Harmonomino: Tetris Agent Optimization

Using Harmony Search & Cross-Entropy Methods

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Background & Motivation

Motivation

- Tetris is a well-studied AI benchmark with NP-hard piece placement
- Hand-tuning evaluation weights is infeasible for 16 features
- Metaheuristic search offers a practical alternative to exhaustive optimization

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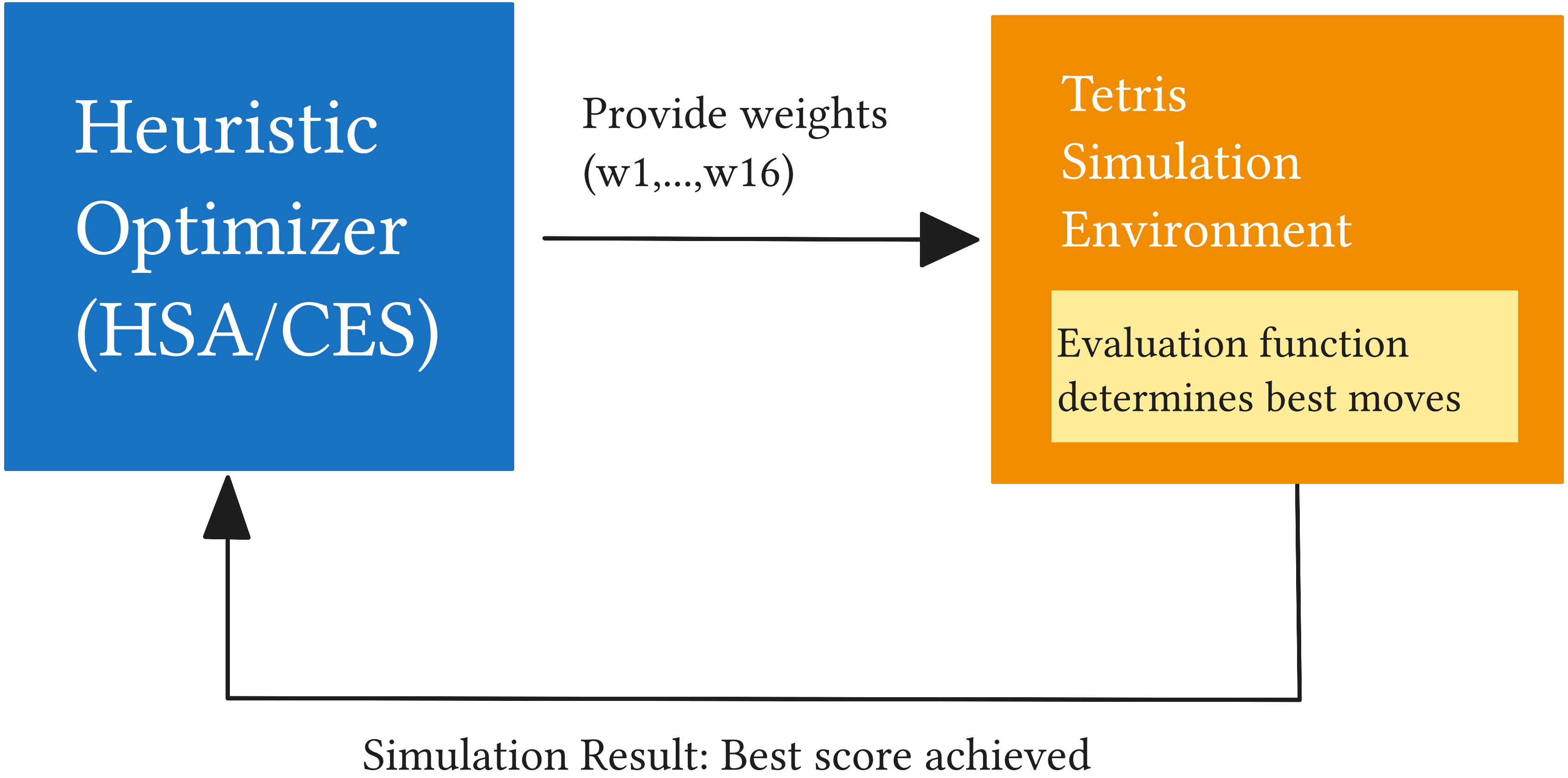
- **Goal:** automatically discover weight vectors that maximize rows cleared

Research Questions

- **RQ1** — How effective is Harmony Search (HSA) at optimizing Tetris agent weights?
- **RQ2** — How does Cross-Entropy Search (CES) compare to HSA?
- **RQ3** — Do the optimized weights converge to stable values?


Heuristic Optimizer (HSA/CES)
Provide weights (w1,...,w16)
Tetris Simulation Environment
Evaluation function determines best moves
Simulation Result: Best score achieved

Agent Architecture

Board $\longrightarrow$ 16 evaluation functions $\longrightarrow$ weighted sum $\longrightarrow$ best placement

Approach & Results

Algorithms

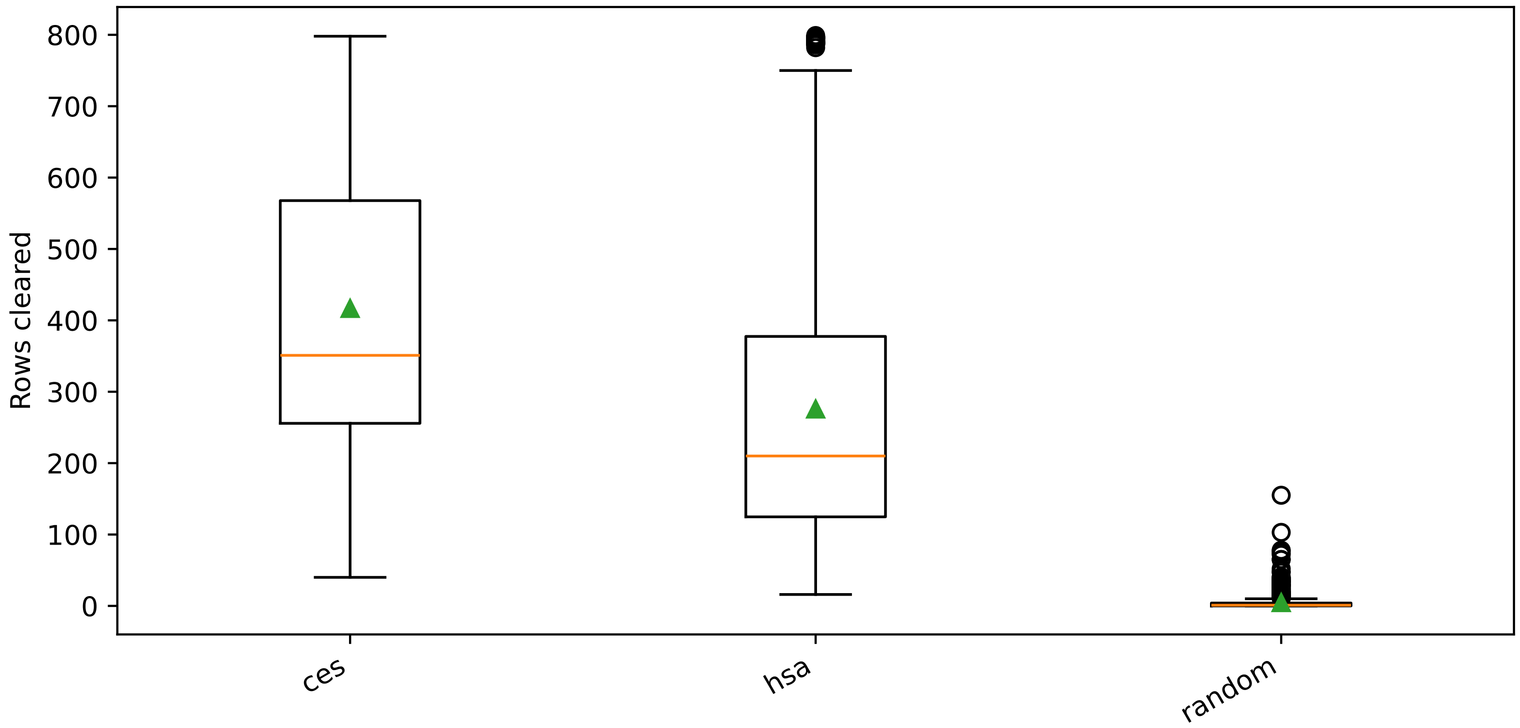
Harmony Search (HSA)

- Population of 5 weight vectors
- 100 improvisation rounds
- HMCR: 0.95, PAR: 0.99
- Bandwidth: 0.1

Cross-Entropy Search (CES)

- 50 candidates per generation
- Top 10 elite selection
- 100 generations
- Gaussian sampling + shrinkage

Performance



Performance

HSA

Mean: 275.737 rows

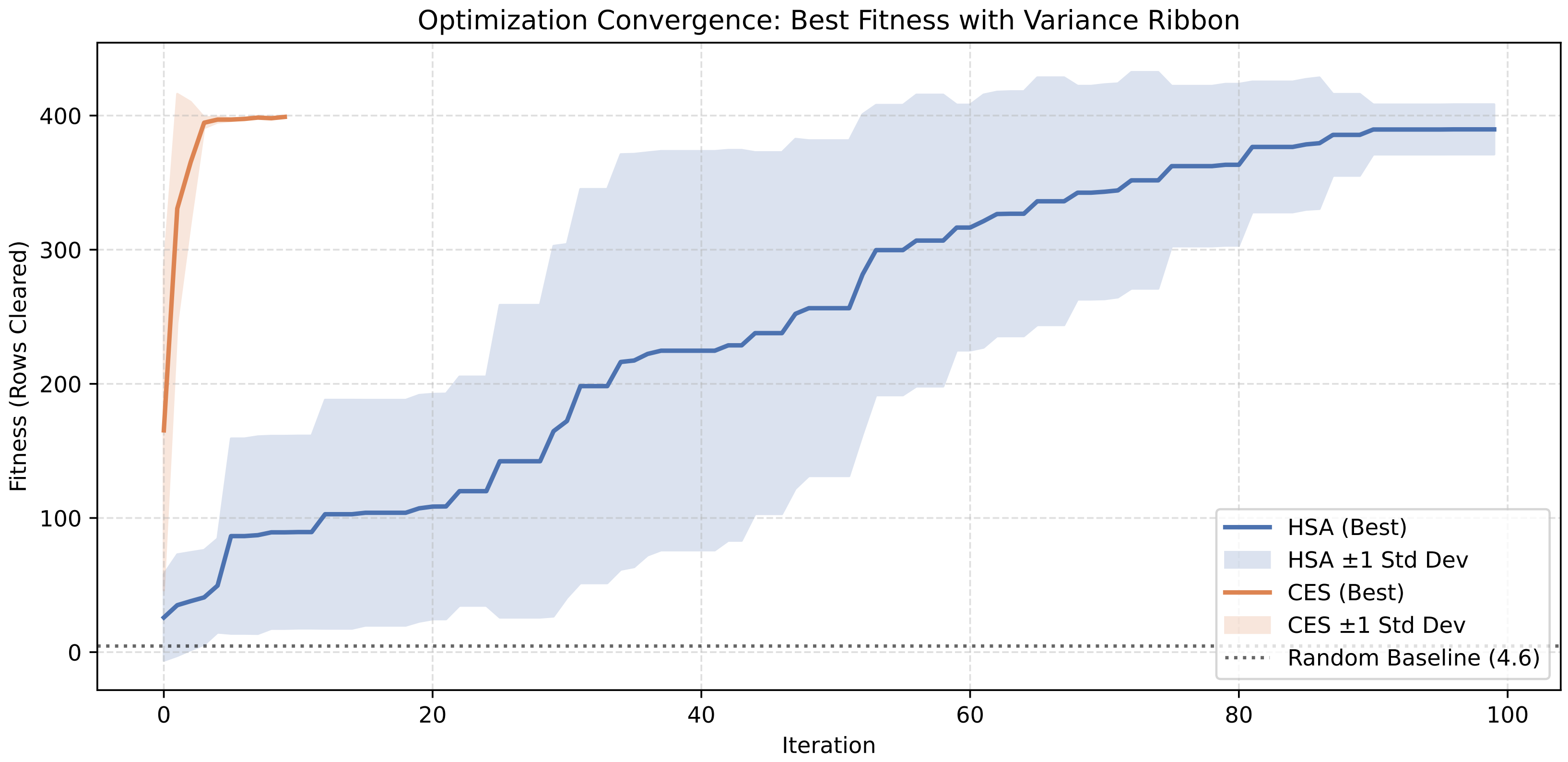
Median: 210.000 rows

CES

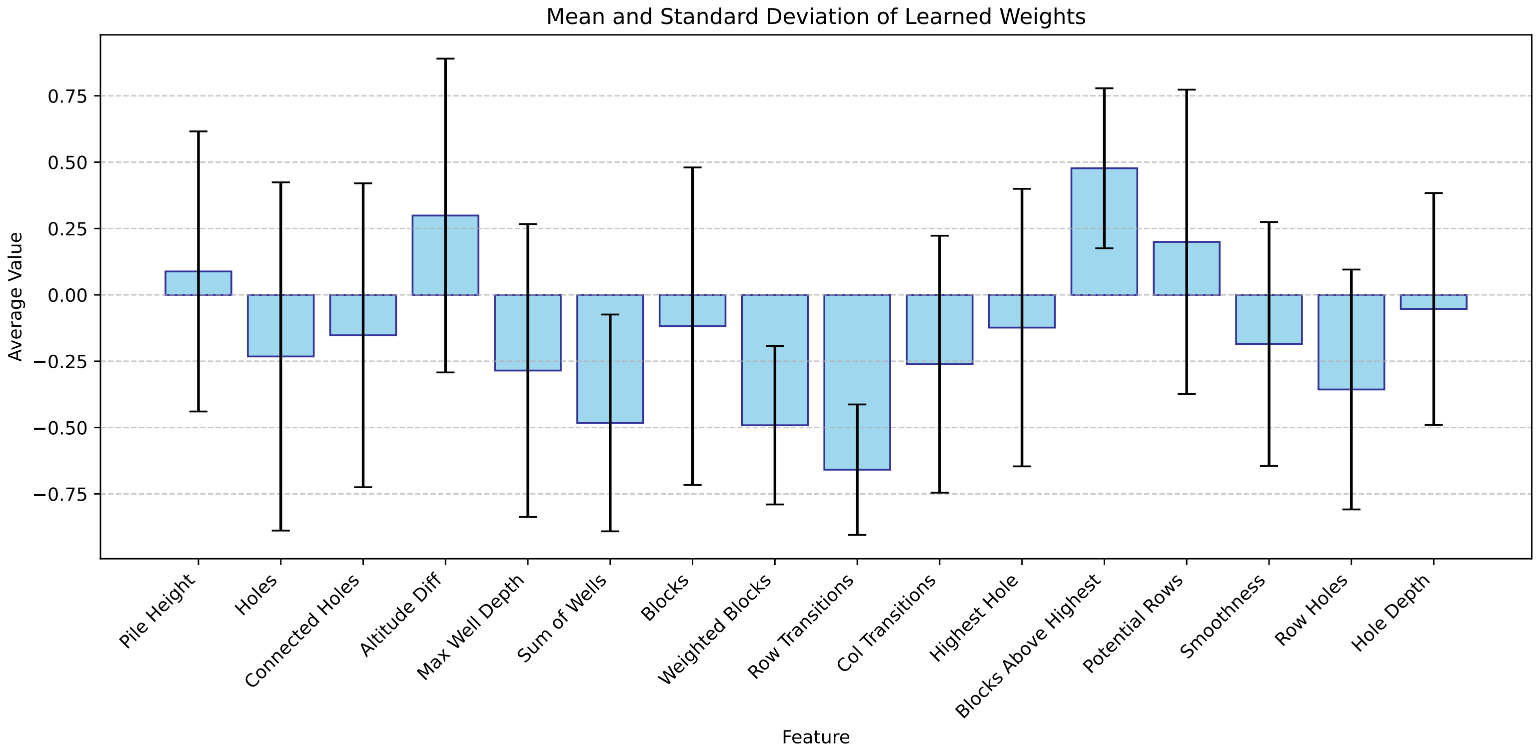
Mean: 416.633 rows

Median: 351.000 rows

Convergence



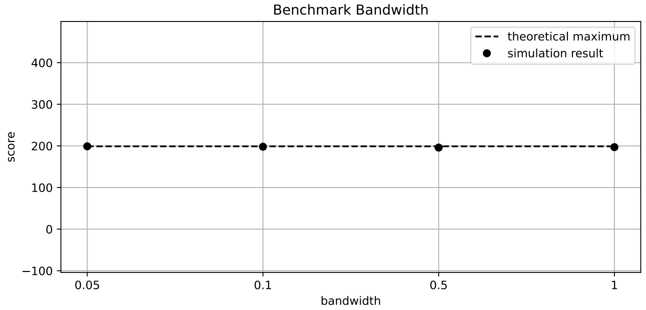
Weight Analysis

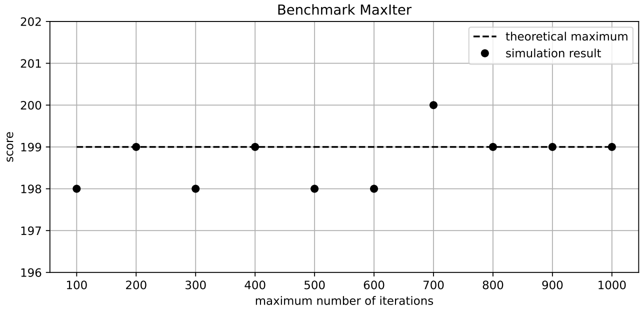


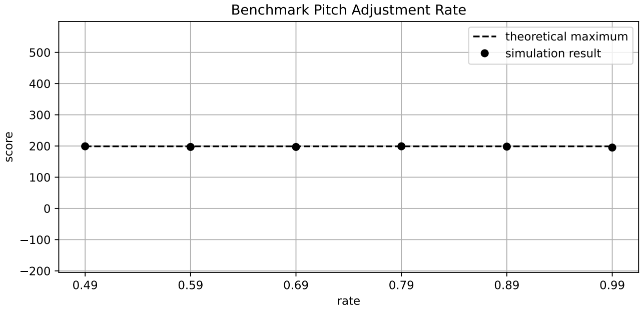
Most stable: w_9 (Row Transitions), w_8 (Weighted Blocks), and w_{12} (Blocks Above Highest)

High variance: w_2 (Holes)

Parameter Sensitivity







Conclusion

Findings

Contributions

- Both HSA and CES successfully optimize Tetris agent weights
- 16 feature evaluation covers pile, hole, well, row, and block metrics
- Subset of weights converge to stable values across runs
- Automated pipeline enables reproducible experiments

Limitations

- Single-piece lookahead only
- Fixed game length caps observable performance
- No T-spin or hold-piece strategies

Future Work

- Multi-piece lookahead and hold-piece integration
- Hybrid algorithms combining HSA exploration with CES exploitation
- Neural-network evaluation functions trained on optimized weights
- Transfer learning across board sizes and rule variants

Thank You!

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Questions?