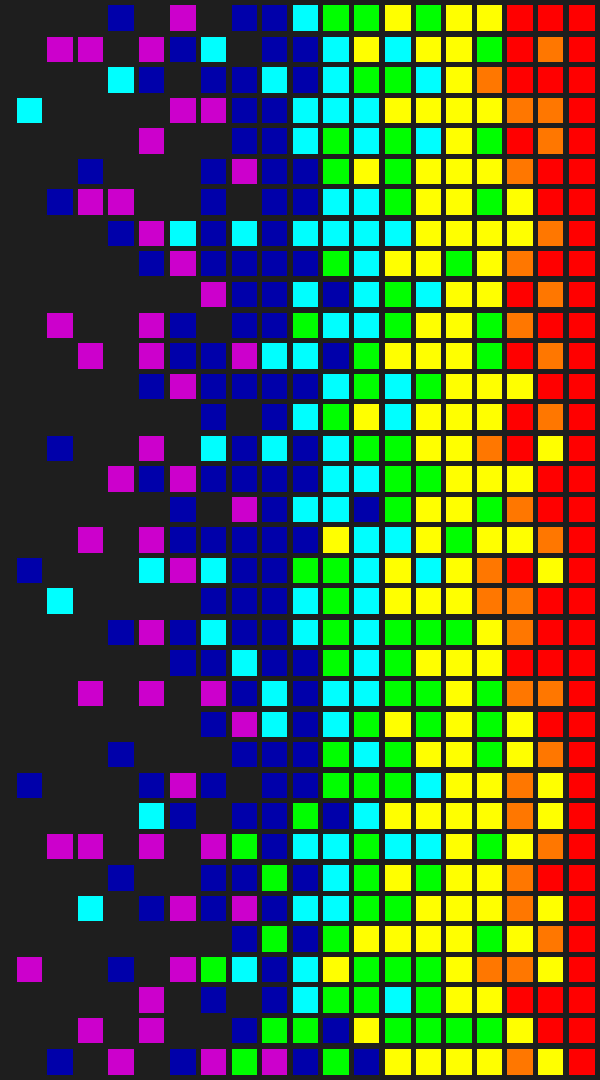


TETRIMAX

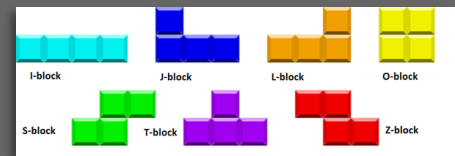
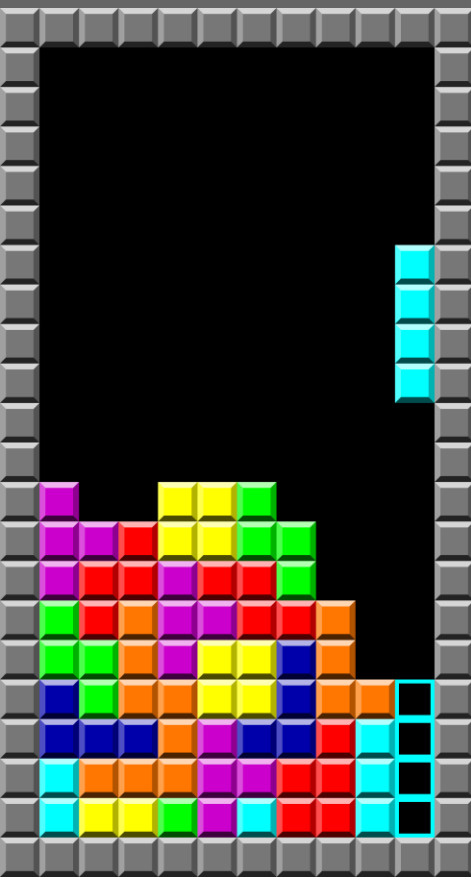
CS 4100 Final Project

Connor Nelson, Mara Hubelbank, Tyler Passerine



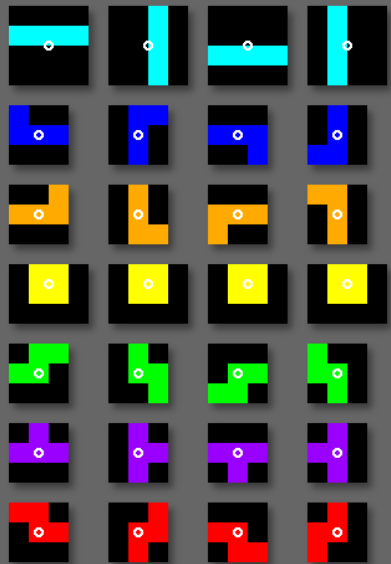
Problem Formulation

- **Project Goal:** Create agents to play Tetris
- **Game Objective:** Clear lines, ideally scoring "Tetris" (4 lines at once)
- **Simplification:** Agents play **asynchronously**, focusing only on choosing the drop action which will result in the best new board.
- **Agent Tasks:**
 1. Take in the current game piece.
 2. Generate all possible drop moves + boards.
 3. Evaluate each board.
 4. Select the move with the highest board rating.



Algorithm Design

- 1st: Expectimax (state space explosion)
- 2nd: Genetic Algorithm Factory → Agents
- Agents are generated through natural selection.
- Agent “Factories”:
 - **Linear**: Agents contain as many weights as features. The output of a given board state is given by $x_1w_1 + x_2w_2 + \dots + x_nw_n$.
 - **Fixed-size NN**: Contains two hidden layers both with as many perceptrons as features.
 - [NEAT-Python](#)



neat-python/**neat-**
python

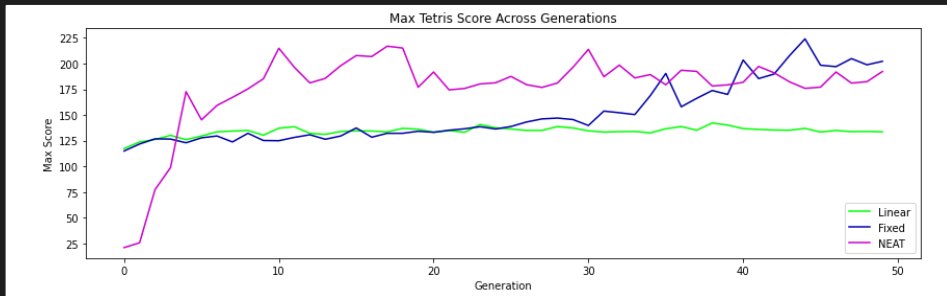
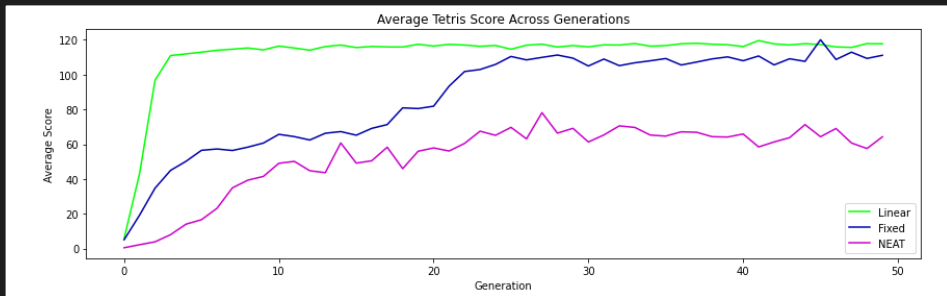
A Python version of the NEAT algorithm
(NeuroEvolution of Augmenting Topologies)

1 Contributor 5 Issues 41 Stars 21 Forks



Performance Analysis

- The less-complex **linear agent** starts off much higher due to population randomness.
- The complex **nonlinear agents** consistently achieve a higher **max score**, because they learn to combine features and score Tetris.
- Which nonlinear agent is "best" depends on the metric of evaluation.



Conclusion & Reflection

- Agents' **goals** significantly impacted how they played.
 - Maximizing **survival** vs. **score**
- By Tetris % metric, our agents performed worse than humans.
 - Feature-based representation → Incomplete view
 - Lack of memory → No piece foresight / predictive analysis
- Project Extensions:
 - Independent, unsupervised agent learning
 - Advanced non-drop moves (ex. T-spins) to mimic human play

Thank you!

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