

# **Harmonomino: Tetris Agent Optimization**

Using Harmony Search & Cross-Entropy Methods

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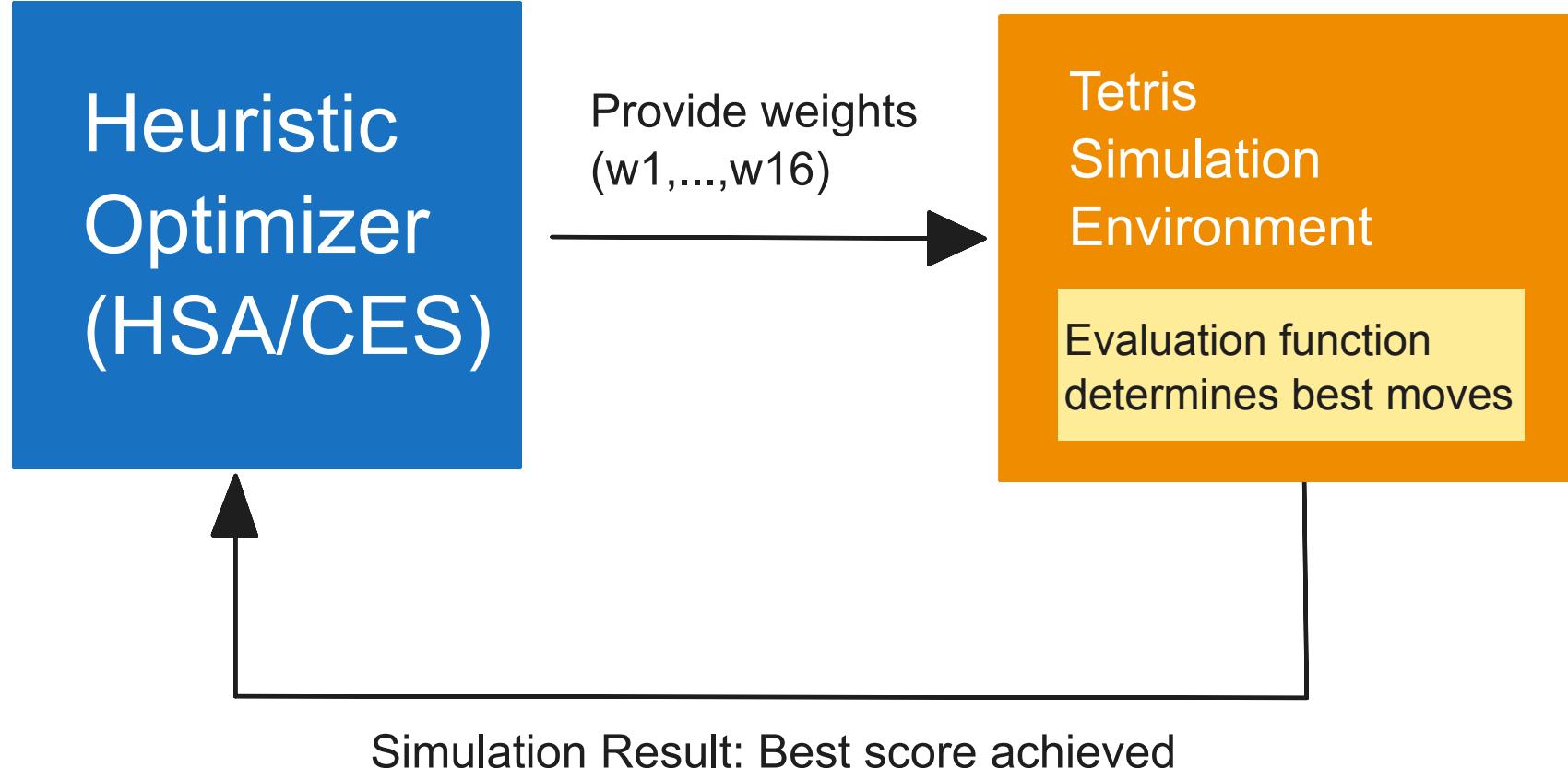
# **Background & Motivation**

- 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?



Board → 16 evaluation functions → weighted sum → best placement

# **Approach & Results**

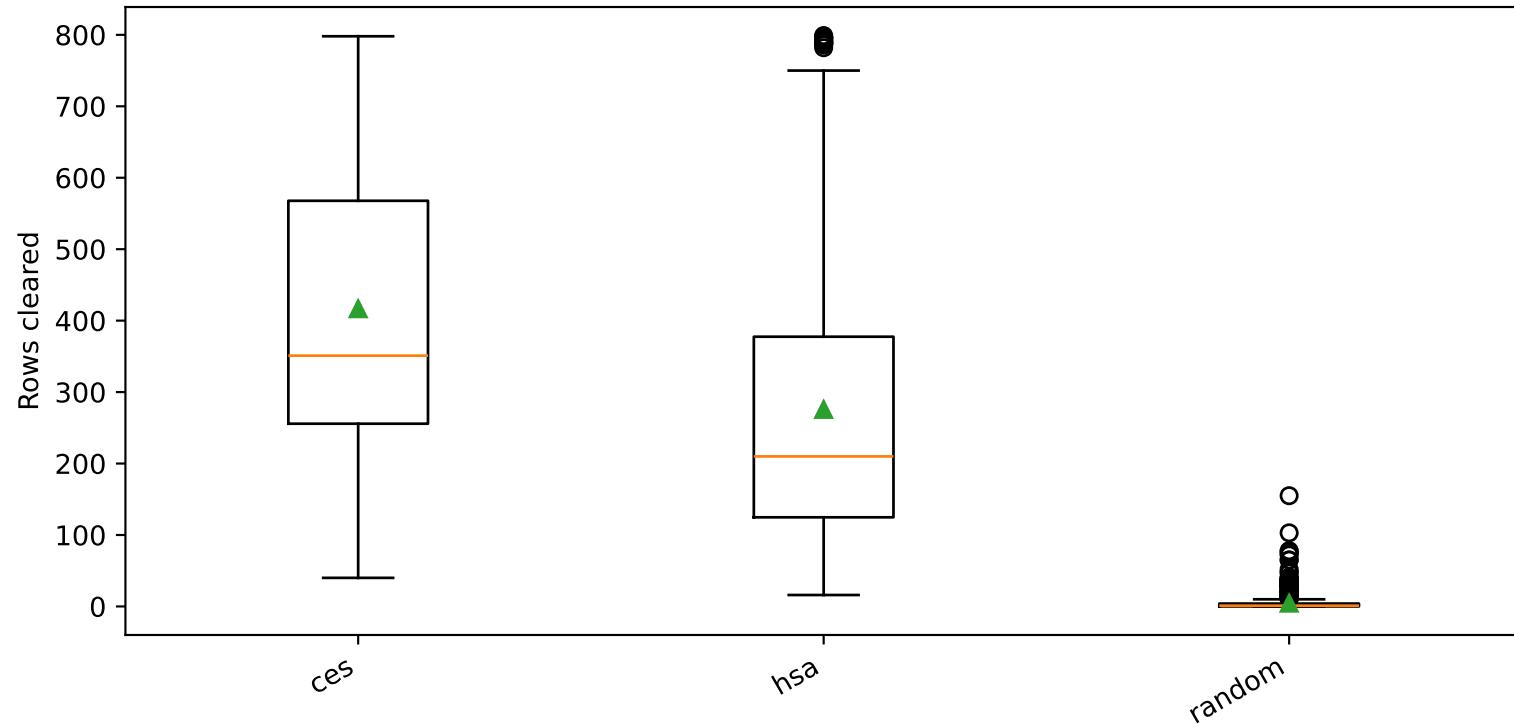
## Harmony Search (HSA)

- 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



## HSA

Mean: 275.737 rows

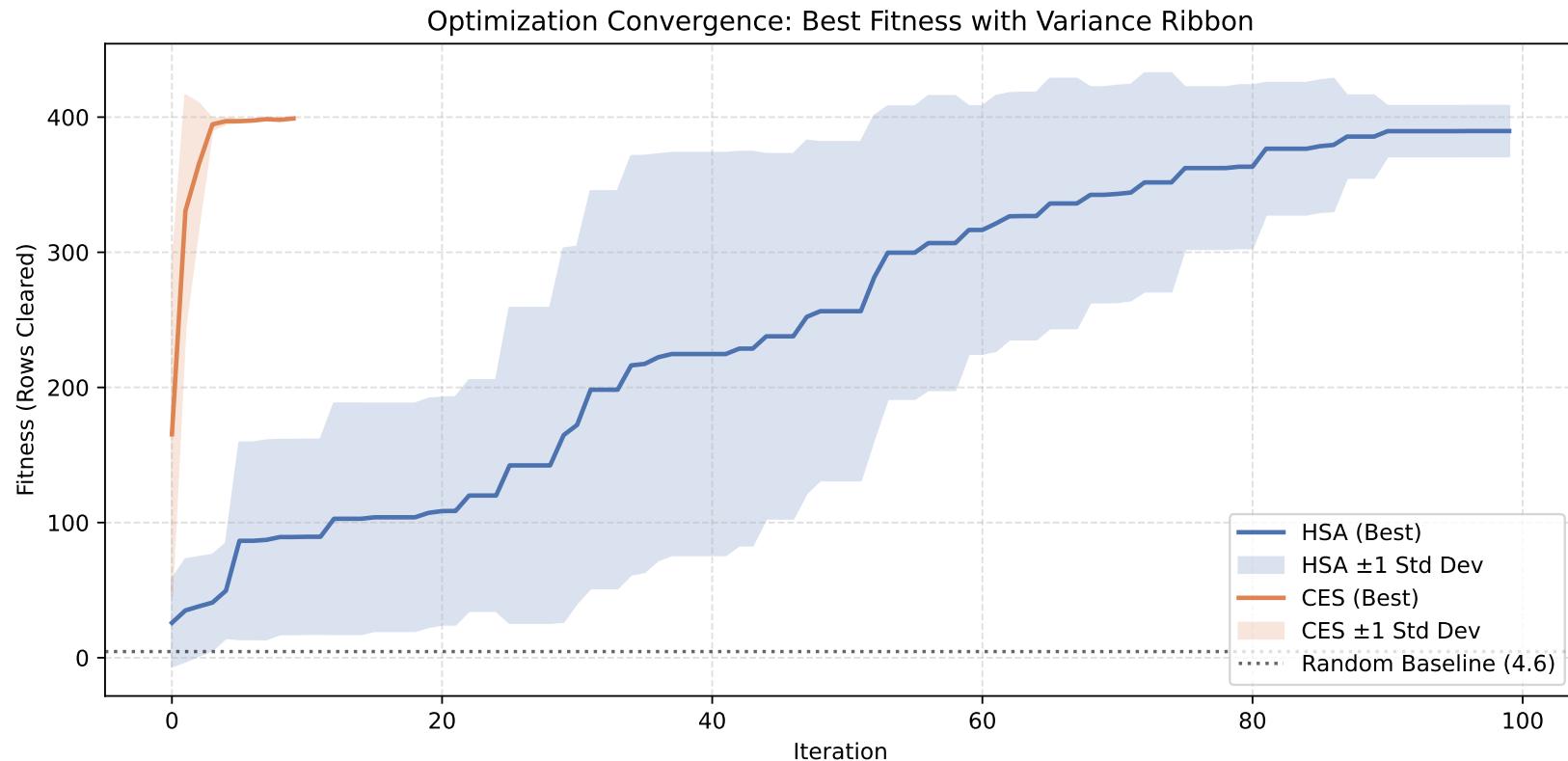
Median: 210.000 rows

## CES

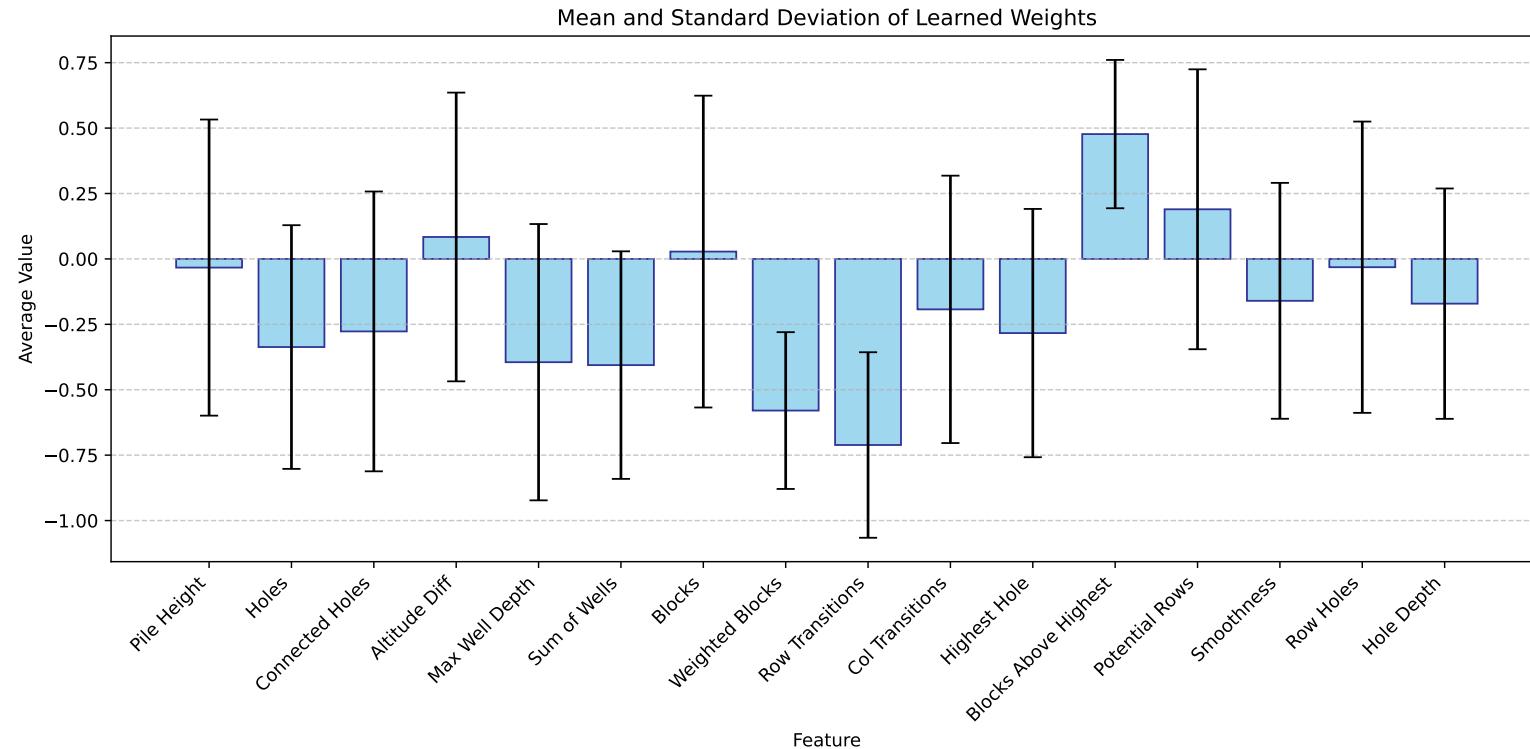
Mean: 416.633 rows

Median: 351.000 rows

# Convergence



# Weight Analysis

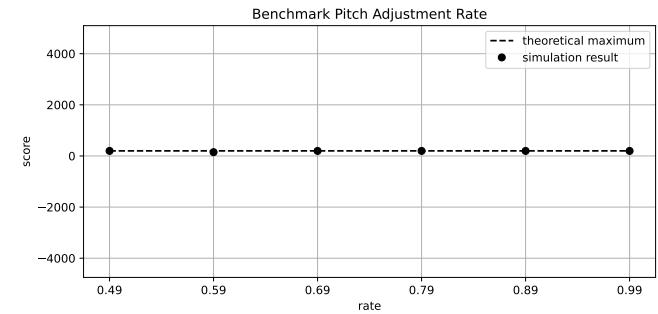
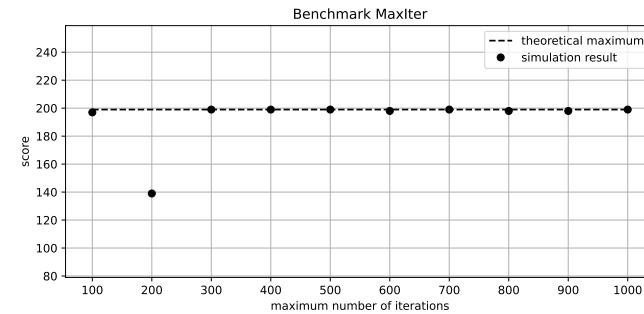
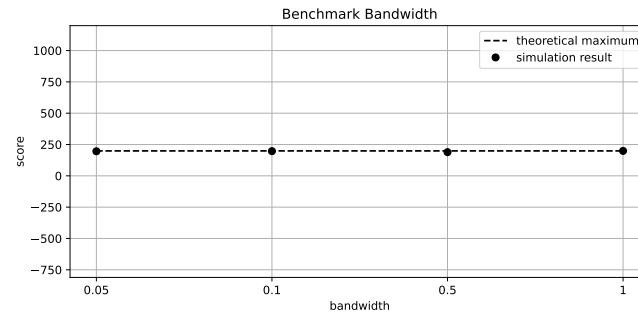


# Weight Analysis

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

**High variance:**

# Parameter Sensitivity



# Conclusion

## 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

- 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?*