

Growing with Big Data, A Tetris Player: Project Report by Group 22 *

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1 Introduction

The purpose of this project is to create a utility based agent to maximise the number of rows removed in a game of Tetris. This tetris playing agent uses a heuristic function to estimate the utility of each state.

In this report, we discuss how this agent was designed and the features used to evaluate the utility of the board. We will also look at how we have implemented and used genetic algorithm to train a tetris agent that could play Tetris decently well, averaging about 19,700,000 lines cleared.

2 Strategy

The agent's heuristic function sums the linear weights $w(k)$ of features $\varphi_k(s)$ (As stated in subsection 2.1) for a given state of the board, s , where n is the number of features as shown below:

$$\hat{V}(s) = \sum_{k=0}^n w(k)\varphi_k(s)$$

Where at every turn, the agent evaluates, among all possible moves using the heuristic function, the move that gives the best utility.

2.1 Features Selected

This is the list of 11 features that we have selected. They allow us to evaluate each state s based on certain characteristics of the board.

- **NUM_ROWS_REMOVED** – Number of rows removed
- **MAX_HEIGHT**
- **TOTAL_HEIGHT**
- **TOTAL_DIFF_HEIGHT** – Sum of all difference in height of all columns
- **LANDING_HEIGHT** – Height of where the next piece lands
- **NUM_HOLES** – Number of empty cells with at least one filled cell above
- **COL_TRANSITION** – Number of filled cells adjacent to empty cells, summed over all columns
- **ROW_TRANSITION** – Same as the above, but applied to rows
- **COVERED_GAPS** – Number of empty cells with a filled cell anywhere above them
- **TOTAL_WELL_DEPTH** – Sum of the depth of all wells
- **HAS_LOST** – Gives a penalty of -10000 if move result in loss, else give 100

2.2 Genetic Algorithm

For our implementation of the genetic algorithm, Each chromosome has a weight vector where each gene (weight value) corresponds to one of the 11 features stated in subsection 2.1, and a fitness score.

*Contributions are weighed by the opacity of the author's name

The fitness score of each chromosome is defined as the mean score of playing 50 games using that individual's chromosome weight.

This is our implementation of the genetic algorithm:

1. Start out with 1000 individuals with random weights. Initially calculate their fitness score.
2. Select 40% of population via Stochastic Universal Sampling to be potential parents
3. Generate 40% of population as offspring by the process below:
 - (a) Randomly select 2 parents from the pool generated above
 - (b) Crossover with 80% chance, by taking weighted average of genes
 - (c) Mutate these 2 offsprings with 8% chance by adding 1/10 times the random gaussian value.
 - (d) calculate fitness score for the 2 offsprings
 - (e) Add to offspring pool
4. Cull bottom 40% and replace with offsprings in offspring pool
5. Repeat steps 2 to 4 for each generation, till convergence

Convergence is determined by the score of the best individual in the population. If this score has not improved for 50 generations, we terminate the algorithm.

2.3 Parallelisation and Speedup

Each generation of the algorithm required running games to evaluate fitness. This meant that as the weights progressively got better, each generation started taking a longer time to evaluate.

We decided to parallelise the games by running each game on its own thread. Playing 100 games each, with a set of decent set of weights ¹, the time taken for the parallelised version was 2059 seconds while the sequential version was 6897, giving a

¹weight vector used $w = [0.00134246, -0.01414993, -0.00659672, 0.00140868, -0.02396361, -0.03055654, -0.06026152, -0.02105507, -0.0340038, -0.0117935, 1]$ played over 200 games in total, 100 games sequentially and 100 games in parallel, with a total average score of 841279

speedup of 3.34 times.

Another way that we have tried speeding up the learning algorithm was to simply reduce the number of rows that the board has. Our team ran 2 instances of the learning algorithm with a smaller board of 9 rows and 13 rows respectively. The instance running with 9 rows, even at later generations, took an average of 30 minutes per generation, while the latter, took an average of 4 hours per generation.

The used for the training and running all the above tests was ;PLEASE WRITE THE SPEC OF NUS CLUSTER SERVER USED, ITS NUS COMPUTING CLUSTER xgp0;

3 Results

The following results are from the weights shown in Table 1. These weights were derived from the instance running GA on a board with 13 rows at generation 132.

Features	Weights
NUM_ROWS_REMOVED	-0.10994115458466136
MAX_HEIGHT	-0.1154697834187254
TOTAL_HEIGHT	-0.04390525258236673
TOTAL_DIFF_HEIGHT	0.017912908135268947
LANDING_HEIGHT	-0.3044476707923254
NUM_HOLES	-0.38617473506172584
COL_TRANSITION	-0.12518629866820255
ROW_TRANSITION	-0.22806177833393343
COVERED_GAPS	-0.7696058904564755
TOTAL_WELL_DEPTH	-0.19377750577164388
HAS_LOST	0.13672271498097804

Table 1: Respective Weights for Features

The result of running 600 games can be seen in Figure 1, while some common metrics of the 600 games can be seen on Table 2.

Features	Weights
Q1 (25th Percentile)	6,307,657.5
Median	13,655,622.0
Q3 (75th Percentile)	25,716,898.5
Mean	19,793,958.2
Max	216,319,742.0
Min	5125.0

Table 2: Common Metrics for the Scores

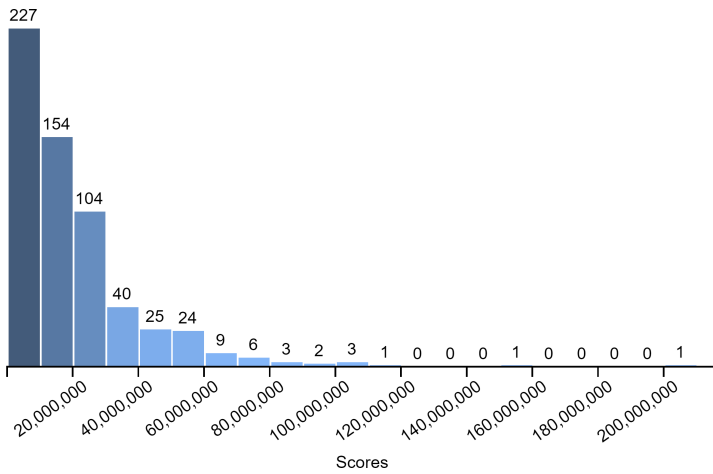


Figure 1: Results from 600 games

As we can see from the result, most of the games played lie below 30 million lines cleared. However we do see a few outliers that broke 50 million lines cleared, including our best run at 216,319,742 lines cleared.

4 Discussion and Findings

The choice of features used within the utility function was extremely important. We initially implemented our most of our original set of features without HAS_LOST, because of how well these features had worked in previous works of tetris playing agents, such as the Tetris applications by Colin Fahey and Pierre Dellacherie [1].

However, most of the features as shown above does not take the next move as a win or loss directly, therefore an important characteristic of the board has not been captured. Implementing HAS_LOST discourages our agent from making a losing move if there are other moves available that will prolong the game.

¡APPEND MORE AND COMPLETE THIS SECTION!!!! THIS IS THE LAST STRETCH!!¿

5 Conclusion

Our aim in this paper was to show we can use Genetic Algorithm to apply to strategies in terms of weights to our feature-based utility function to evaluate the best moves. We have showed that the algorithm could settle at a good set of weights, despite not having a guarantee that each consecutive generation would improve. The set

of weights that we have derived based on these features could then be used in as a starting point in another algorithm in order to learn the optimal weights. One example may be Least Square Policy Iteration by Lagoudakis and Parr [2], of which our Tetris problem could be tailored to fit a control problem as stated by Lagoudakis.

We also think that in order to design a utility based agent that could play well, we should not only rely optimising the weights for a set of features, but we should also choose good features as well. As discussed above, having a set of features that could better represent the state of the game results in an agent that could potentiall play better. Perhaps another interesting area to research would be looking into creating algorithms that could optimise and learn new features of the board state, and thus the utility function, instead of only its weights.

References

- [1] Colin P. Fahey, Tetris AI, 2003
<https://www.colinfahey.com/tetris/tetris.html>
- [2] Michail G. Lagoudakis, Ronald Parr. *Journal of Machine Learning Research* 4 (Dec), 1107-1149, 2003