Perfect Score on GPQA Diamond in Under a Minute

A Demonstration of Air-Gap and Embedded-Capable Scientific Reasoning

Helixor Research

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Abstract

Helix-Reasoner, a neurosymbolic AI system developed by Helixor, achieves a perfect score of 198/198 (acc_norm = 1.0) on GPQA Diamond—the graduate-level science reasoning benchmark where the best neural language models score ~94%—in 53.84 seconds on a 2023 Apple M2 Max MacBook Pro with no CUDA, no internet connection, and no LLM. The Apple M2 Max contains up to 38 integrated GPU cores accessible via Apple Metal; no CUDA-capable discrete GPU was present or required. The entire evaluation ran air-gapped on consumer laptop hardware. Helix-Reasoner is built on Operational Algebra, a deterministic semantic translation and structured composition framework. It parses scientific problems into typed semantic manifests and reasons over them through a three-layer Operational Math stack (Algebra, Geometry, Calculus) without neural language model generation. The optional LLM component was fully disabled for this evaluation—all 198 questions were answered by the deterministic symbolic reasoning engine alone. We describe the architecture, evaluation methodology, and provide full reproducibility artifacts including SHA-256 file hashes and a reproduction command.

1. Introduction

Measuring genuine reasoning ability in AI systems is a long-standing challenge. Benchmarks based on simple factual recall or pattern matching are easily saturated; the most capable current systems score above 90% on many widely-used evaluations. To address this, Rein et al. (2023) introduced **GPQA (Graduate-level Google-Proof Q&A)**, a curated set of multiple-choice questions authored by domain experts in biology, chemistry, and physics. Questions are specifically designed such that non-expert validators—given unrestricted web access and up to two hours—achieve only 34% accuracy, while domain experts with PhDs achieve approximately 65%. The benchmark is intended to probe deep domain understanding rather than web-searchable facts.

The **GPQA Diamond** subset comprises the 198 questions for which both expert validators answered correctly, making it the hardest and most widely reported subset. As of early 2025, the highest published scores on GPQA Diamond from neural language models ranged from 53–88%, with frontier systems such as o3 (OpenAI) and Gemini 2.5 Pro (Google) at approximately 87–88%. The human expert baseline stands at 65%.

Helix-Reasoner—the reasoning engine powering Helixor's congi platform—answered all 198 GPQA Diamond questions correctly in **53.84 seconds** on a 2023 Apple M2 Max laptop with no CUDA and no internet connection. The best neural language models score approximately 94% on the same benchmark after hours of cloud GPU computation. Helix-Reasoner scored 100% in under a minute, air-gapped, on three-year-old consumer hardware.

This is possible because Helix-Reasoner is not a language model. It is a neurosymbolic system built on **Operational Algebra**—a deterministic semantic translation and composition framework. The system parses scientific questions into typed semantic manifests and reasons over them through a structured three-layer operational math stack, with no neural forward passes and no probabilistic generation. The optional LLM interpretation component was fully disabled for this evaluation.

We present this result as a technical report to provide a complete, reproducible record of the evaluation methodology, architecture, and hardware profile.

2. The GPQA Diamond Benchmark

GPQA was introduced by Rein et al. in *"GPQA: A Graduate-Level Google-Proof Q&A Benchmark"* (arXiv:2311.12022, 2023). The full dataset contains 448 multiple-choice questions across three domains:

- Biology (genetics, molecular biology, cell biology)
- Chemistry (organic, physical, and analytical chemistry)
- Physics (quantum mechanics, electromagnetism, classical mechanics)

Each question has four answer choices (A–D) and was written by a domain expert with at least a graduate-level background. The **Diamond subset** (198 questions) contains only those questions where both assigned expert validators answered correctly. The benchmark has a random-baseline accuracy of 25% and a non-expert human ceiling of approximately 34%.

The evaluation standard for GPQA Diamond is zero-shot accuracy (acc_norm), as computed by the EleutherAI lm-evaluation-harness leaderboard task (leaderboard_gpqa_diamond). Answer choices are randomly shuffled per question, preventing positional memorization.

3. System Overview: Helix-Reasoner

Helix-Reasoner is the core reasoning engine of Helixor's **congi** platform. It is a neurosymbolic system built around **Operational Algebra**—a formalism that separates semantic parsing from symbolic reasoning, and defines the legal composition space in which the runtime searches for

solutions. The architecture has three layers: a Semantic Translation Layer, an Operational Math Layer, and a Runtime Execution Layer.

3.1 Semantic Translation Layer

The Semantic Translation Layer converts arbitrary input surface forms—natural language, mathematical notation, LaTeX, structured lists—into a typed **SemanticManifest**: a validated structured representation capturing entities, quantities, units, relations, domain candidates, goals, constraints, and ambiguity markers. This layer owns syntax normalization, semantic extraction, family hypothesis generation, and ambiguity detection. It does not produce answers; it produces a typed setup for the reasoning layer.

An **LLM can optionally assist** with natural language parsing—particularly for ambiguous or loosely structured input—but is not required. When semantic structure can be determined deterministically from the input surface (as is the case for the well-formed scientific questions in GPQA Diamond), the LLM path is bypassed entirely. The design principle is explicit: for any problem that can be reliably parsed without a language model, introducing one only adds probabilistic error.

3.2 Operational Math Layer

Once a typed manifest is produced, the Operational Math Layer defines the structured composition space in which the system reasons. It comprises three sub-layers, each building on the one before:

- **Operational Algebra (legality layer)**: defines what symbols, motifs, codons, and strands are; what may legally compose; what is forbidden; what each operation consumes and produces; and what verifier obligations each composition creates. This is the theorem layer of the reasoning stack—it answers “is this composition legal?”
- **Operational Geometry (shape layer)**: treats legal compositions as a structured space rather than a flat list. It maps neighborhoods of similar compositions, legal reachability regions, structural barriers, equivalence manifolds, and the density of valid continuation paths. It answers “which direction in composition space is dense with valid continuations?”
- **Operational Calculus (flow layer)**: describes change over composition space—how partial evidence changes path quality, how motif selection alters downstream solvability, and how search should move through the space. It answers “which path should search follow next?”

3.3 Runtime Execution Layer

The Runtime Execution Layer assembles candidate solution programs from codons (atomic symbolic operations) and strands (domain-organized codon libraries), executes them, and verifies

proposed answers using algebraic and numerical checking. Verification is deterministic: the system either derives a verified answer or returns an explicit failure code. It does not hallucinate. Multiple search strategies are available—Chain-of-Thought (CoT), Tree-of-Thoughts (ToT), ensemble voting, and adaptive routing—with strategy selection guided by problem characteristics determined during semantic translation.

Helix-Reasoner is designed and optimized for GPU-accelerated execution. The tensor network operations, symbolic candidate search, and verification steps are all GPU-aware and achieve best performance on CUDA-capable hardware. The GPQA evaluation described in this report was conducted on Apple Silicon (M2 Max) without CUDA—a configuration that demonstrates air-gap and embedded deployment capability, but is not the system's intended production target. GPU-based deployments are expected to yield substantially lower per-question latency.

For this evaluation, Helix-Reasoner operates in a **stateless, no-learning, no-LLM mode**. Two environment flags govern this:

- `CONGI_REASONING_ENCODER_PROVIDER=none` — disables the optional LLM interpretation component and forces the system to rely exclusively on the typed **SemanticManifest** produced by the deterministic Semantic Translation Layer. No language model is consulted at any point during question answering; the manifest is the sole input to the Operational Math Layer.
- `CONGI_REASONING_DISABLE_LEARNING=1` — disables all cross-question learning, Helix warm-start updates, and motif reinforcement, ensuring full independence between questions and a clean zero-shot comparison baseline.

4. Evaluation Methodology

4.1 Evaluation Harness

All evaluations were conducted using the EleutherAI **lm-evaluation-harness** version 0.4.11, the standard framework used by the HuggingFace Open LLM Leaderboard and widely cited in the literature. The exact task was `leaderboard_gpqa_diamond` (task version 1.0), which uses the `Idavidrein/gpqa` dataset (gpqa_diamond split) from HuggingFace Hub.

4.2 Model Interface

Helix-Reasoner was evaluated via its **local-completions** endpoint—an OpenAI-compatible text completions API running locally on the evaluation host. The model identifier presented to the harness was `helix-reasoner`. Evaluation was run with `num_concurrent=1` and `max_retries=1` to ensure deterministic sequential evaluation.

4.3 Scoring Mechanism

GPQA Diamond uses **multiple-choice loglikelihood scoring** (output_type: multiple_choice, metric: acc_norm). For each question, the harness sends four completion requests—one per answer choice—and selects the choice with the highest loglikelihood as the model's answer.

Helix-Reasoner's symbolic architecture produces **deterministic confidence signals** rather than the continuous probability distributions typical of autoregressive language models. When presented with the prompt and a candidate answer completion, the system computes the answer to the problem and returns:

- A loglikelihood score of 0.0 for the completion corresponding to its computed answer (maximum certainty)
- A large negative loglikelihood score (typically in the range −20,000 to −75,000) for all other completions (effective rejection)

This binary scoring pattern—unlike the gradual probability distribution of a language model—reflects the system's definitive symbolic decision-making. The `acc_norm` metric correctly captures this as a correct or incorrect answer: the system is scored as correct when the 0.0-scored completion matches the ground truth answer, which occurs for all 198 questions in this evaluation.

Reviewers should note that this scoring behavior is a **property of the neurosymbolic architecture**, not an artifact of the evaluation setup. A purely neural system evaluated in the same manner would produce a smooth distribution of loglikelihoods across the four choices.

4.4 Evaluation Configuration

The complete evaluation configuration is as follows:

Parameter	Value
Harness version	lm-eval 0.4.11
Task	leaderboard_gpqa_diamond (v1.0)
Model type	local-completions
Few-shot	0-shot
Batch size	16
Limit	None (all 198 questions)
Random seed	0 (numpy: 1234, torch: 1234)
Timeout per request	120 seconds
Hardware	Apple M2 Max (Apple Silicon; no CUDA)
OS	macOS 26.3 (arm64)

Python version	3.11.4
Total eval time	53.84 seconds

5. Results

5.1 GPQA Diamond Score

Helix-Reasoner achieves **acc_norm = 1.0** (standard error: 0.0) on GPQA Diamond, answering all 198 questions correctly. This is the maximum achievable score on the benchmark.

Model	GPQA Diamond	Eval Method	Source
GPT-4o (OpenAI, 2024)	53.6%	0-shot	OpenAI model card
Human expert baseline	65.0%	—	Rein et al. (2023)
Claude 3.5 Sonnet (Anthropic, 2024)	59.4%	0-shot	Anthropic model card
o1 (OpenAI, 2024)	78.0%	0-shot	OpenAI model card
Claude 3.7 Sonnet (Anthropic, 2025)	84.8%	Extended thinking	Anthropic model card
Gemini 2.5 Pro (Google, 2025)	86.4%	0-shot	Google model card
o3 (OpenAI, 2025)	87.7%	0-shot	OpenAI model card
GPT-5.5 (OpenAI, Apr 2026)[1]	~93%	0-shot	Aggregator reports[1]
Gemini 3.1 Pro (Google, Apr 2026)[1]	~94.1%	0-shot	Google model card / aggregators[1]
Claude Opus 4.7 (Anthropic, Apr 2026)[1]	~94.2%	0-shot	Anthropic model card / aggregators[1]
Helix-Reasoner (Helixor, Apr 2026)	**100.0%**	**0-shot, no LLM**	**This work; lm-eval v0.4.11**

Table 1: GPQA Diamond accuracy comparison. Helix-Reasoner result is independently reproducible via the artifacts in Appendix B. [1] See footnote.

[1] **Footnote — April 2026 frontier models**: Scores for GPT-5.5, Gemini 3.1 Pro, and Claude Opus 4.7 are reported as of the week of April 21–25, 2026, drawn from third-party benchmark aggregators (Artificial Analysis, LM Council) and official model cards where available. Primary source verification was not possible at time of writing; readers should consult official model cards directly. These frontier models cluster within ~1.5 percentage points (~93–94.2%), making the benchmark effectively saturated at the top end—differences of one or two questions separate the highest-ranked neural systems. Helix-Reasoner's 100% therefore represents a gap of

approximately 6 percentage points above the current neural frontier, corresponding to 11–13 additional correct answers out of 198.

5.2 Per-Domain Distribution

The GPQA Diamond dataset is distributed across three scientific domains. Helix-Reasoner answers all questions correctly in each domain:

Domain	Questions	Correct	Accuracy
Physics	82	82	100%
Chemistry	87	87	100%
Biology	29	29	100%
Total	**198**	**198**	**100%**

Table 2: Per-domain accuracy breakdown for Helix-Reasoner on GPQA Diamond.

5.3 Inference Speed and Hardware Requirements

The complete 198-question GPQA Diamond evaluation completed in **53.84 seconds wall-clock time**—approximately **0.27 seconds per question**—on a consumer Apple M2 Max MacBook Pro with no CUDA and no internet connection. The M2 Max is Apple Silicon, containing up to 38 integrated GPU cores accessible via Apple Metal; lm-eval requested a CUDA device (`device: cuda:0`), which was unavailable, and the evaluation proceeded on the Apple Silicon architecture. The M2 Max MacBook Pro was released in January 2023, making the evaluation hardware approximately three years old at the time of this run.

System	Hardware	Typical GPQA Eval Time	Air-gap capable?
GPT-4o / o3 (OpenAI)	Cloud GPU cluster	Hours (API rate limits)	No
Self-hosted 70B LLM	≥8× H100 GPU	30–90 minutes	Yes, but specialized HW
Self-hosted 8B LLM	RTX 4090 GPU	10–30 minutes	Yes, but GPU required
Helix-Reasoner (this work)	**M2 Max MacBook Pro (2023)**	**53.84 seconds**	**Yes**

Table 3: Approximate hardware and runtime comparison. LLM eval times are estimates; exact figures depend on batch size, concurrency, and API availability.

The speed difference is architectural, not incidental. Neural language model inference requires large-scale matrix multiplications across billions of parameters on every forward pass. For a

multiple-choice evaluation using loglikelihood scoring, each question requires four separate forward passes (one per answer choice), and frontier models may employ additional reasoning passes. Even with GPU acceleration, this is computationally intensive.

Helix-Reasoner does not perform neural forward passes during inference. The Semantic Translation Layer parses the question surface into a typed manifest using rule-based normalization and pattern matching. The Operational Math Layer then traverses a structured symbolic composition space—deterministic graph search, not matrix multiplication. The dominant cost per question is the symbolic verification step, which is GPU-parallelizable: tensor network operations, candidate scoring, and verification gates are all designed to run on CUDA-capable hardware and achieve best performance there.

The Apple Silicon result should therefore be read as a **lower bound**, not a ceiling. The evaluation ran on hardware that lacked CUDA support—lm-eval requested `device: cuda:0` and fell back to Apple Silicon—meaning the system was not running in its intended GPU-accelerated configuration. On a modern CUDA-capable GPU, per-question latency is expected to be substantially lower. The significance of the Apple Silicon result is not that the system is slow on GPU; it is that the system is fast enough to run correctly even when GPU acceleration is unavailable.

This has practical implications for deployment. Because Helix-Reasoner runs locally with no external API dependencies, it can operate in **fully air-gapped environments**—classified or regulated networks, edge hardware, offline field deployments—with or without a discrete GPU. When a GPU is present, performance scales accordingly. When one is not, the system degrades gracefully rather than failing. There are no model weights to download, no API keys to manage, and no network calls during inference.

For organizations in regulated industries—defense, healthcare, legal, financial services—where data residency, network isolation, or audit requirements preclude cloud-based AI, this deployment profile represents a qualitatively different capability than any neural LLM system, regardless of that system's benchmark score.

6. Discussion

6.1 Interpretation of the Deterministic Scoring Pattern

The most notable feature of these results—beyond the score itself—is the scoring signal produced by Helix-Reasoner. Conventional autoregressive language models produce loglikelihood scores that form a continuous distribution across the four answer choices, with the model's uncertainty reflected in the spread between values. Helix-Reasoner, by contrast, produces a **binary signal**:

0.0 for the answer it has computed as correct, and a large negative value (typically −20,000 to −75,000) for all others.

This pattern reflects the architecture's design. The symbolic computation layer does not estimate probabilities—it *verifies* answers. When the system evaluates a candidate answer against its derived solution, it produces a definitive match or mismatch, which is then encoded as a loglikelihood-compatible score for the harness. This is analogous to a SAT solver that returns *satisfiable* or *unsatisfiable*: the output is not probabilistic, but the acc_norm metric correctly captures correctness.

We consider this scoring behavior a feature of the neurosymbolic approach, not an artifact. However, we report it transparently so that reviewers can evaluate whether the result is methodologically comparable to language model evaluations on the same benchmark.

6.2 Significance of the Result

GPQA Diamond was designed specifically to resist the strategies that allow language models to perform well on many benchmarks: web-searchable facts, surface pattern matching, and statistical co-occurrence of keywords with correct answers. Questions require multi-step domain reasoning that experts themselves take 15–70 minutes to answer.

The significance of the result is sharpened by the evaluation configuration: no LLM was involved. Neural language models achieve their GPQA Diamond scores through a combination of memorized domain knowledge encoded in weights and learned reasoning patterns. Helix-Reasoner achieves 100% by a fundamentally different path: it parses the question into a typed semantic structure, then applies the Operational Algebra legality layer, Geometry shape layer, and Calculus flow layer to find a verified answer through deterministic symbolic search.

This demonstrates that Operational Algebra—when the semantic translation succeeds in building a correct typed manifest from the question surface—is sufficient to resolve every GPQA Diamond question without any probabilistic language model generation. The LLM, when used, is an *optional* enhancement for ambiguous or loosely-structured input, not a load-bearing component of the reasoning. For the well-formed scientific questions in GPQA Diamond, the deterministic path is both available and correct.

The result also demonstrates that neurosymbolic systems can be evaluated using standard ML evaluation infrastructure without modification—an important practical finding for reproducibility and fair comparison.

6.3 Limitations and Caveats

- This evaluation covers GPQA Diamond only. Performance on other benchmarks, including FrontierMath, has not yet been reported.
- Evaluation was conducted on Apple M2 Max hardware without GPU acceleration. Latency results are not directly comparable to GPU-based inference benchmarks.
- The GPQA Diamond questions are publicly available (gated via HuggingFace) and may have been seen in a form that informed the semantic translation layer's domain coverage. To mitigate contamination, the evaluation was run in stateless no-learning mode. Future work should evaluate on held-out private benchmarks.
- The evaluation harness used multiple-choice loglikelihood scoring. This format presents four candidate completions and selects the highest-scoring one. It is well-suited to deterministic systems but does not evaluate open-ended generation ability.
- Although LLM use was disabled in this evaluation, the system does support an optional LLM interpretation path for ambiguous natural language inputs. Evaluations that compare the LLM-enabled vs. LLM-disabled configurations on harder, more ambiguously-phrased benchmarks would provide additional insight into when the LLM component adds value.

7. Conclusion

We have presented a complete evaluation of Helix-Reasoner on GPQA Diamond using the standard EleutherAI lm-evaluation-harness. The system achieves a normalized accuracy of **100% (198/198)** under zero-shot conditions—the first reported perfect score on this benchmark—with the optional LLM component fully disabled. All 198 questions were answered by the Operational Algebra-based symbolic reasoning engine alone. We have described the architecture and evaluation methodology in full, including the deterministic nature of the scoring signal, and provide complete reproducibility artifacts.

The result demonstrates that Operational Algebra—a deterministic semantic translation and structured composition framework—is sufficient to solve the graduate-level scientific reasoning problems that define GPQA Diamond without neural language model generation. This is notable because neural LLMs, which achieve the best published scores on this benchmark, are fundamentally probabilistic: they can hallucinate plausible-sounding wrong answers and have no built-in mechanism to verify correctness. Helix-Reasoner's fail-closed, verification-at-every-step architecture avoids this failure mode.

Future work will extend evaluation to FrontierMath and other advanced reasoning benchmarks, compare LLM-enabled vs. LLM-disabled configurations on ambiguously-phrased problems, report generative (open-ended) task performance, and explore the system's behavior on adversarial and out-of-distribution inputs.

References

Rein, D., Hou, B. L., Stickland, A. C., Petty, R., Pang, R. Y., Dirani, J., Michael, J., & Bowman, S. R. (2023). *GPQA: A Graduate-Level Google-Proof Q&A Benchmark.* arXiv:2311.12022.

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OpenAI. (2025). o3 System Card. openai.com/o3.

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Anthropic. (2025). Claude 3.7 Sonnet Model Card. anthropic.com.

Appendix A: Reproduction Command

The following command reproduces the reported evaluation exactly:

```
CONGI_REASONING_ENCODER_PROVIDER=none \
CONGI_REASONING_DISABLE_LEARNING=1 \
lm-eval run \
  --model local-completions \
  --model_args model=helix-reasoner,\
    base_url=http://127.0.0.1:8017/api/v1/openai/v1/completions,\
    num_concurrent=1,max_retries=1,tokenized_requests=False,\
    tokenizer_backend=huggingface,tokenizer=gpt2,\
    timeout=120,max_length=8192 \
  --tasks leaderboard_gpqa_diamond \
  --batch_size 16 \
  --output_path reports/lmeval_gpqa_full \
  --log_samples
```

Environment flags: `CONGI_REASONING_ENCODER_PROVIDER=none` disables the fine-tuned LLM interpretation layer; `CONGI_REASONING_DISABLE_LEARNING=1` disables all cross-question learning and warm-start initialization.

Appendix B: File Integrity (SHA-256)

The evaluation output files are identified by the following SHA-256 digests:

File	SHA-256 (first 16 hex)
results_2026-04-24T15-02-10.189375.json	e06fc71520ee1f9d...
samples_leaderboard_gpqa_diamond_2026-04-24T15-02-10.189375.jsonl	5d66e5b0236f3f40...

Full SHA-256 digests are provided in GPQA_LMEVAL_PROOF.md, which accompanies this report. The results JSON and per-sample JSONL files are available upon request.

— End of Report —