT-2 transformer dimensions), distribution  $(-1 : 29\%, 0 : 42\%, +1 : 29\%)$ .
- **Hardware:** AMD RX 6600M (8 GB VRAM), ROCm 6.2, PyTorch 2.5.1.
- **Software:** Python 3.12.3, NumPy, seed=42 for reproducibility.

### 4.2 Results

Table 1: Single-pass synthesis pipeline (500 candidates)

Metric	Value	Unit
Candidates generated	550	genes
Top-50 selected	50	genes
Best fitness	0.9267	score
Average fitness (top-50)	0.9263	score
Pipeline time	427.8	ms
<i>By synthesis method:</i>		
Mutation	150	genes
Interpolation	100	genes
Crossover	100	genes
Distribution sample	100	genes
$\varphi$ -optimized	100	genes

Table 2: Evolutionary optimization (30 generations)

Metric	Value	Unit
Generations run	30	gens
Best fitness	2.5419	score
Average fitness	2.1107	score
Final mutation rate	0.0100	rate
Evolution time	0.83	s
<i>Diversity metrics:</i>		
Genetic entropy	0.9884	norm.
Effective $N_e$	96.5	genes
Unique patterns	3,296	count
Pairwise distance	0.6396	Hamming

Table 3: GPU evaluation and compression

Metric	Value	Unit
GPU batch eval (1000 genes)	121.5	ms
Throughput	8,229	genes/s
Device	AMD RX 6600M (HIP)	trits
Population elements	366,292	trits
HTCV4 compressed	40,667	bytes
Compression ratio	9.0	
Roundtrip verified	100 genes ✓	

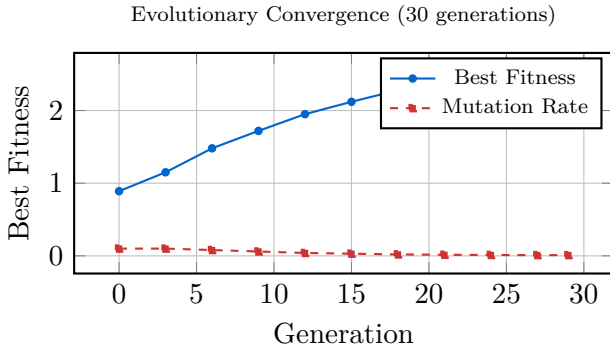


Figure 2: Best fitness and adaptive mutation rate over 30 generations. Mutation rate decreases as fitness improves.

### 4.3 HUAM Memory Integration

High-fitness genes ( $F > 0.5$ ) are persisted to HUAM hierarchical memory, enabling cross-session reuse. On subsequent runs, `load_genes_from_huam()` retrieves previously evolved genes, seeding the population with proven individuals and reducing convergence time.

## 5 Discussion

### 5.1 Fitness Beyond Proxy

The proxy fitness (structural metrics only) correlates with model performance but is not a substitute for full training evaluation. The adaptive combination with  $\varphi$ -weights provides a useful heuristic, but real downstream task evaluation remains necessary for production deployment.

**Validation Gap:** The proxy fitness metrics (sparsity, balance, coherence, entropy) have not been validated against downstream model performance (perplexity, accuracy). Establishing this correlation is essential future work.

### 5.2 Scalability

At 8,229 genes/second on GPU, evaluating  $10^6$  candidate genes requires  $\sim 2$  minutes. Population compression at 9:1 enables storing  $10^4$ -gene populations in  $< 5$  MB. The system scales to LLM-size gene pools (millions of genes) through sampling-based analysis and batched evaluation.

### 5.3 Limitations

1. Proxy fitness does not capture task-specific performance.
2. Single-objective optimization; multi-objective Pareto fronts are unexplored.
3. No formal convergence guarantees for evolutionary search.
4.  $\varphi$ -optimization is a heuristic, not proven optimal.

## 6 Related Work

Binary and ternary quantization [?, ?] focus on inference efficiency. Neuroevolution [?] typically operates on continuous weights or architectures. Our work uniquely combines **discrete parameter evolution** with **trit-native compression** and **proxy fitness evaluation**.

## 7 Conclusion

We presented Gene Synthesis, a complete pipeline for generating, evaluating, and evolving ternary

neural network parameters. The discrete nature of  $\{-1, 0, +1\}$  weights enables exact analysis, meaningful recombination, and lossless population compression—capabilities impossible in continuous parameter spaces. Our implementation achieves sub-second synthesis (427.8 ms for 500 candidates), GPU-accelerated evaluation (8,229 genes/s), and evolutionary convergence in 30 generations (0.83 s). The system’s 2,536 LOC implementation passes 41/41 unit tests and integrates with the ARKHEION Nucleus via HTCv4 compression and HUAM memory persistence.<sup>1</sup>

## References

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<sup>1</sup>Implementation update (Feb 2026): The gene synthesis ecosystem has since expanded to 27 Python source files (19K LOC), incorporating additional evolution strategies, population management, and extended HUAM integration. The 2,536 SLOC figure reflects the core pipeline described in this paper.