**Tetris AI**

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# Introduction

# Genetic Algorithm

## Literature Review

There have already been a number of approaches to create a Tetris AI with Genetic Algorithms. However it is difficult to compare the results between different approaches due to different rulesets for the game, different scoring methods and the time they gave their algorithm. Results in the millions (lines cleared) might have taken months to run.

The most fundamental piece in the attempt to build a tetris AI is done by Fahey (2012). Amongst the history and famous projects of tetris, he covered the best observed performance of a hand-crafted algorithm (6 features; weights tuned via trial and error) by Dellacherie, clearing an average of 660,000 lines.

Thiery and Scherer (2009) achieved average scores of around 35,000,000 cleared lines with a modified evolutionary approach. Their cross-entropy method uses a gaussian distribution to generate new generations. The mean and variance of this gaussian distribution is obtained from the best candidates in the generation before. Additionally, a noise term works similarly to the idea of the mutation rate.

Lee (2013) developed a classical genetic algorithm with only 4 features that had already cleared over 2,000,000 lines by the time he had to stop it (running time ~ 2 weeks).

Young (2018) shows that with the number of features the results get less of an increase per new generation but take longer to converge, resulting overall in higher scores.

An approach to increase the efficiency (average points per move) was done Lewis (2015). He used feature selection to decrease the feature set to 10 features and the result was a candidate that survived an average of 180,000 moves, scoring 2.5 points per move.

Cheung et al. (2015) tried to optimize a number of parameters. Their approach to get a faster learning process was to decrease the height of the tetris field by half. They also discussed other options that could help with the computational expensiveness. Stopping the algorithm, after it failing to make process over a certain amount of iterations prevents unnecessary generations. However the idea of a changing mutation rate had no impact on the performance.

Line limits are introduced by Shahar and West (2010). They found that with both a 100 and 1000 line limit the algorithms tended to do more combos (up to 75% tetris (4 lines cleared at once)) to produce higher scores.

Both a linear and an exponential evaluation function are used by Böhm et al. (2005), while their agent knew also the form of the next tetrimino. It cleared 480,000,000 lines with the linear approach and 34,000,000 with the exponential function.

Despite potentially big differences in the results, all papers show reasonably good results compared to humans (world record: below 1.4 million cleared lines[[1]](#footnote-1)). Differences can be explained by different design choices of the game itself. In general with results passing through millions of cleared lines, failing the game might be just bad coincidence (e.g. a large number of S and Z tetriminos are much more difficult to clear in a field with width 10[[2]](#footnote-2)).

## Our Approach

### General Idea

The general functionality of a Genetic Algorithm is derived from Biology. At the core of it, we have the optimization problem: Where should the current tetromino be placed? An evaluation function computes a score of the tetromino on every possible position (potentially also with regards to the next following tetrominos) based on the dot product of a feature vector and a weight vector.

The feature vector describes the state of the game (e.g. altitude/height of filled tiles or number of lines cleared). It is a design choice and it is stable throughout the game.

The weight vector is the objective of the optimization. We want our weights to produce the optimal evaluation function to achieve the best performance in our Tetris AI. To get the optimal weights we use a process derived from evolution:

We start with Generation 0, where all weights are randomized. We have a population (N) of different candidates - different weight vectors but same feature vectors, forming N different evaluation functions that are able to play the game. The overall performance of a candidate (or “chromosome”) is evaluated via a fitness function.

After each iteration we simulate natural selection. The better a candidate performs, the more likely it will contribute to the next generation. This is done with different operators:

* Selection: Candidates are added to the next generation without changes.
* Mutation: The candidate is added with some small changes to the weights.
* Crossover: A pair of candidates is combined into a new candidate.

The population size will stay the same after each iteration. The goal is to evolve the weights to their optimal values by increasing the performance with each generation.

### Design Choices

The design choices include:

* Population size N
* Number of games each candidate plays in each generation to receive its score
* Feature selection
* Randomized values
* Allocation of natural selection operators (Crossover-rate, Mutation-rate, Selection-rate)
* Intensity of mutation
* Form of crossover
* Tetris field height & width
* Move definition
* Move Bounds (how long is the game allowed to be)
* …

As the current record values for Tetris with a genetic AI are insanely high and we are both limited in time and in computing power, I decided not to hunt for new record values but to test and show what the genetic approach is capable off.

In order to get a cheaper computation, we have got a number of options on which I will comment shortly:

* Decreasing population size (N): would result worse outcomes and less variation between the genes. This could also lead to local maxima. To prevent local maxima, I took the approach of Young (2018) to take a starting population with a size 10 times higher than following populations.
* Decreasing number of games per candidate and generation: This could again lead to skewed outcomes. I will stick to 20 games per candidate and generation as suggested by Cheung et al. (2015).
* The approaches of Cheung et al. (2015) to speed up the learning process (stop learning process after a number of iterations without progress and reducing the height of the field by half) sound promising and I will try to implement them. Reducing the height by half should lead to a set of weights that should also perform very well on the full height as it is more fitted to surviving than to score high points.
* Reducing the width of the field would disturb the general flow of the game and it would make the results particularly uninteresting for comparisons.
* The idea of Shahar and West (2010) to implement boundaries to the length of the game should decrease the expense massively. Besides this, it promises to show another interesting aspect of the genetic algorithm: Provided with the number of points to score, instead of using the number of cleared lines it evolved towards scoring more combos by taking more risk.

### C

# Reinforcement Learning

## Literature Review

## Our Approach

### A

### B

# Conclusion

# Appendix

# References

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1. Guinness World Records [↑](#footnote-ref-1)
2. Fahey(2012) [↑](#footnote-ref-2)