Exploiting Failure in Evolution

Variants of FI-2Pop in the Lunar Lander Game Environment

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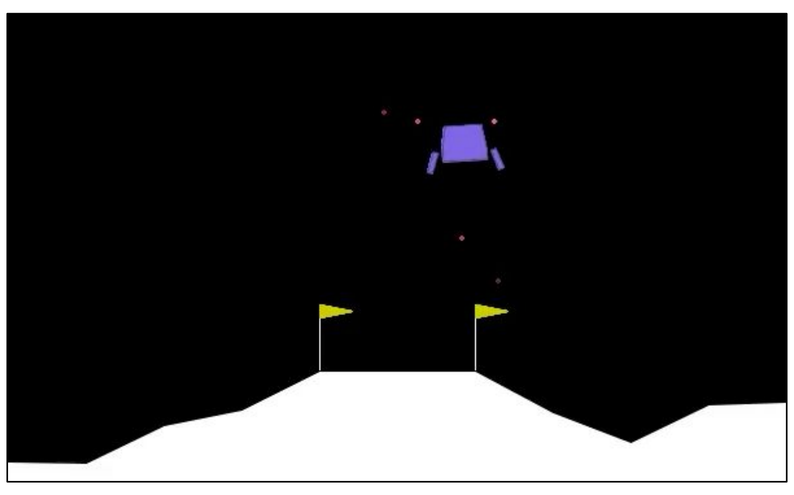
Introduction & Background

Algorithms typically try to minimize errors and failures. However, this research seeks to challenge this paradigm by investigating the potential advantages of failure. We explore failure-preserving evolutionary algorithms in the context of the Lunar Lander game environment (*below*) where the purple lander is the agent.



Goal & Hypothesis

Goal: Examine failure-preserving evolutionary algorithms through MAP-Elites[1], FI-2Pop[2], and FI-2Pop with MAP-Elites.

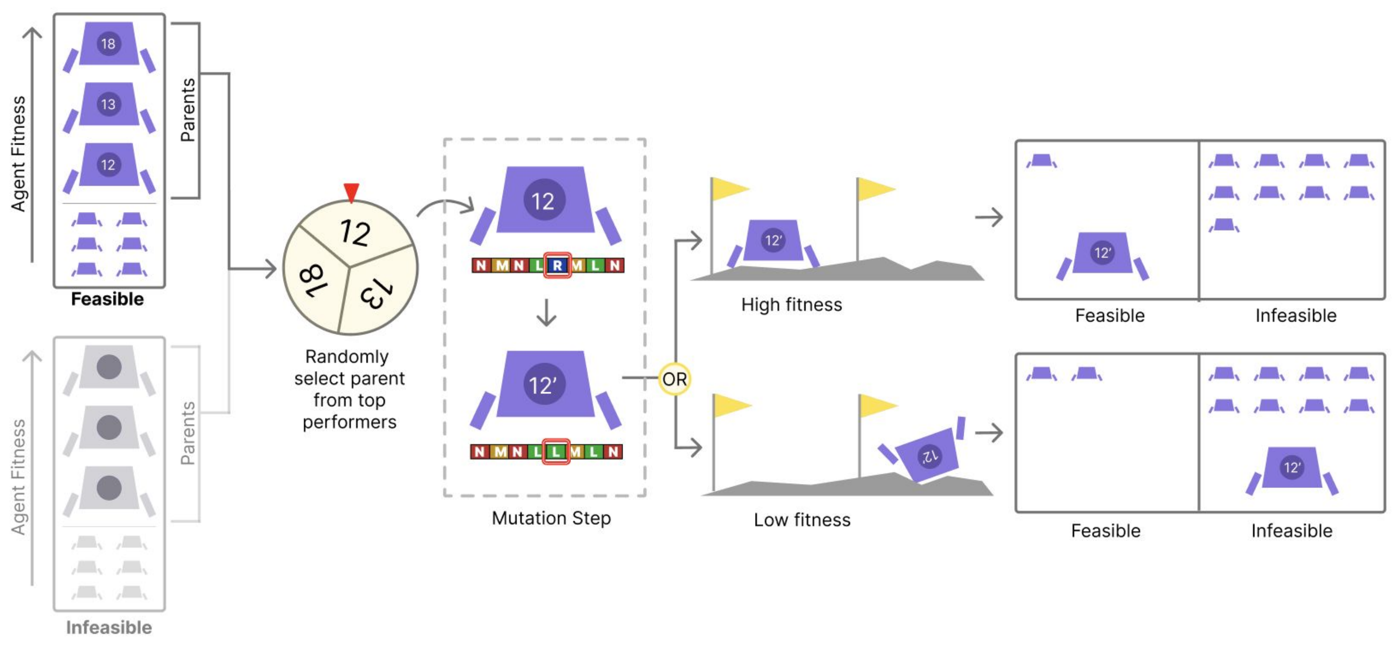
Hypothesis: Preserving individuals that are typically discarded will result in higher performance.

Methods

We ran these algorithms with 100,000 agents and selected the highest fitness agents:

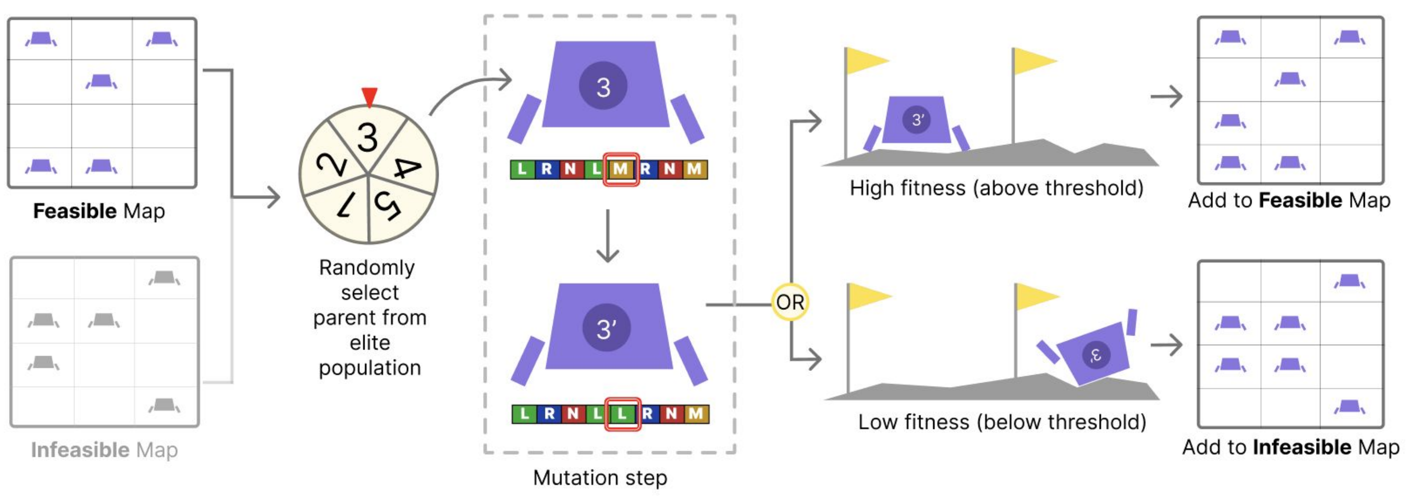
- **Random Search (RS)**: (*baseline 1*) Search a randomly-initialized group of agents.
- **Evolution Strategy (ES)**: *(baseline 2)* Over successive generations, regenerate the entire population by mutating the previous generation's fittest agents.
- **MAP-Elites**: Maintain "elites", which represent the fittest agents of a feature niche in a 2D map.
  - + *mortality: old agents are removed from the map*
- **FI-2Pop**: Modify ES by maintaining two populations (feasible/infeasible) based on some fitness-based threshold.

Example of one step of the loop:



- **MAP-Elites with FI-2Pop**: Modify MAP-Elites by maintaining two feature maps (feasible/infeasible).

Example of one step of the loop:



Visualization

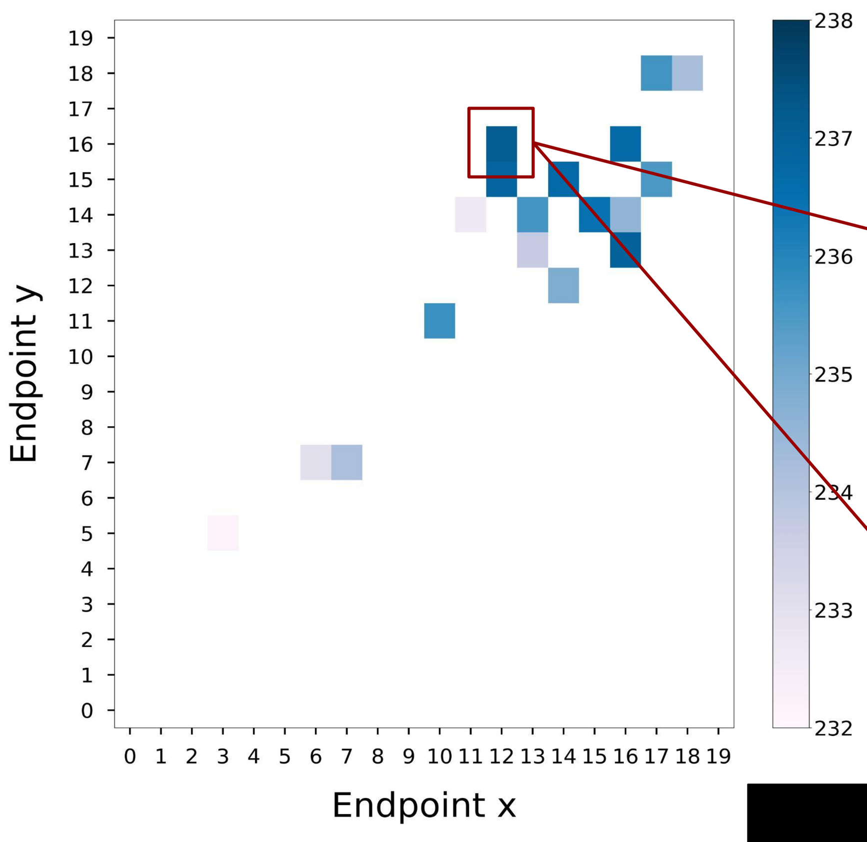
Scan for the MAP-Elites heatmap progression and notable agent GIFs.

Accomplishments

- Added mortality to MAP-Elites implementation.
- Optimized evolution strategy algorithm with heap-based parent selection.
- Parallelized testing to run trials ≈6.675 times faster.
- Validated implementation using previous paper results (RS, ES, MAP-Elites).
- **Adapted and implemented the FI-2Pop algorithm both on its own and with MAP-Elites.**
- **Experimented with a dynamic feasible/infeasible boundary within FI-2Pop runs.**

Results & Discussion

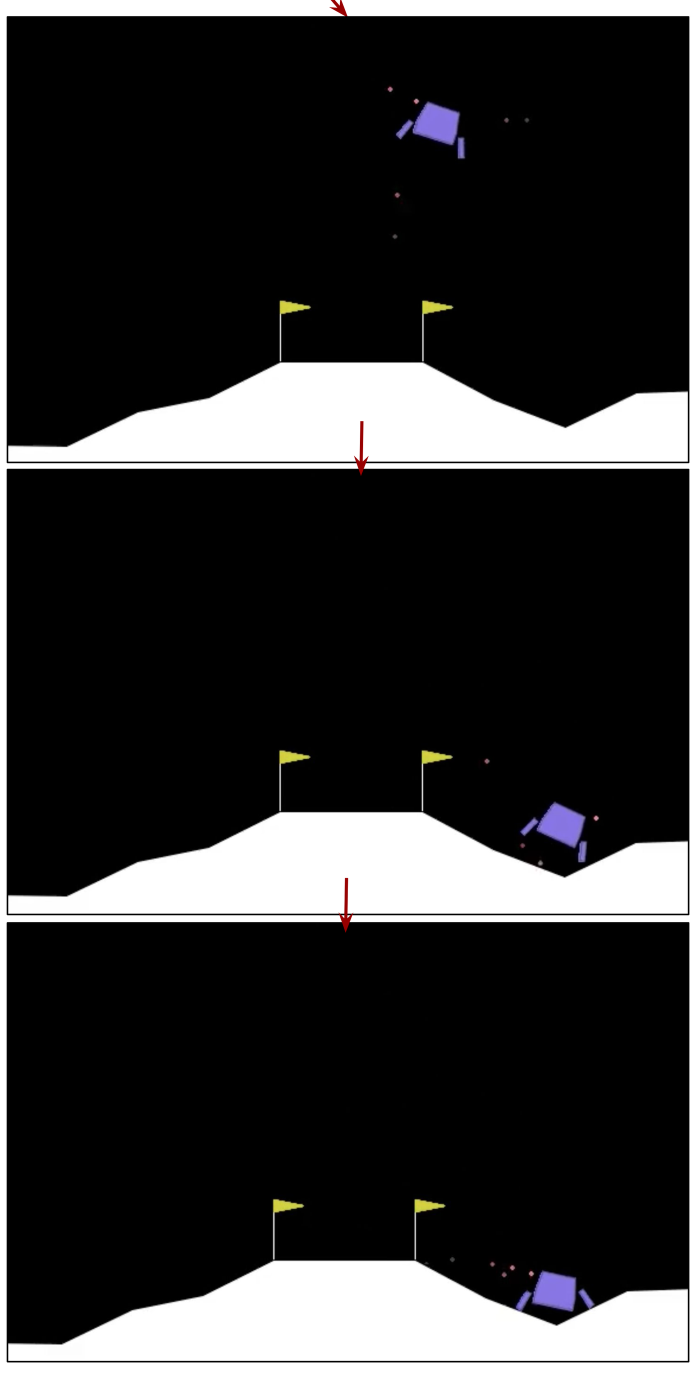
Below is the aggregated heatmap (*left*) of the best agents from each of 20 runs of MAP-Elites using the endpoint feature dimension with one trial's best agent (*right*).



Fitness: 237.278
Endpoints: (0.591, -0.215)
Agent #: 14415

Reward Hackers

The best agents from all 20 trials had fitness values of well over 200, making each of them "solutions" to the game. We observed a "tap-dancing" behavior that maximizes the agent's reward without landing between the flags. The best performer is shown on the right.



Future Work

- Experiment with the best ways to explore the infeasible population by modifying the FI-2Pop algorithm with and without MAP-Elites.
- Continue running experiments to submit a paper to GECCO (Genetic and Evolutionary Computation Conference) in January 2025.

References

1. Pugh, J. K., Soros, L. B., & Stanley, K. O. (2016). Quality Diversity: A New Frontier for Evolutionary Computation. Frontiers in Robotics and AI, 3.
2. Kimbrough, S. O., Koehler, G. J., Lu, M., & Wood, D. H. (2008). On a Feasible–Infeasible Two-Population (FI-2Pop) genetic algorithm for constrained optimization: Distance tracing and no free lunch. European Journal of Operational Research, 190(2), 310–327.
3. Klimov, O. (n.d.). Gymnasium documentation. Lunar Lander - Gymnasium Documentation.

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