Evolutionary Coding Agents

Automated Discovery At Scale 2026

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Summary of Contents

About

A bit about me:

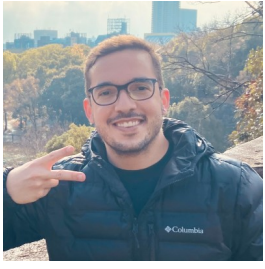
- ML Research Scientist at Inter&Co
- MS Candidate in Computer Science at UFMG
- Creator of CodeEvolve; Contributor to OpenEvolve

Co-Authors:

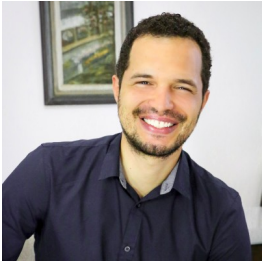
- Collaborative effort across Inter Science, UFMG and WPI.
- Specializing in NLP, Representation Learning and Recommender Systems.

H.A.

Fabricio Murai



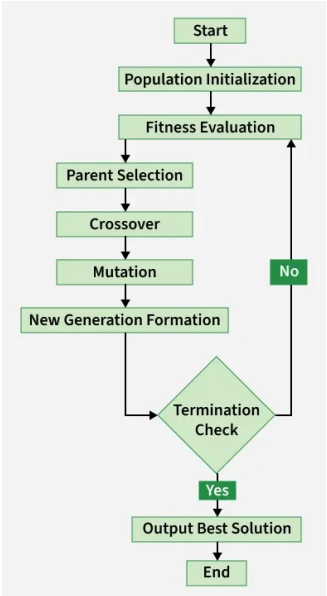
Leandro Campos



Diego Ferreira

Evolutionary Algorithms

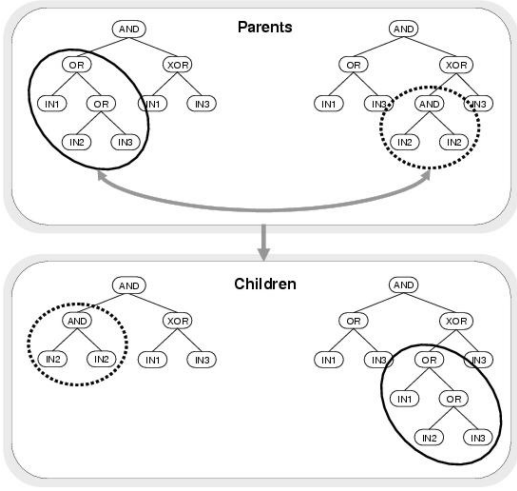
- **Origins:** Modern GP was popularized by John Koza in 1992 as an extension of Genetic Algorithms.
- **The Process:**
  - *Selection*
  - *Crossover*
  - *Mutation*
- **Goal:** Automated discovery of executable code that optimizes a given fitness function.



Representing Code

From Trees to Tokens

- **Classic GP:** Programs are typically represented as **Abstract Syntax Trees (ASTs)**.
- **The Bottleneck:**
  - AST-based crossover/mutation is effective for small functions but scales poorly.
  - Hard to maintain long-range dependencies and global structure in large codebases.
- **The LLM Paradigm Shift:**
  - LLMs allow for **natural language-guided** mutations.
  - Agents can reason about code semantically rather than just manipulating syntax nodes.



Traditional Subtree Crossover Operation

Evolutionary Loop for Agents

Solutions/Prompts $\rightarrow$ Selection $\rightarrow$ Crossover/Mutation (LLM) $\rightarrow$ Evaluation (Sandbox)

Iterative Code Refinement

- **1. Initialization:** A diverse population of initial solution attempts (prompts/code) is generated.
- **2. Selection:** Parent solutions are chosen based on some selection policy (e.g. fitness-based, uniformly random, etc).
- **3. Variation (LLM):** LLMs act as intelligent crossover and mutation operations, generating new solutions.
- **4. Fitness Evaluation:** New solutions are executed in a sandboxed environment, performance metrics and fitness are computed.
- **5. Termination:** The cycle repeats until the desired fitness is achieved or the computational budget is exhausted.

LLMs for Code Generation

- **Initial Breakthroughs:** Early integration of LLMs in program synthesis (e.g., AlphaCode) proved models could generate competitive code.
- **The Evolutionary Shift:** Moving from simple zero-shot generation to "Evolution through Large Models" (ELM).
- **FunSearch & EoH:** Demonstrated that LLMs could discover new mathematical knowledge and optimize heuristics.
- **AlphaEvolve:** A critical milestone bridging the gap by synthesizing **end-to-end programs** at scale.

Google DeepMind

***AlphaEvolve*: A coding agent for scientific and algorithmic discovery**

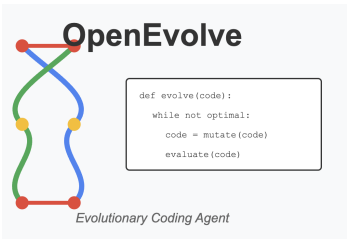
Alexander Novikov*, Ngân Vũ*, Marvin Eisenberger*, Emilien Dupont*, Po-Sen Huang*, Adam Zsolt Wagner*, Sergey Shirobokov*, Borislav Kozlovskii*, Francisco J. R. Ruiz, Abbas Mehrabian, M. Pawan Kumar, Abigail See, Swarat Chaudhuri, George Holland, Alex Davies, Sebastian Nowozin, Pushmeet Kohli and Matej Balog*

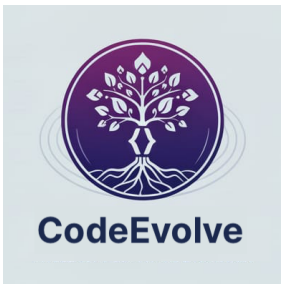
Google DeepMind[1]

OSS Frameworks

Democratizing Algorithmic Discovery

- Inspired by the success of AlphaEvolve, a wave of Open-Source Software (OSS) frameworks has emerged to provide transparency and reproducibility.
- **Some of the Frameworks:** OpenEvolve, ShinkaEvolve, ThetaEvolve, CodeEvolve, SkyDiscover, and many others.

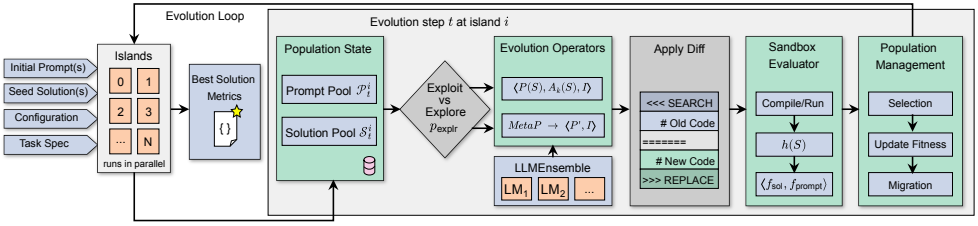




Overview of CodeEvolve

A Transparent Framework for Meta-Optimization

- **Island-Based GA:** Maintains diversity through isolated populations and parallel search trajectories.
- **Weighted LLM Ensemble:** Dynamically selects the best-performing models for specific mutation tasks.
- **Modular Operators:**
  - *Inspiration-based Crossover:* Recombines logic from top-tier "parent" programs.
  - *Meta-Prompting:* Evolves the instructions themselves to guide the search.
  - *Depth-based Refinement:* Targets specific code segments for local exploitation.



Architecture of the CodeEvolve Evolutionary Pipeline

LLM Backbones

Comparing Proprietary and Open-Weight Models

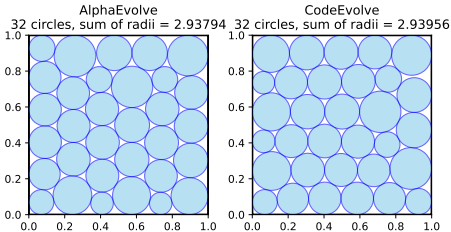
- Our experiments evaluate the scalability and reasoning capabilities of:
- **Gemini 2.5 (Flash/Pro):** Serving as the high-throughput, closed-source baseline for complex reasoning.
- **Qwen3-Coder-30B:** Representing the state-of-the-art in open-weight coding models.
- **Key finding:** Open-weight models often match or exceed closed-source performance at significantly lower compute costs.

Google Gemini 2.5

Alibaba Qwen3-Coder30B

Benchmark Problems

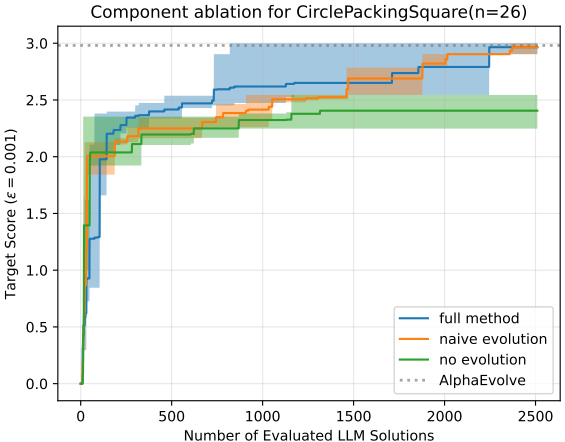
- **Geometric Packing:** Packing circles and hexagons in order to optimize a given metric.
- **Min-Max Distance Ratio:** Placing points in d-dimensional space to minimize the ratio of maximum to minimum distance.
- **Autocorrelation Inequalities:** Constructing optimal step-functions for convolution bounds in additive combinatorics.
- **Evaluation:** Programs are executed in a sandbox and scored against rigid mathematical fitness signals.

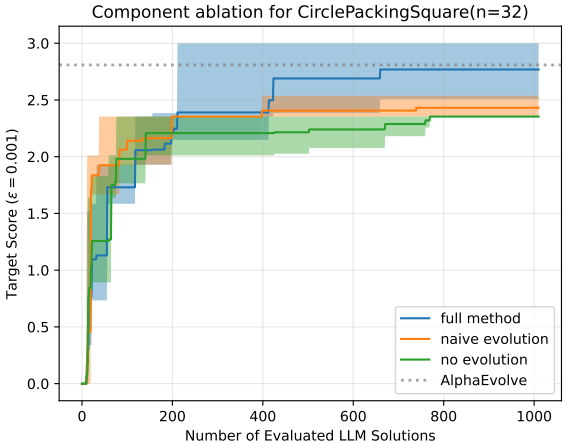


Overview of Results

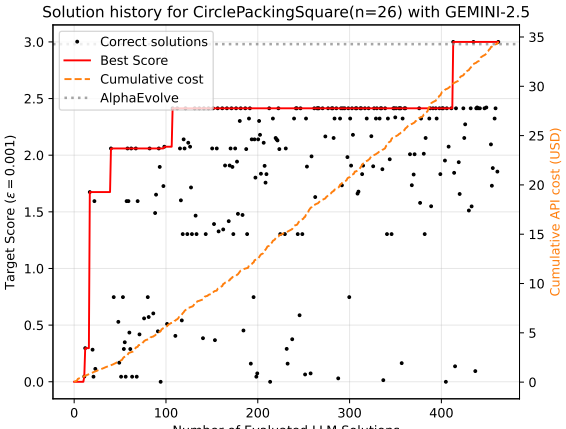
Problem	AlphaEvolve	CodeEvolve	
	Gemini 2.5	Qwen3-30B	Gemini 2.5
`CirclePackingSq` ($n = 26$) ($\uparrow$)	2.63586	**2.63598**	2.63597
`CirclePackingSq` ($n = 32$) ($\uparrow$)	2.93794	**2.93956**	2.93950
`CirclePackingRect` ($n = 21$) ($\uparrow$)	**2.36583**	2.36339	**2.36583**
`HexagonPacking` ($n = 11$) ($\downarrow$)	**3.93009**	4.02786	3.93794
`HexagonPacking` ($n = 12$) ($\downarrow$)	**3.94191**	4.01092	4.00001
`MinMaxDist` ($n = 16, d = 2$) ($\downarrow$)	12.88927	12.88925	**12.88923**
`MinMaxDist` ($n = 14, d = 3$) ($\downarrow$)	4.16585	4.16765	**4.16579**
`FirstAutocorrIneq` ($\downarrow$)	**1.50316**	1.51343	1.55438
`SecondAutocorrIneq` ($\uparrow$)	**0.96102**	0.88110	0.87067

Does Evolution Matter?

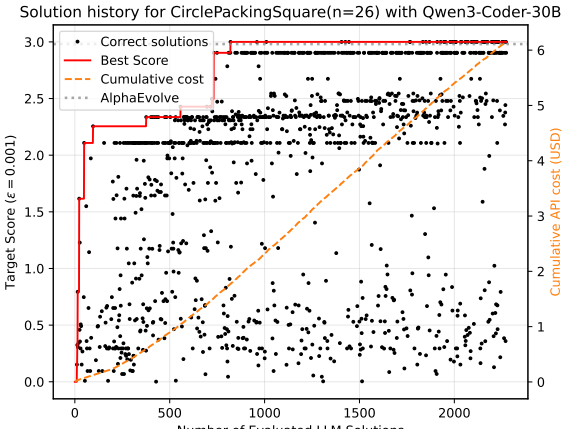




Sample Efficiency



Gemini 2.5 Convergence Profile



Qwen3-Coder-30B Convergence Profile

Conclusion

The Power of Evolution-Augmented LLMs

- **Synergy is Key:** Combining evolutionary search with LLMs creates a discovery engine far more powerful than zero-shot prompting alone.
- **Evolution as an Equalizer:** Experiments show that the evolutionary loop allows OSS models like Qwen to match or surpass proprietary ones.
- **Strategic Independence:** This paradigm reduces dependency on closed-source APIs, offering a path toward high-performance, private, and reproducible automated discovery.
- **The Loop $>$ The Model:** The architecture of the search process is often more critical for discovery than the raw size of the underlying LLM.

Current Limitations

- **Hyperparameter Complexity:** The system introduces numerous "knobs" that are difficult to tune without significant compute.
- **Expertise Barrier:** While the frameworks are open, they still require specialized knowledge to adapt to new domains.
- **Computational Cost:** Iterative refinement remains expensive, requiring efficient inference management to stay practical for large-scale tasks.

Next Steps

Toward Standardized Discovery

- **Standardized Benchmarking:** The field is moving rapidly; we need a "CodeNet" or "ImageNet" equivalent for evolutionary discovery to compare frameworks fairly.
- **Unified Evaluation:** Establishing sandboxed, reproducible evaluation setups.
- **Community Collaboration:** Bridging the gap between the various OSS groups to build a robust, modular ecosystem for the research community.

Thank you!

Questions?

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CodeEvolve GitHub