NOVA IMS

COMPUTATIONAL INTELLIGENCE FOR OPTIMIZATION

Playing snake with genetic algorithms

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https://github.com/stuartgo/cifo

INTRODUCTION

In this project we aimed to implement a genetic algorithm (GA) able to optimize the set of weights of an artificial neural network so that it was able to successfully play a snake game. After implementing the game, we tested multiple combinations of genetic operators, selected the best ones, and carried out further experimentation by changing specific parameters, applying elitism, and modifying the fitness function (FF).

INITIAL EXPLORATION

Initially, we decided to implement the snake game, the state representation, and the FF with custom functions built from scratch. After extensive experimentation we realized the GAs were not converging, even after several generations. Therefore, we ended up retrieving the code for the snake game and part of our testing structure from similar projects to have a better baseline to experiment with. This resulted in fewer game bugs and successful convergence.

Once we had a model that seemed to improve over time, we implemented the genetic operators. Specifically, we implemented standard mutation, creep mutation, and geometric semantic mutation. Creep mutation is very similar to standard mutation, but the random value is less arbitrary as it is limited to the range between the highest and lowest values present in the weights vector [1]. Regarding crossover, we implemented standard, uniform, and geometric semantic crossover. Uniform crossover, specifically, selects a gene from either parent with 50% probability [1]. As for the selection methods, we tested fitness proportionate, ranking, and tournament selection.

During our first attempts we quickly discovered that applying GAs, at least to this specific problem, was computationally demanding, especially since each GA has to be run multiple times so that different algorithms can be adequately compared. This forced us to move away from the brute force strategy of testing every possible combination of genetic operators with each version of elitism, state representation and FF. As such, we started with a preliminary test of different combinations of genetic operators to select the most promising before moving on to elitism and finetuning the fitness functions.

PROBLEM REPRESENTATION

To tackle this optimization task we built an artificial neural network (ANN) with an input layer with 12 neurons (number of input parameters), a single hidden layer with 32 neurons (chosen arbitrarily), and an output layer with 4 neurons (the four possible directions the snake can move in). This network allowed us to represent each snake, *i.e.*, solution, as a set of 512 weights ($12 \times 32 + 32 \times 4$). The input layer was changed after selecting the best performing combinations of genetic operators to see if it could be improved (see: *State Representation*). The genetic operators were all written to use maximization as an optimisation technique, but equivalent functions for minimisation were written where necessary.

In more detail, the input vector consisted of 4 values that detect “danger” around the head of the snake, 4 more values representing the direction in which the snake is moving, and 4 other values representing where the apple is relative to the snake. After several failed attempts at

implementing our own snake game and choosing our own input, the final decision was made based on existing projects. Using these 12 features as input expedited convergence, thus decreasing the number of generations required to achieve a reasonable performance.

For each generation, we considered a population of 50 snakes, where each snake was allowed a total of 5000 moves. This means that a snake can die multiple times within those 5000 steps, at which point it will be reset to try again. It also ensures that . After each generation, 12 individuals were chosen based on the selection operators. These were then used to breed the next generation and, if elitism was enabled, were themselves copied into the next generation. This is slightly different from the approach mentioned in the booklet and the practical classes, where a new pair of parents is selected for each crossover event. Because the selection was made from a breeding pool, an additional degree of randomness is introduced. Concretely, randomness is introduced by the selection functions themselves when building the *breeding_pool*, and again when selecting the individuals from that pool.

For our initial testing we adapted the FF from an existing project (*Eq. 1*) to ensure that we had a working function before running 27 different models [4]. Each model was run 30 times, totalling 810 runs.

$$f = -150 * deaths + 5000 * record - 1000 * penalty - 100 * steps\ per\ food \quad \textbf{(1)}$$

The result of the FF can be interpreted as the snake's score, which increases whenever a snake achieves a highscore and decreases for one of three reasons. First, the score decreases if the snake dies. Second, a penalty is applied to prevent infinite loops, *i.e.*, situations where a snake keeps "going around the block", which is actually quite common in early generations. Specifically, the score decreases if a snake goes 200 steps without eating anything, at which point the snake is reset. Finally, inefficient snakes, as determined by a higher average number of steps per food eaten, are punished.

As for the parameters for the various operators we used a breeding pool of size 12, a creep mutation rate of 0.1, standard mutation rate of 0.05, ms for geometric semantic mutation of 0.1 and a tournament size of 15. Breeding pool size was chosen based on similar projects, while the mutation rates were set based on some preliminary tests with some guidance from literature [2]. The ms was set based on literature and tournament size was tuned based on values given in the referenced booklet [3].

INITIAL EVALUATION

While evaluation of the results was done via the fitness function, the values returned by it are not particularly informative. As such, we kept track of statistics that are easier to interpret, such as the average number of deaths, maximum score, overall average score, and maximum average score (the snake with the highest average score in a generation). As a criterion to select the best models we used the mean average score of the last generation across 30 independent runs. This created a nice separation where the top 6 models (out of 27) had a score that was at least twice as good as the model in the 7th position. The models selected are shown in *Table 1*, and an overview of their fitness values throughout the different generations is provided in *Figure 1*.

Table 1. Top 6 genetic algorithms (GAs) for optimisation of the snake game. Selection of best performing GAs was made based on the average score of the final generation. In total, 27 combinations of different mutation, crossover, and selection operators were tested, with each combination being run a total of 30 times. Average: mean average score of the last generation. Max score: best score across all generations.

Mutation	Crossover	Selection	Average	Max score
Creep	Standard	Tournament	4.40 ± 1.28	36 ± 7.67
Creep	Uniform	Tournament	2.16 ± 0.37	11 ± 2.14
Standard	Geometric	Tournament	1.35 ± 0.01	14 ± 2.29
Standard	Uniform	Tournament	1.24 ± 0.20	10 ± 3.61
Creep	Geometric	Tournament	1.39 ± 0.22	20 ± 3.87
Geometric	Geometric	Tournament	1.10 ± 0.05	4 ± 1.13

As seen in the previous table, one of the deciding factors seems to be the selection algorithm, given that tournament selection was used in all of the best models. This is likely related to the fact that, out of a randomly selected pool of individuals, those with the best fitness get selected, and those individuals continue to perform well in the following generations. Besides tournament selection, the best model implemented creep mutation and standard crossover to obtain a significantly better performance than the model that ranked second (*Fig. 1*).

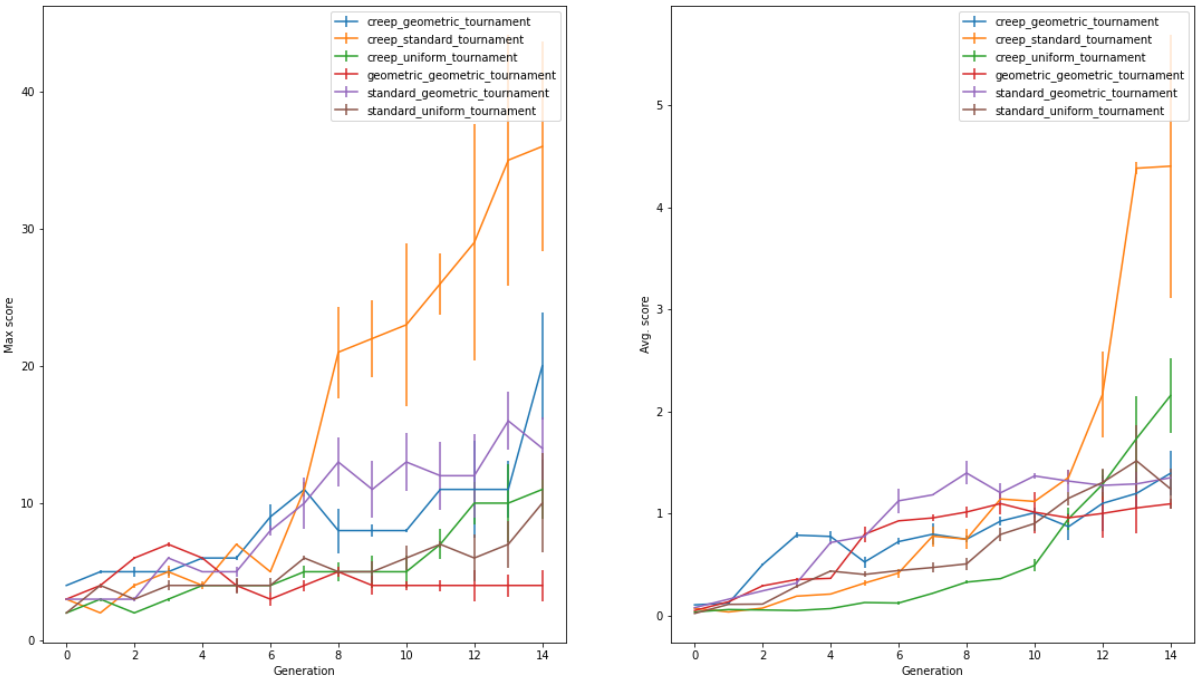

Fig 1. Maximum (left) and average (right) scores for the 6 best performing genetic algorithms. The algorithm leading to the highest maximum score used creep mutation, standard crossover, and tournament selection, and was also the algorithm leading to the highest average score in the last generation. Results shown for each generation were obtained by averaging the results of 30 independent runs.

It is important to note that, even if the average score of the snakes increases over time, most snakes still performed quite poorly, even in the final generation. This was also applicable to our best performing GA where, despite a few snakes achieving a fairly high score (>15 points), most had a weak performance and scored less than 5 points (*Fig. 2*).

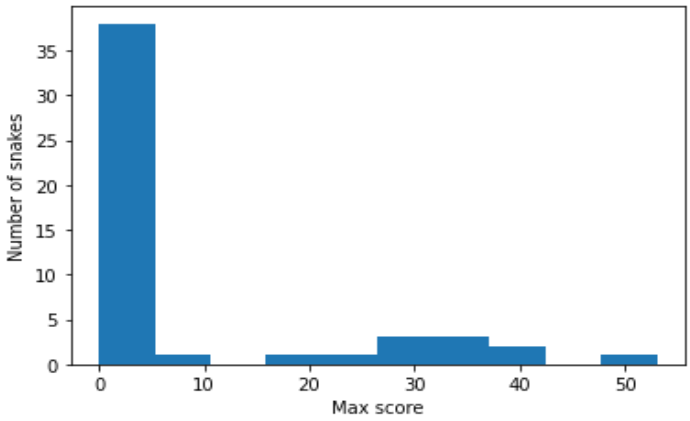

Fig 2. Distribution of snakes based on their maximum score for the last generation of the best performing algorithm. The best performing algorithm used creep mutation, standard crossover, and tournament selection (*creep_standard_tournament*), as shown in Table 1. The algorithm was run for 15 generations. Results shown refer to a single run but are representative.

This preliminary screening allowed selecting the best performing combinations of genetic operators for the problem at hand, but we acknowledge that it has a few limitations. Namely, it is entirely possible that further parameter tuning would make models that were not selected better than those that were. However, this was a compromise we needed to make due to limited time and computational power. Testing multiple combinations of operators multiple times is demanding by itself, and including different hyperparameters and potentially elitism at this stage would exponentially increase the amount of time required for this initial test.

EXPERIMENTING WITH STATE REPRESENTATION

The already described state representation was iteratively developed to capture the information that is essential for the snake to make decisions. We also tested a more complex complex state representation with a matrix representing the board with 1s where the snake is, 2 for the food, and 0s otherwise. This was run for 15 generations with little sign of improvement, and the maximum score for the best 6 models was always 3. This is probably due to the complexity of the state, capturing the mapping with the now much larger input layer to the output layer might have converged with more generations, but it's hard to say.

EXPERIMENTING WITH FITNESS FUNCTION

As seen previously, the FF has a tendency to create a few very good individuals while the vast majority of the snakes have very low fitness and produce low scores. To improve this we experimented with a new FF:

$$f = -100 * deaths + 8000 * record - 2000 * penalty$$

For one, the penalty of each death was reduced in an attempt to increase diversity in later generations. Furthermore, we increased the reward for achieving a record. The penalty was also increased so that an individual is punished any time it returns to an already visited state, to avoid looping snakes. Finally, we also tried removing the penalty for snakes that followed an inefficient path between current position and the position of the food, to promote exploration of the map. However, this FF led to results that were considerably worse than the previous FF. In fact, the best snake obtained using this modified FF had an average score that was about one-fourth of the score of the worst snake obtained using the previous FF. This was true even after training the model for a longer time.

ELITISM

We tested the models both with and without elitism (*Fig. 3*). In the case of the former, the entire parent pool was copied to the next generation. In general, elitism improved the results obtained for the top 6 GAs (*Table 1*). This was particularly noticeable for the already best performing *creep_standard_tournament* algorithm. This makes sense, since elitism ensures that the best performing snakes of a previous generation are not lost when creating a new generation. Based on the results obtained, it is likely that these snakes continue to perform well as generations progress.

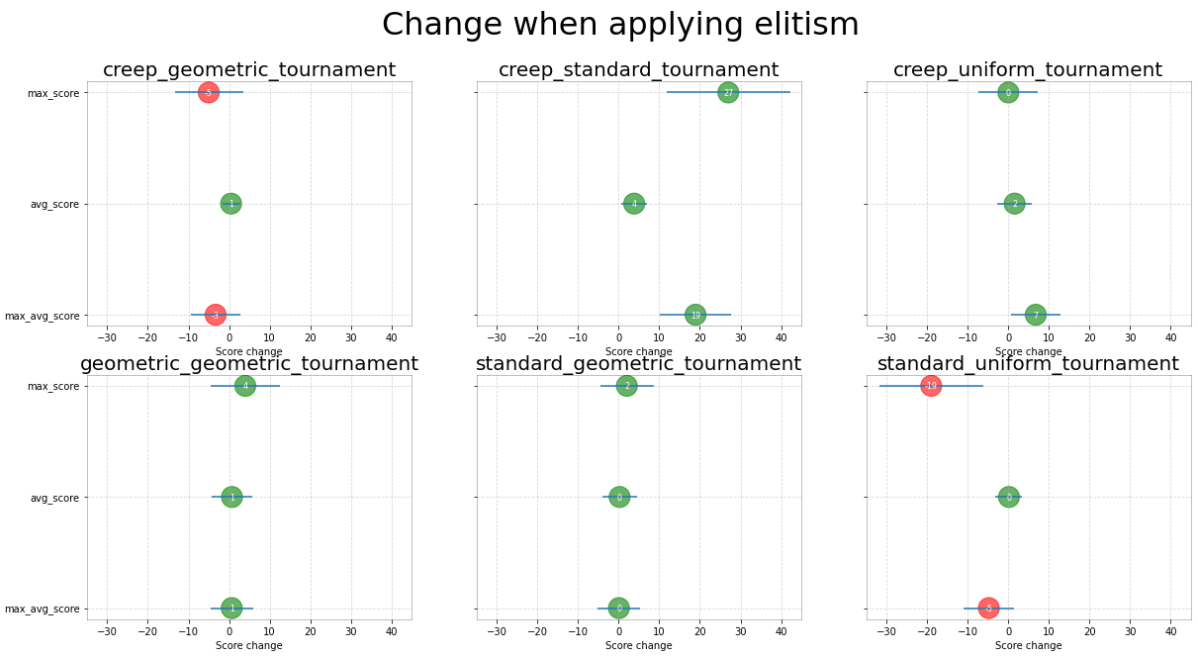

Figure 3. Changes in maximum score, maximum average score, and overall average score when elitism was applied to the 6 best performing GAs. GAs were run for 15 generations. Red circles indicate a worse score after applying elitism, while green circles indicate an improvement. Results were obtained after averaging the results of the last generation across 30 runs.

CONCLUSIONS AND FUTURE WORK

Overall, we consider that the main goal of this project, *i.e.*, building a model able to autonomously play snake, was achieved. When using the most promising GA to optimize the weights of the neural network the maximum score was 58 after only 50 generations, which we consider to be satisfactory. However, it is important to note that for every tested combination of genetic operators, the average snake got a fairly low score. Ideally, instead of producing only a few very good snakes, the model would lead to an overall improvement of the population over time. This can probably be achieved with further experimentation and fine-tuning of the fitness function and of the parameters used for the genetic operators. Changing the structure of the neural network might also improve the results obtained and merits further work.

WORK DISTRIBUTION

Work was split evenly, with everyone contributing to both the code and the report. A good understanding of the code was required so that it could be run simultaneously in multiple computers.

REFERENCES

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[3] Geometric Semantic Genetic Programming Algorithm and Slump Prediction,2017, Xu, Shen
[4] https://github.com/davide97l/Snake-Battle-Royale