

# Harmonomino: Tetris Agent Optimization

Using Harmony Search & Cross-Entropy Methods

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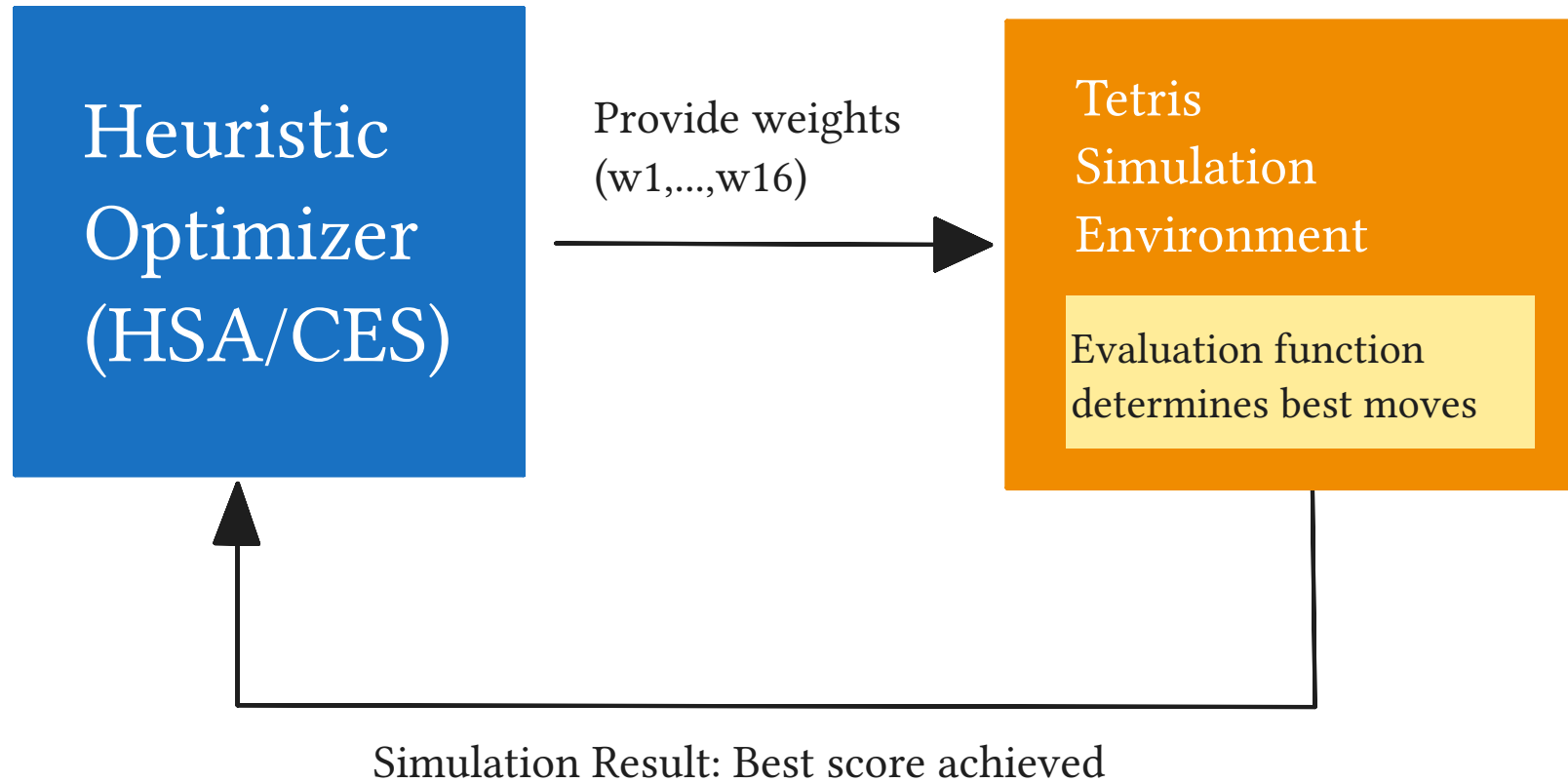
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# Background & Motivation

- Tetris is a subproblem in the category of tiling problems and is a well-studied AI benchmark with NP-hard piece placement
- The game is simple to understand but difficult to master, making it an ideal testbed for optimization techniques.
- Hand-tuning evaluation weights is infeasible for 16 features
- Metaheuristic search offers a practical alternative to exhaustive optimization

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- Metaheuristic search offers a practical alternative to exhaustive optimization
- **Goal:** automatically discover weight vectors that maximize rows cleared

- **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?



The agent that plays Tetris consists of the following components: Board  $\rightarrow$  16 evaluation functions  $\rightarrow$  weighted sum  $\rightarrow$  best placement

Mathematically the objective function to maximize with respect to the weight vector  $w$  can be expressed as:

$$V(s) = \sum_{i=1}^{16} w_i \cdot f_i(s)$$

where every evaluation function  $f_i$  maps a board state  $s$  to an integer value.

ID	Evaluation Function
ef01	Pile Height
ef02	Holes
ef03	Connected Holes

ef05	Altitude Diff
ef06	Max Well Depth
ef07	Sum of Wells
ef09	Blocks
ef10	Weighted Blocks
ef11	Row Transitions
ef12	Col Transitions
ef13	Highest Hole
ef14	Blocks Above Highest
ef15	Potential Rows



ef16	Smoothness
ef18	Row Holes
ef19	Hole Depth

# ***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

## Harmony Search (HS) Algorithm

Introduced by Geem et al. (2001), HS is a metaheuristic inspired by the **musical improvisation process**.

**Musicians seek “pleasing harmony” through three strategies:**

1. **Memory:** Playing a known piece from memory.
2. **Variation:** Playing something similar with slight adjustments.
3. **Randomness:** Composing freely from random notes.

The algorithm maintains a **Harmony Memory (HM)** containing a population of solution vectors.

Mechanism	Description
HM Consideration	Copying a value from HM with probability $r_{\text{accept}}$
Pitch Adjustment	Perturbing a value with probability $r_{\text{pa}}$
Randomization	Sampling a completely new random value

> **Key Advantage:** Unlike Genetic Algorithms (which use two parents), HS considers **all** solutions in the HM simultaneously.

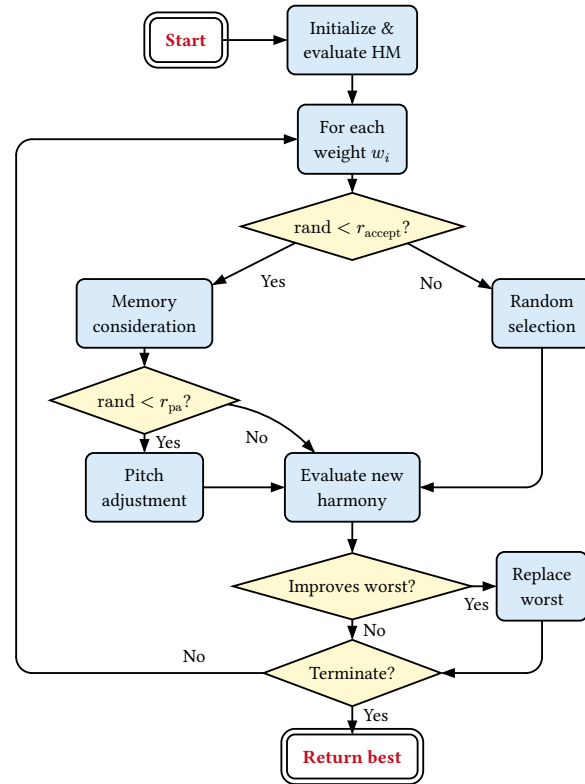
Romero et al. (2011) pioneered the use of HS for Tetris:

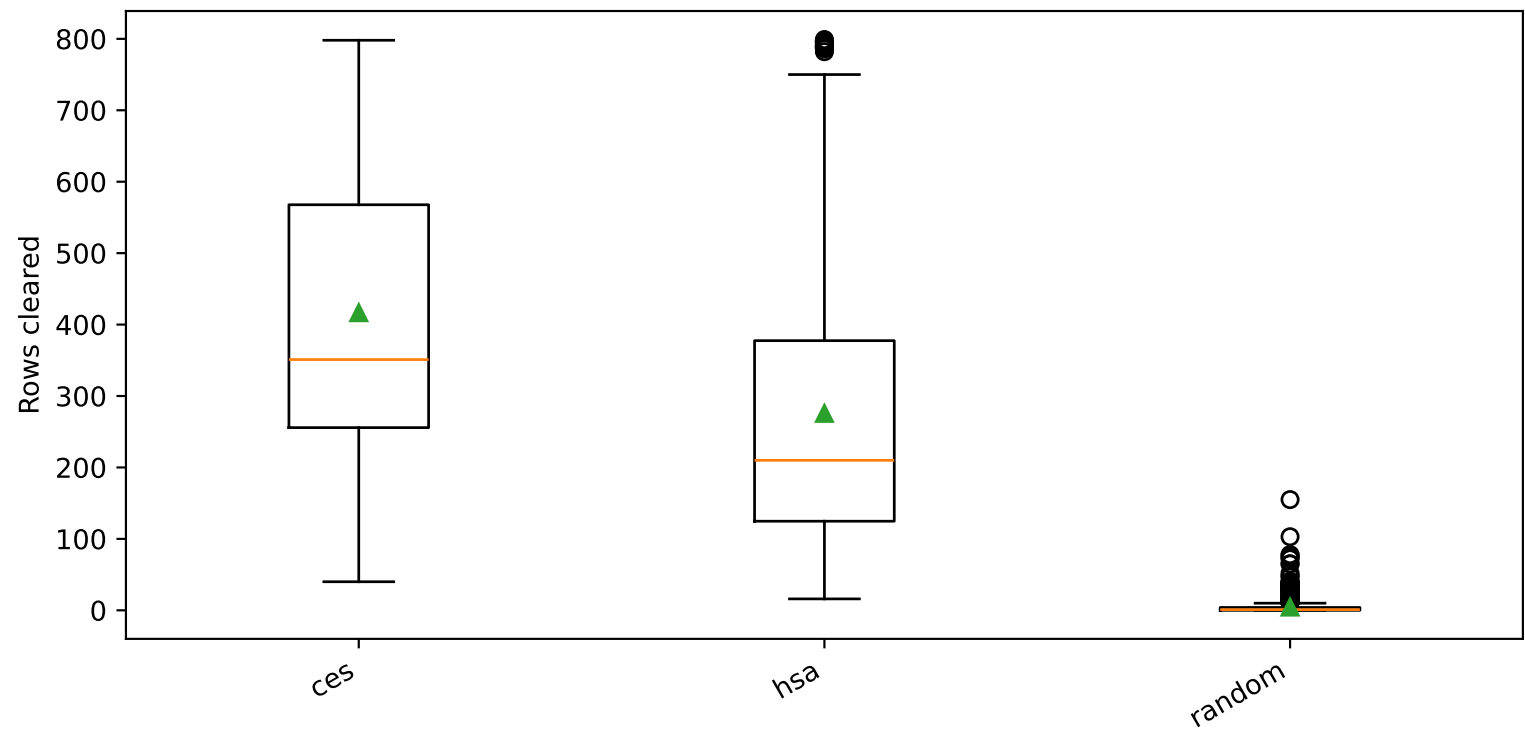
Feature Set: **16 board feature functions**. **Configuration:** Harmony Memory size of 5.

Results: - Efficiently discovered high-quality weight configurations.

- Achieved a spawned-pieces-to-cleared-rows ratio near the **theoretical optimum of 2.5**.









## HSA

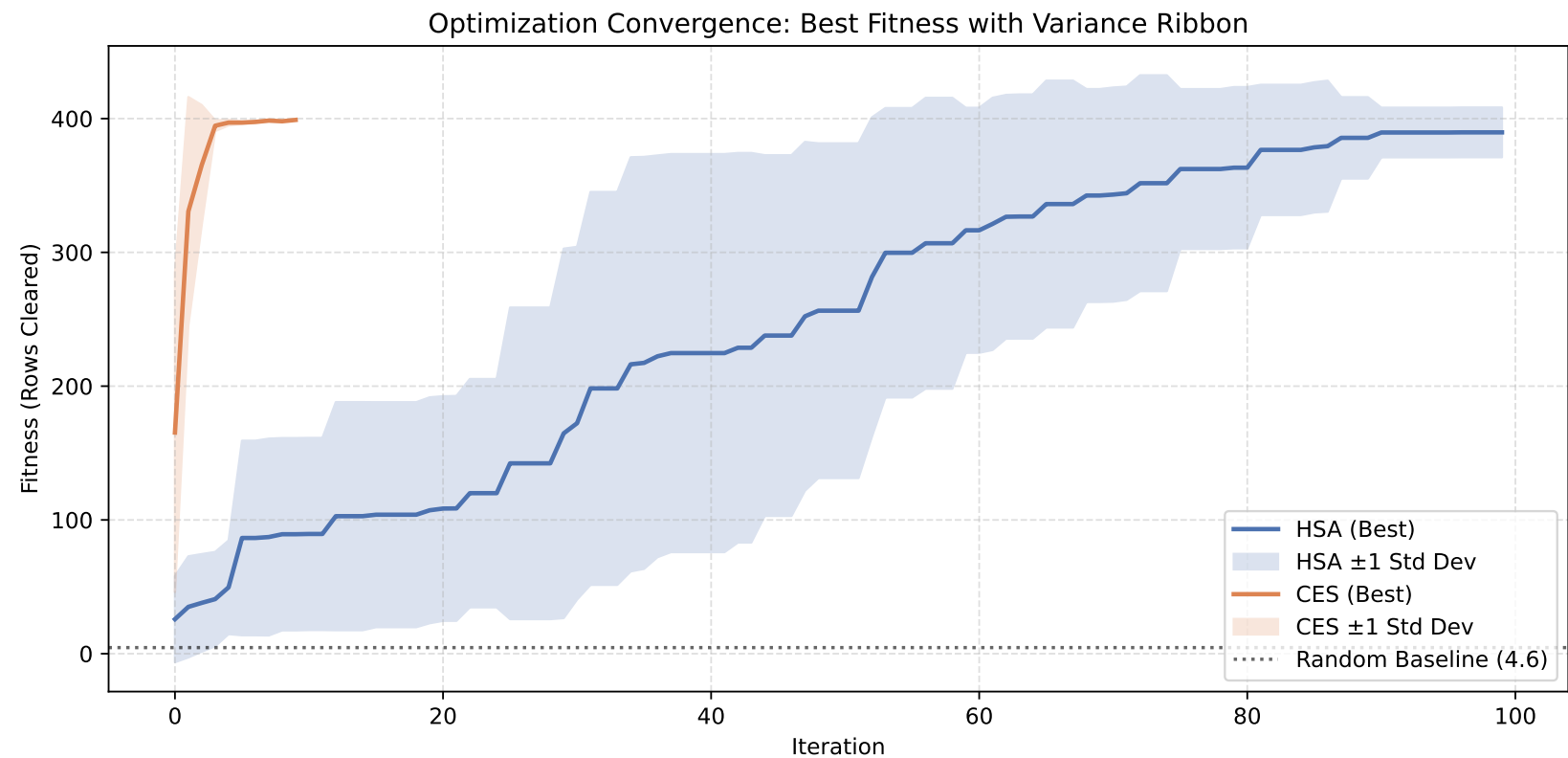
Mean: 275.737 rows

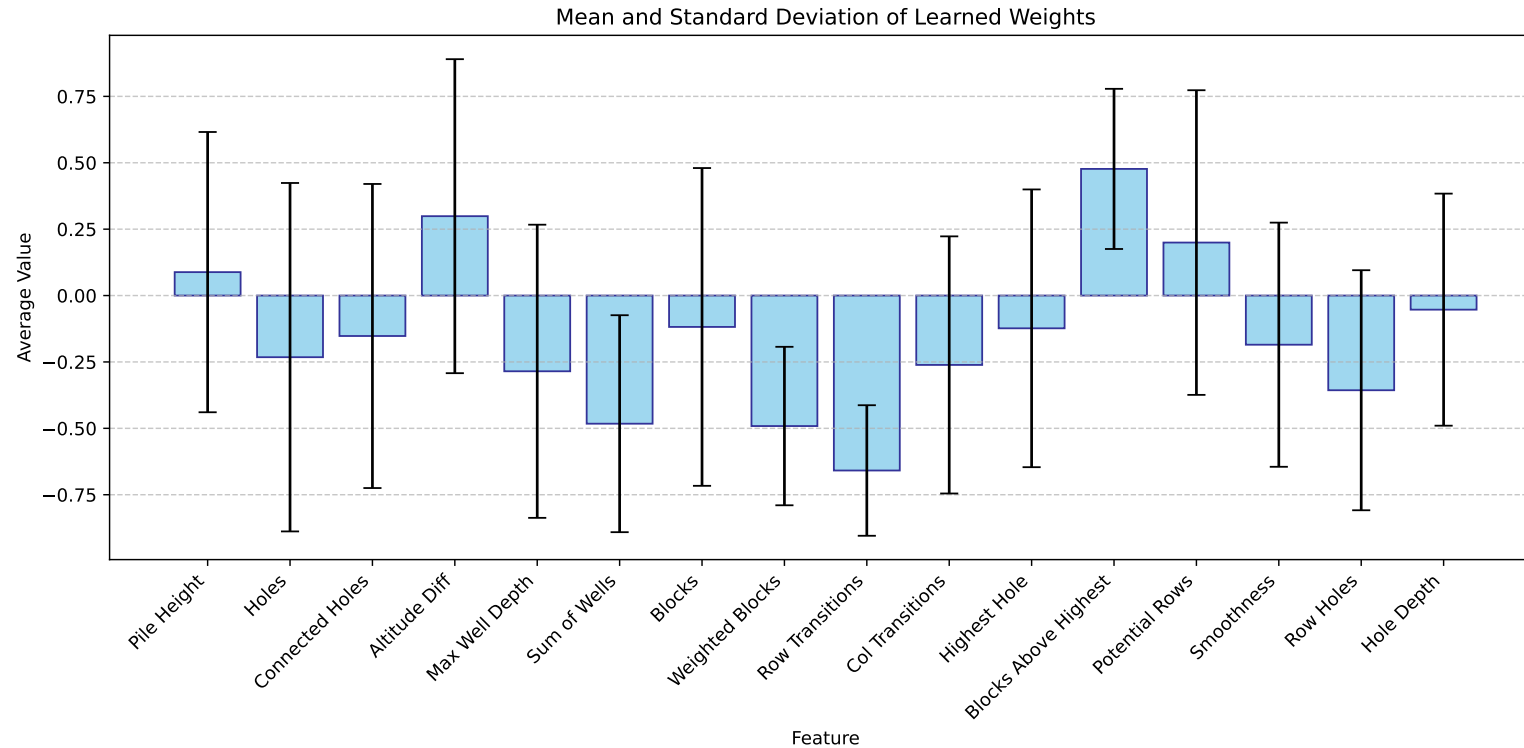
Median: 210.000 rows

## CES

Mean: 416.633 rows

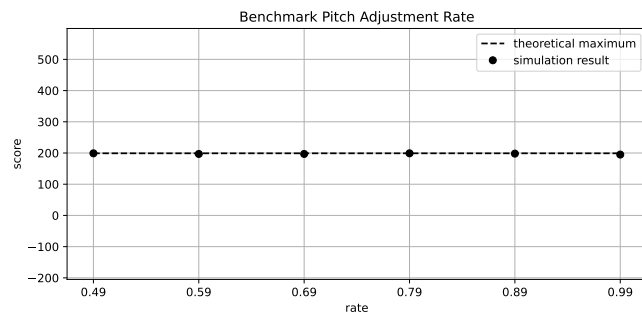
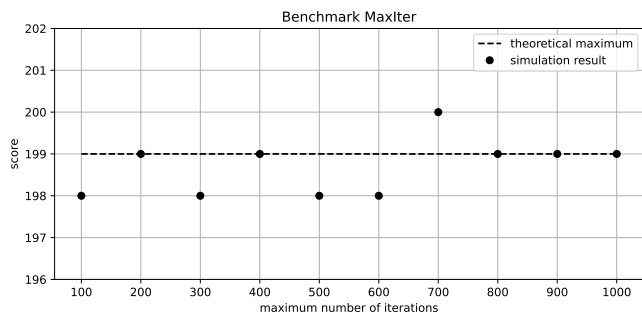
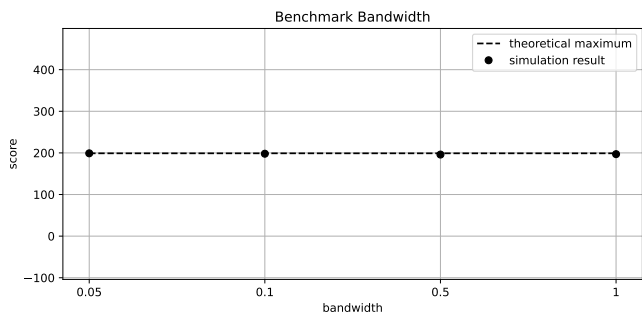
Median: 351.000 rows





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

**High variance:**  $w_2$  (Holes)



# 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?*